Crowding Out and Crowding In of Private Donations and Government Grants

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Abstract

A large literature examines the interaction of private and public funding of charities, much of it testing if public funding crowds out private funding. In this paper I look for two alternative phenomena, using a large panel data set gathered from nonprofit organizations' tax returns. First, I look for crowding out in the opposite direction: increased private funding may cause reduced public funding. Second, I examine how funding may act as a signal of charity quality, and thus crowd in other funding. I find evidence that government grants crowd in private donations, with a larger effect for younger charities, consistent with signaling. Regression point estimates indicate that private donations crowd out government grants, but they are not statistically significant.

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Public goods are often provided by both governments and individuals. The interaction of these two sources may affect the overall level of funding. In response to an increase in government spending on a public good or charity, individuals may reduce their contributions. The same effect can occur in the opposite direction. If a government sees that private donations to a charity have risen, then it may reduce its support of that charity. Additionally, some funding may crowd in other funding if it signals charity quality.

The literature on crowding out extends back to Warr (1982) and Roberts (1984), who show theoretically that an exogenous increase in government funding to charities decreases private donations dollar-for-dollar. Some empirical studies, including Kingma (1989), find support for such crowding out, but typically at a rate less than one-for-one. [1] Some studies find crowding *in*; Khanna and Sandler (2000) find this for charities in the UK, and Payne (2001) finds this for academic research institutions. Crowding in may occur if grants provide a positive signal of charity quality.[2] A signaling model of contributions to charities is presented in Payne (2001), Vesterlund (2003), and Andreoni (2006), where "seed money" from large donors or announcements of previous donations increase others' donations by acting as a signal of the charity's quality. Evidence of this effect is found in a field experiment in List and Lucking-Reiley (2002).[3]

That literature focuses solely on how government spending affects individual giving. This paper also examines the opposite direction of causality: do private contributions to charities affect public contributions? I look for evidence of either crowding out or crowding in in both directions using data on private and public contributions to charities. I also examine whether crowding in is consistent with quality signaling.

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[1] One explanation for partial crowding out, provided by Andreoni (1989), is that individuals are "impure altruists" in that they receive a "warm glow" from their own giving, independent of the level of the public good. For more recent evidence of crowding out, Parker and Thurman (forthcoming) find that government provision of open space can crowd out purchases from private land trusts, Dokko (2009) finds that government contributions to arts groups via the National Endowment for the Arts crowded out private donations, Brown and Finkelstein (2008) find that Medicaid crowds out private insurance, and Gruber and Hungerman (2007) find that New Deal programs during the Great Depression crowded out church spending on social services.

[2] Rose-Ackerman (1986) describes other conditions under which government grants can crowd in private donations. For instance, matching grants are likely to spur an increase in donations. Grants may also come with mandated regulatory changes that make the charity more appealing to donors. If a charity exhibits economies of scale, then increased government revenue reduces the marginal cost of providing the service, making private donations more effective.

[3] Landry et. al. (2006) also find some evidence that seed money increases others' contributions, but they find a stronger effect from being entered in a lottery for a cash prize when donating and from the physical attractiveness of the person asking for a contribution. Lange (2006) develops a model where the lottery prize money is provided by donors and thus acts similarly to seed money.

This paper makes two contributions to the literature on crowding out and crowding in of charitable giving. First, though numerous papers test whether government grants crowd out private donations to charities, none can be found that test for crowding out in the opposite direction using micro-level data.[4] In fact, a negative correlation between government and private funding of charities could be evidence for crowding out in either direction. Here, I test for causality in both directions, using instrumental variables for identification. Second, I test if crowding in can be explained by signaling. I use a panel of financial data from almost 30,000 charities over six years.

I find that government grants crowd in private donations, with a dollar increase in government grants leading to an increase in private donations between 15 and 30 cents. This result is robust to various specifications of the data sample. I also find that this crowding in is consistent with signaling, since the rate of crowding in is larger for younger charities. These are charities about which less information is likely to be known by donors, and thus the signal value of a grant ought to be larger. For the oldest charities, the crowding-in effect disappears. Estimates of the effect of private donations on government grants are not significant, but the point estimates are negative, indicating crowding out.

The presence of crowding in of contributions to charities is of concern to both governments and individuals who make these contributions. A government might choose an optimal level of provision of a charity or public good and adjust its funding to reach that level. Without accounting for the crowding in response by private donors, funding may exceed the optimal level. Likewise, if the level of private donations affects government support, then an individual's optimal level of giving ought to account for the reaction of government grants. Many worry that large increases in private funding for global public health initiatives, including large grants from the Gates Foundation, are causing local governments to reduce health spending, evidence of crowding out of government grants.[5]

A theoretical model is not presented here but is available in an earlier working paper version of this paper (Heutel 2009) or an online appendix. Here I summarize the main intuitive findings of the model that guide the empirical work. The one-for-one crowding out result from

[4] Garrett and Rhine (2010) use time series data on aggregate government and private contributions to charities to test for Granger causality in both directions. They find evidence that grants crowd out donations and that donations crowd out grants for some types of charities and some types of government funding.
[5] See Cohen (2006) and Smith and MacKellar (2007).

Warr (1982) and Roberts (1984) assumes that government grants are set exogenously and private donors respond to them. An alternative assumption is that private donations are exogenous, and the government chooses a level of contributions to maximize social welfare in response. Under this assumption a symmetric result is found: private donations crowd out government grants at a one-for-one rate. The model can be extended a number of ways, by including a warm glow effect, modeling governments as non-benevolent, including charity response, or considering various equilibria in which both private donors and governments move endogenously. The warm glow effect in particular changes the magnitude of crowding out; it will be at a rate less than one-for-one. But the main finding is sustained: government grants can respond to private donors in the same way that private donors can respond to government grants. The first empirical question is the following: do private donations crowd out government grants?

The second empirical question is generated by extending the model to allow for imperfect information. Supposing that governments observe a charity's quality while private donors do not,[6] government can use its funding to signal quality. If the government signals higher quality with higher funding, then a crowding-in effect will emerge: higher government grants will cause higher private donations. The magnitude of this crowding in depends on how individuals' beliefs about charity quality are influenced by government grants, i.e., the strength of the signal. The crowding-in effect exists alongside the crowding-out effect; it is not clear which effect dominates. The second empirical question is thus the following: is there any evidence of crowding in, either of private donations by government grants or in the opposite direction?

The finding of crowding in is not definitive evidence of signaling, since crowding in could materialize for other reasons. So, where I do find crowding in, I also investigate if the crowding in is consistent with signaling. The crowding-in effect occurs only when there is imperfect information about charity quality. It is likely that information about charity quality varies by charity. What types of charities might be more well-known to potential donors? Older charities are more likely to have well-established reputations; younger charities are more likely to be unknown by donors. I therefore expect that the crowding-in effect from signaling will be larger for younger charities than for older charities. Another empirical question is the following: where there is crowding in, does its magnitude vary by charity age?

[6] This supposition can be reversed to yield symmetric results.

Charities typically advertise the grants they receive from both governments and private grant makers on their websites, in newsletters, and in press releases. If government grants crowded out private giving, it is unlikely that charities would make public the receipt of such grants. On the other hand, grants signaling quality and crowding in donations are more consistent with this observed behavior.

I. Data

The data on nonprofit organizations come from IRS tax returns filed by eligible organizations. These data are collected and distributed by the National Center for Charitable Statistics (NCCS) at the Urban Institute.[7] They are based on the Forms 990 or 990EZ that must be filed by all 501(c)(3) nonprofit organizations except for religious organizations and any organization with less than $25,000 in gross receipts.[8] These data from 1998-2003 are contained in the Guidestar-NCCS National Nonprofit Research Database, which contains 1,388,480 observations from all public charities that filed within those fiscal years. The data set does not include 501(c)(3) private foundations, which receive most of their money from investments and endowments and use it primarily to make grants to organizations rather than directly for charitable services; private foundations file IRS Form 990-PF.

Organizations are classified according to the National Taxonomy of Exempt Entities (NTEE), a system developed by the NCCS. The NTEE divides charities into 645 centile level codes, collapsible into 26 major groups and 10 major categories. In order to make my results more comparable with prior research, I limit my scope to a particular set of charities. Most research in crowding out or crowding in of charitable donations has examined social service charities, and so I select organizations from the following NTEE categories: crime, employment, food and nutrition, housing, human services and community improvement.[9]

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[7] http://nccs.urban.org.

[8] Religious organizations receive over half of all charitable giving in the United States (Ronsvalle and Ronsvalle, 2001). Religious organizations that receive the majority of their revenue from serving the general public are required to file Forms 990. These include the Sisters of Mercy hospital chain and Lutheran Social Services. About 15,000 such religious organizations were required to file in 2001. Examining donations to Presbyterian Church congregations, Hungerman (2005) finds that government provision of charitable services crowd out church donations by 20-38 cents on the dollar.

[9] These are the organizations listed under the 1-digit NTEE codes of I, J, K, L, P and S. This is the same set of codes used by Andreoni and Payne (2003) for their set of social service organizations. Andreoni and Payne (2003) also exclude some organizations that they describe as not directly providing services, while I include all 501(c)(3) organizations in those categories (see their fn 15).

The large data set, containing entries from all 501(c)(3) nonprofit charities that filed with the IRS between 1998 and 2003, is useful for analysis but also presents problems with messy data. Froelich et. al. (2000) discuss the adequacy and reliability of the data from IRS Form 990. They find that the reported data are fairly consistent with more detailed audit information, especially in the basic categories of contributions, programming, and fundraising. Still, I undertake measures to clean the data. The data set contains 339,716 observations on 76,725 charities. I drop observations for which there is clear evidence of reporting error. Some charities report revenues by category (e.g. private donations, government grants) that do not add up to the reported level of total revenues. Likewise, for some charities the expenditures do not add up correctly. I purge all of these observations from the data set, leaving 321,094 observations (95%) and 75,226 charities (98%). Though the data are a panel, it is a very unbalanced one. To compensate, I include in the base case regressions only those charities that appear for all six years, leaving 175,242 observations (55% of the previous total) and 29,207 charities (39%). Below, I consider how limiting the data set to a balanced panel affects both the summary statistics and the regression results. Finally, I eliminate charities that ever report a negative value for private donations, government grants, or program service revenue, eliminating an additional 69 charities (only 0.2%). Regressions are performed on this cleaned data sample as well as on a number of subsamples that eliminate certain types of charities or observations, as described below. In general, the results that I obtain in the base case are robust to these different sample specifications. This is especially important to note for this application, since previous authors have found that when working with data from Form 990s the choice of sample matters greatly for the results.

Previous authors have found discrepancies or errors in similar data sets, especially in the identifier variables for the charity's type (NTEE code) and state. Among the charities in the balanced panel, none change their NTEE code over the six year period. Some charities (1,206, or 4.1%) do change states. This could be due to data error, which is problematic since many of my control variables and instruments are at the state-year level. Or, it could result in the charity actually relocating, in which case I want to take advantage of that variation. I identify the charities that are erroneously coded as changing states in the following way. Of the charities that are reported to change states, 830 of them (68.8%) have the same state listed for five out of the six years, and the year in which the state is listed differently is not the first or last year of the sample. As it is unlikely that a charity would relocate one year and then relocate back the following year, I interpret these observations as errors and replace the state variable with the state from the charity's other five observations. The remaining 376 charities either moved in the first or last years of the sample period or had more than one year in a different location, and I do not change the state variables for them. An inspection of the scans of the original 990 forms for several of these charities supports this distinction between those that actually moved and those that were inaccurately reported.[10]

Table 1 presents revenues aggregated into four main categories and compares summary statistics from the full, uncleaned data set to those from the smaller sample used in the analysis. Private donations include direct and indirect public support.[11] Government grants and program service revenue have their own categories,[12] and the remaining revenues are classified as "other." I also present statistics on charities' reported fundraising expenditures. Table 1 shows that the mean values are all much higher than the median values, and even the 75th percentile values, suggesting a data set that is skewed towards high-revenue organizations. The differences between corresponding statistics in the full data set and the cleaned sample are small; the mean values of all variables are smaller and the median and 75th percentiles are larger in the limited data compared to the full set. The limited data are slightly less skewed than the full data, and hence performing econometric analyses on this limited sample may overemphasize the effect from larger charities.

II. Econometric Strategy

Fundamentally, two different empirical questions are investigated. First, do government grants affect private donations to charities? Second, do private donations affect government grants? While numerous papers have tested for causality in the first direction, no paper has examined causality in the opposite direction using panel data on a large number of charities. Because of these two questions, I run two separate regressions, one in which the level of private donations to a charity is the dependent variable and the level of government grants is an

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[10] Simply dropping all charities that report moving states from the regression analysis results in coefficients of approximately the same value as in the base case.

[11] Indirect public support is comprised mainly of donations given to the charities collected by federated fundraising agencies, such as the United Way.

[12] Program service revenue is the money collected from the services that form the organizations' exemption from tax. For example, a hospital would count as program service revenue all of its charges from medical services.

independent variable, and one with those two variables reversed. Initially I merely identify whether crowding out or crowding in occurs in either direction, and I do not attempt to account for its source. Following these initial regressions, I will test whether any crowding in that I find is explained by signaling. I show that crowding in is stronger among those charities for which less information is known by donors, i.e. younger charities.

The estimating equations take the following form:

$$y_{it} = \beta x_{it} + \boldsymbol{BX_{it}} + \alpha_i + \gamma_t + e_{it}$$

The dependent variable y_{it} is either the level of government grants or the level of private donations for charity i in year t, depending on which regression is run. The right-hand-side variable of interest, x_{it}, is the opposite value (i.e. x_{it} is government grants when y_{it} is private donations, and vice versa). The net crowding-out or crowding-in effect is β. A vector of controls $\boldsymbol{X_{it}}$ is included for each observation. I exploit the panel nature of the data by including an organization-fixed effect and a year-fixed effect, α_i and γ_t, respectively.[13] The error is e_{it}.

The estimate of β will clearly be biased since both private donations and government grants are determined endogenously. A common shock, for instance an increase in demand for a charity's services, may affect both donations and grants simultaneously in the same direction, biasing upwards β. Alternatively, endogeneity could bias the estimate downwards. A restructuring of the charity could cause it to reallocate its funding between donations and grants, which would create a negative correlation between these two values not due to crowding out. To overcome this bias and identify β, I utilize instrumental variables. (Regressions in both directions without using instrumental variables are presented in the online appendix.)

Two separate sets of instrumental variables are required: one for each direction of causality. First, in the regression where private donations are the dependent variable and government grants are the endogenous regressor, appropriate instruments must be relevant (affecting the level of government grants) and excludable (not directly affecting the level of private donations). For this set of instruments, I use state-year-level measures of government transfers to individuals from Supplemental Security Income (SSI) programs.[14] This represents the overall level of transfers and government giving in a state a particular year. Some states may

[13] The Hausman specification test rejects the assumption that the unobservable effect is uncorrelated with the other regressors, so a fixed-effects model is employed rather than a random-effects model.

[14] Khanna and Sandler (2000), Andreoni and Payne (2003), and Payne (1998) use similar instruments. Data are available from the U.S. Social Security Administration website.

be more "generous" in their giving, and these instruments ought to proxy that.[15] The generosity of government is determined in a political process, and thus it may be directly correlated with private donations and fail the exogeneity requirement: more generous donors elect more generous governments. This is controlled for by the inclusion in the set of controls $\boldsymbol{X_{it}}$ of the political and economic variables described below. The maintained assumption is that whatever variance in a state's SSI transfers not accounted for by political or economic variables ought to capture something about the government itself rather than about the underlying electorate, and thus these instruments ought to satisfy the exogeneity assumption.

Second, instrumental variables for private donations ought to affect private donations but not government grants directly. I use one instrument for private donations, available at the charity-year level: membership dues. Funding from individuals can come from two sources, listed separately on the Form 990: direct public support (donations) and dues. Though it may appear that membership dues are just an alternative way to classify private contributions, there are well-defined differences between the two funding sources, as delineated in the Form 990 instructions. Charities are instructed to report as dues only those payments that "compare reasonably" with available membership benefits. Examples of benefits listed in the instructions include subscriptions to publications or newsletters and reduced-rate admissions to events. If membership dues exceed the value of such benefits, then charities are instructed to report the difference in value as donations, not dues.[16] Dues are thus what members pay for the *private goods* consisting of membership benefits, not the *public good* that is the charity's primary purpose. The amount of dues that a charity receives is likely to be correlated with the amount of private donations received, since charities with higher membership bases may get more of both types of revenues. However, given that charities provide public goods only using monies from

[15] Though the basic level of SSI benefits is set at the federal level, many states choose to supplement that value. I also used the level of OASDI benefits as instruments, but adding those had no effect on the results.

[16] The wording from the 2003 Form 990 Instructions (nearly identical for all sample years) is: "Dues received by an organization, to the extent they are more than the monetary value of the membership benefits available to the dues payer, are a contribution that should be reported on line 1a [private donations]." Also: "If a member pays dues mainly to support the organization's activities and not to obtain benefits of more than nominal monetary value, those dues are a contribution to the organization includable on line 1a." After the 2007 tax year, the Form 990 was substantially redesigned, and membership dues are no longer reported as a separate category. (Dues are now included with program service revenue, not with private donations.)

their contributions and not using monies from dues, the level of government grants ought not to respond to the level of dues.[17]

There are several caveats to this instrument choice. First, there may be reporting error. Though charities are clearly instructed to delineate appropriately between dues and contributions, they may neglect to do so. Second, the instrument may be irrelevant; dues may not correlate with donations. Third, the exogeneity assumption may fail, if governments do in fact respond to the level of dues, treating them as contributions to a public good.

Though the exogeneity assumption cannot directly be tested, the regression results can shed some light on the validity of the identification strategy. On the whole, identification of the effect of government grants on private donations is more successful than identification of the effect in the other direction. First-stage results from both regressions are available in the online appendix. The F-statistics for the significance of the instruments in the first stage are all greater than ten for the regressions where government grants are the endogenous regressors and SSI transfer payments are the instruments, but the F-statistics are all less than ten for the first-stage regressions where private donations are the endogenous regressors and dues are the instrument. This suggests that dues may be a weak instrument for private donations, and that those regression results ought to be interpreted with caution. In fact, in the second-stage regression estimating the effect of private donations on government grants, the coefficient is not significantly different from zero.

An additional consideration involves the response of the charity itself to grants and donations. In particular, a growing literature examines how a charity's fundraising expenditures change in response to government grants (Andreoni and Payne 2003, 2010). Fundraising is therefore included in the regressions where private donations are the dependent variable. Furthermore, since fundraising expenditures are endogenously determined, I add instrumental variables for fundraising. I use two different variables at the charity-level as instruments for fundraising expenditures. First, I use the amount of administrative expenditures reported by a

[17] An alternative instrument for private donations that I investigated is a measure of the price of a dollar of charitable donation based on the state's income tax and rules for allowing deductions of those contributions. This, however, is a poor instrument because the donations to a charity in a particular state do not necessarily come from donors within that state, because tax rates are heterogeneous within a state, and because tax rates are likely to be directly correlated with government budgets and hence grants to charities.

charity on the Form 990.[18] Since the same personnel can be employed to do both administrative and fundraising tasks, the two types of expenditures may be correlated. In years when an organization has a higher level of management expenses, it is likely to be able to spend more effort and money on fundraising; the first stage regression results support this claim. Furthermore, the level of private donations that a charity receives in a given year ought not to be affected by management expenses, since management expenses are expressly *not* those expenses used in soliciting funds (i.e., fundraising expenses).[19] Second, I use the total liabilities of the charity reported in the current year. The idea behind this instrument is that it measures the financial security of the organization, which will help determine its fundraising strategy independent of private or public funding. A charity that in a particular year faces a less secure financial status (as measured by higher total liabilities) may seek to increase its fundraising expenditures to compensate; this claim is verified in first stage regression results. A charity's financial security could directly affect its level of private donations if donors respond to this level of financial security (e.g. a donor does not want to give money to a charity that is on the verge of collapse). However, it is unlikely that donors have information on the contemporaneous financial conditions of a charity, at least not to the extent that a charity has. Donors may perceive an overall level of a charity's well being, but this is controlled for with a charity fixed effect. [20]

Finally, I discuss the control variables $\boldsymbol{X_{it}}$ that are added to all of the regressions. At the charity level, these are the level of program service revenues and all other revenues. Furthermore, I gather a number of state-year or county-year level variables to control for economic, demographic, and political conditions. These are matched to the charity by the state or county where the charity is located. From the Bureau of Labor Statistics I obtain the county-year level unemployment rate, and from the Bureau of Economic Analysis the county-year level income-per-capita and total population. At the state-year level I include the fraction of the population 65 or older, the fraction of a state's US Congress and Senate delegations that are

[18] According to the instructions for the Form 990, administrative expenses, or "management and general" expenses, are a charity's "expenses for overall organization and management, rather than for its direct conduct of fundraising activities or program services."

[19] Breman (2008) uses the same variable to instrument for fundraising expenses in a data set from Swedish charities. She notes that in the Swedish data, some of the management expenses are used towards soliciting government grants. In the US data from the Form 990s used here, however, this is not the case.

[20] This same argument is made in Andreoni and Payne (2010), who use this variable as an instrument for fundraising along with another variable that is unavailable in my dataset: occupancy expenses.

Democrats, and a dummy for whether the state governor is a Democrat. Political and economic variables may have important effects on the levels of both private and public contributions to charities. A state with a higher proportion of Democrats in power is likely to be composed of more liberal citizens who may be more willing to provide financial support for charities. Likewise, Democratic congresses may be more willing to approve higher levels of funding for these groups. If so, leaving out political proxies causes an upward bias on the coefficient of interest.

III. Results

The results for these instrumental variables, fixed effects model regressions are presented in Tables 2 and 3. Table 2 presents the results from regressions where private donations are the dependent variable and government grants are the endogenous regressor; Table 3 presents the results from regressions where these are reversed. In column 1 are the base case results, using the full sample of cleaned data. The tables report the F-statistic for the significance of the instruments in the first-stage of the regression, the Hansen overidentification test J-statistic, and the Cragg-Donald F-statistic for weak instruments. The reported standard errors are robust to heteroskedasticity and autocorrelation, using a Newey-West kernel-based estimator of the variance matrix.

The coefficient of interest in the regressions in Table 2 is that of government grants. The expected sign of this coefficient is ambiguous. Absent government signaling of charity quality, it should be negative, indicating crowding out. Signaling can cause crowding in, making the coefficient positive. In the first column, the coefficient is positive though not quite statistically significant (the p-value is 0.102). This is evidence for crowding in rather than crowding out, consistent with results found by Khanna and Sandler (2000) and Payne (2001). Program service revenue is positively correlated with private donations in most columns, and other revenues are negatively correlated with private donations, though neither is statistically significant. Fundraising expenditures increase private donations. The coefficients on the state- and county-year level controls are generally insignificant.

Columns 2 through 6 present robustness checks by contracting or expanding the data sample. The model of crowding out depends on either governments or individuals being able to respond to the level of giving from the other. Thus, an effect of timing might not be captured entirely in this static model. Therefore, I use lagged values for the endogenous regressor and instruments in column 2. This lowers the coefficient value, and it becomes insignificant. This suggests that the crowding in effect occurs within the fiscal year, rather than as a lagged effect.

It is possible that crowding out or crowding in is only applicable to a subset of the charities, for two reasons. First, while some of the controls and instruments are at the state-year level, not all of the charities operate only in the state where they are registered. Many are national organizations that accept donations and possibly government grants from other states. For these charities, these instruments and controls are unlikely to be good predictors. Though I cannot know for certain which organizations are national and which are local, column 3 excludes those whose names begin with "National," "American," or "North American." I also exclude organizations classified as support organizations under the NTEE taxonomy.[21] These organizations do not directly provide services but support organizations or individuals who do provide services through management and technical assistance, fundraising, and public policy analysis. Second, many of the charities receive no government grants throughout the entire six-year sample period, and many receive no private donations throughout the period. Such charities are likely to receive no funding at all from one of these two sources, even in response to a change in the other funding source, and thus I also exclude them from the regressions in this column. Limiting the sample in this way slightly increases the magnitude of the coefficient, and it maintains about the same level of significance.

Column 4 limits the dataset in another way. Some types of nonprofits in the dataset may not truly be providing public goods, though they are granted nonprofit status. For example, arts organizations like theatre companies or symphony orchestras provide output that is excludable and rival.[22] While the data set here does not contain arts organizations, it includes some types of charities whose claim to providing public goods may be similarly suspect. The organizations that I consider to fall into this category and that are dropped from the regressions reported in column 4 include low-income and subsidized rental housing, senior citizens' housing and retirement communities, residential care and adult day programs (including adult day care and hospice), and centers to support the independence of specific populations (including senior

[21] These are organizations whose last two digits of the NTEE centile code are less than 20.
[22] Though of course whenever donors are motivated by altruism for these recipients, these are in fact public goods.

centers, developmentally disabled centers, and homeless centers). In this regression, the coefficient on government grants is again positive and is statistically significant at the 1% level.

Column 5 presents regression results when the data set is limited using a different criterion. Outliers are always problematic, and perhaps they are especially problematic for these data. I have already eliminated charities and observations for which there is clear evidence of accounting or reporting error, for example those whose summed categorical revenues do not add up to the reported total revenues. Even absent these obvious irregularities, though, one may worry about charities reporting unusually high levels of donations or grants. In column 5, I eliminate the influence of the largest charities by dropping from the sample those observations whose private donations are in the top 5% of the total distribution and those observations whose government grants are in the top 5%. This refinement does not substantially change the regression results. Finally, under data cleaning a large fraction of organizations was removed for not being in the panel for all six years. Column 6 thus replicates the regression results without removing charities based on the number of years in which they appear in the dataset. The coefficient of interest, on government grants, is larger by about a factor of two from the previous columns, but is no longer significant.

Overall, Table 2 suggests that a dollar increase in government grants to a charity increases the charity's private donations by about 15 to 30 cents. Though generally significant at only the 10% level, the results are robust to different specifications of the data sample. Table 2 presents the F-statistic for the joint significance of the instruments in the first-stage regression; they are strongly significant in all columns. Table 2 also presents the Hansen J test statistic from a test of overidentifying restrictions, possible because the number of instruments exceeds the number of endogenous regressors. The null hypothesis of this test is that the instruments are valid, so a rejection calls into question the validity of the instruments. The null hypothesis cannot be rejected in any columns. Finally, Table 2 presents the value of the Cragg-Donald F-statistic from Stock and Yogo (2005), a test for weak instruments. It should be noted that, though the F-statistics on the instruments from the first stage regression are high, the Cragg-Donald F-statistics are quite low compared to their critical values.

Table 3 presents the regressions in the opposite direction, where the level of government grants is the dependent variable and the level of private donations is the endogenous regressor. Column 1 is the base case, column 2 is with lagged regressors and instruments, columns 3 through 5 limit the sample as described above, and column 6 includes the unbalanced panel. The coefficient of interest is on private donations and is negative in five out of the six columns, but it is not significantly different from zero in any of these columns. The magnitudes of the point estimates are large, suggesting that private donations crowd out government grants by 30% to 190%. But this evidence is weak, because of both the lack of a significant coefficient and the weak instrument issues described earlier. Furthermore, the regression results from column 5, which eliminate the top 5% of charities measured by government grants or private donations, give a positive coefficient that is significant at the 10% level. The results in this direction are thus both mixed and weak. Other regressors are more significant. Program service revenue is negatively correlated with government grants, as is the county unemployment rate. The large Cragg-Donald statistics indicate that, though the instruments are somewhat weak, the 2SLS results are not misleading.

In addition to being robust to these alternative sample specifications, the results for the regressions where private donations are the dependent variable are robust to estimation by LIML instead of 2SLS and to tests of weak instruments based on the conditional likelihood ratio from Moreira (2003), though these regression results are not reported.[23] These results are also robust to estimating the equations simultaneously using 3SLS.[24]

Crowding in by Charity Age

The analysis finds evidence that government grants crowd *in* private donations for these charities. But is this due to signaling? The signaling explanation depends upon uncertainty among donors as to the charity quality. Thus a measure of uncertainty about charity quality will be beneficial in testing the signaling theory: charities about which individuals know less should experience larger crowding in effects than charities that are well known. How can the "uncertainty" about a charity be measured?

I use the age of the charity, as measured by the date that the IRS bestowed it nonprofit status. Older charities are likely to be better known by donors. If so, the signaling effect for older charities should be smaller than for younger charities. By interacting a charity's age with

[23] Software for implementing the Moreira (2003) test of weak instruments is available on Moreira's website: http://www.economics.harvard.edu/faculty/moreira/softwaresimulations.html. In general, the weak instrument problem only appears with a large number of (weak) instruments (Bound et. al. 1995).

[24] Monte Carlo studies comparing system estimators to equation-by-equation estimators have found that the efficiency advantages of the former are modest in finite samples (see Greene 2003, p. 451).

the value of government grants, I can determine if the crowding in from government grants depends on age.[25] The results for this exercise are presented in Table 4, which reports results from regressions where private donations are the dependent variable, government grants and fundraising expenditures are endogenous regressors, and the same instruments and controls are used as in Table 2 (though not reported). Additionally, charity age and an interaction of age with grants are included.[26] These results support the theory, with significant results everywhere except for column 2. The coefficient on government grants is positive and varies between about 0.8 to 1.3. The coefficient on age indicates that a charity aging by one year increases its donations by between $2,500 and $14,000, though the coefficient is not significant. Finally, the coefficient on the interaction term is strongly significant in all columns and indicates that the crowding in effect decreases by less than half a cent to four cents on the dollar per year the charity has been around. In the first four columns, the ratio of the coefficient on government grants and the coefficient on the interaction term indicates that grants crowd in private donations for charities younger than 40 years old and crowd out donations for charities older than 40. In the last column this figure is closer to 30 years old. This supports the theory that older charities receive less of a signal from receipt of grants, and so the value of crowding in is less.[27]

Contemporaneous and Cumulative Grants

The econometrics are static. Since charities exist for many years, the effects from crowding out or from signaling are likely to last for more than just a single year. It thus seems appropriate to consider dynamic extensions of the empirical results. One would expect that the signaling effect is likely to be cumulative over time: a grant signaling high quality in period t will positively influence donations not just in period t but also in periods t+1, t+2, etc. This is because the quality of a public good is persistent over time. Whether or not the crowding out

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[25] An alternative measure of charity uncertainty might be generated using publicly available ratings of charities from organizations such as Charity Navigator. However, these ratings only cover a very small fraction of charities and have not been around long enough to cover all years in the data set.

[26] The age variable is unavailable for 7.4% of organizations, and it is clearly inaccurate (i.e. shows an origination date later than 1998, when the charity was in existence and filing tax returns) for an additional 1.1%, thus the number of observations in these regressions is lower than in previous tables.

[27] Crowding in should also be expected if government funding comes in the form of matching grants. Unfortunately, no information about matching is available in the data. Some of the crowding in phenomenon may be explained by matching grants, though matching grants do not explain why crowding in is less for older charities (unless they receive a lower fraction of their government grants in the form of matching grants). Matching, in the context of intergovernmental grants, is studied in Baicker and Staigler (2005) and Klor (2006).

effect is cumulative or merely contemporaneous depends upon whether the utility from the public good is from a stock or a flow good. If a flow good, then the crowding out from government grants in period *t* will negatively affect private donations only in period *t*. If the public good is a stock good, then the government grants in period *t* will crowd out donations in future periods as well. Thus, the two effects of government grants found here, from both crowding out and signaling, are likely to be long lasting, and the duration of the effect for each may differ.

This is tested empirically in Table 5 by regressing private donations (in year t) on both contemporaneous government grants (from year t) and on cumulative government grants (the sum of grants to a charity in all years up to $t-1$). Each regression in Table 5 includes all of the same controls and instruments as in Table 2, though they are not reported. In all three columns, the coefficient on contemporaneous grants is significantly positive, ranging from 17 cents to 26 cents on the dollar. In none of the columns is the coefficient on cumulative government grants significant though it is always less than zero. This suggests that the crowding in effect is in fact contemporaneous; private donors respond to the current year's level of government grants and not lagged values. An alternative way to look dynamically at the data, to see if current values of donations, say, are affected by lagged values of government grants, is through a vector autoregression (VAR). However, testing for Granger causality in either direction using panel data VAR methods developed in Holtz-Eakin et. al. (1988) fails to find causality from lagged values of government grants or private donations.[28] The data used are annual, limiting how much the effect of timing can be observed. If a grant early in one year affects donations later in the same fiscal year, then that dynamic response cannot be measured with annual data.

IV. Conclusion

The prediction of crowding out of private donations by government grants, proposed in Warr (1982) and Roberts (1984), has had numerous empirical investigations. Many studies, including Kingma (1989) and Payne (1998) find evidence of partial crowding out. Other papers, including Khanna and Sandler (2000) and Payne (2001), find evidence of crowding in. Though

[28] Garrett and Rhine (2010) perform VARs on time series data of aggregate annual private donations and government grants to charities.

their results differ, most of these papers have in common that they use a relatively small sample of charities, and they test for crowding out or crowding in only in one direction.

Here I extend that literature by looking at a large data set that includes most charities that file Form 990 with the IRS, which includes all non-religious charities with at least $25,000 in gross receipts. The first main contribution is the empirical examination of crowding out in the "opposite direction": private donations crowding out government grants. The second main contribution is to test if contributions can act as signals for charity quality, leading to crowding in. I find evidence that government grants crowd in private donations, and this crowding in appears to be due to signaling, since crowding in is larger for younger charities about which donors know less. The evidence for crowding out or crowding in in the opposite direction is weak. No significant results are found, but point estimates suggest that private donations may crowd out government grants.

One empirical extension to this paper is to test for signaling from private donations by taking advantage of a distinction between two types of private donations: those from individuals and those from private foundations. Foundations (or trusts, corporations, or estates) are likely to devote resources to researching charities and thus may have more information about charity quality. Their grants may thus act as a quality signal. In fact, charities typically advertise receipt of grants from both governments and private organizations, indicating that they expect these announcements to crowd in donations. Unfortunately, the data from the IRS Form 990s do not allow this level of disaggregating. Contributions from individuals, as well as trusts, corporations, estates, and foundations, are all listed under the same category of "direct public support." If another data source disaggregated private donations into contributions from individuals and contributions from private foundations, then this extension may give empirical support to private donations acting as signals.

What are the policy implications of these findings? Governments fund public goods, including but not limited to those provided by charities, and hopefully governments would do so to increase social welfare by overcoming the free rider problem inherent in public goods. The large prior literature on crowding out suggests that governments ought to acknowledge the effect that their giving has on private giving and set their level of grants appropriately. The signaling model and empirical results presented here buttress that suggestion and add that the government's grants can influence individuals' donations not only through their effect on the level of the public good provision but also through their effect on individuals' information about the quality of the public good. Governments should "worry" about the negative effect that their grants can have due to crowding out; they should also "worry" about how the signal value of their grants can have positive effects on giving. The paper's results are also relevant to private donors, especially large donors like foundations who may influence government grants or other private donations through the crowding in or crowding out effects of their contributions.

A number of additional questions, clarifying these effects and the appropriate policy responses for governments and private donors, may be answered in further research. I have identified that government grants crowd in private donations for the charities in this data set, and I have supplied some evidence that this crowding in arises from the signaling value of the government grants. Further research could verify that signaling is the true cause of crowding in or examine other potential reasons for crowding in, for example economies of scale in a charity's provision of public goods. This may be answered using similar data on actual contributions or in a controlled laboratory setting. Further research could also address the question of the disparity in results between the many papers that find crowding out of private donations and the many, including this one, that find crowding in. An extension using data from other charities besides social service charities would be useful. Finally, development of a thorough theoretical model to capture the many effects that could cause crowding in or crowding out in either direction, that may include charity fundraising, multiple public goods or charities,[29] and dynamics, would be a helpful addition to the literature.

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[29] Models that consider multiple public goods include Bergstrom et. al. (1986), Mutuswami and Winter (2004), and Ghosh et. al. (2007). Empirically, Parker and Thurman (forthcoming) find both crowding out and crowding in for two different government programs preserving open space, and Albers et. al. (2008) examine public provision of land reserves and find crowding in in California and crowding out in Illinois and Massachusetts. Payne (2001) finds crowding out of government grants to teaching colleges but crowding in for research universities.

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Table 1

Summary Statistics – Charity Revenues and Fundraising

	Number of Observations	Number of Organizations	Mean ($1,000s)	Standard deviation ($1,000s)	Median ($1,000s)	75th percentile ($1,000s)
Full Sample	339,716	76,725				
Private Donations			334	4790	44	165
Government Grants			521	3476	0	156
Program Service Revenue			972	9413	61	396
Other Revenue			111	1345	8	43
Fundraising Expenditures			25	510	0	2
Cleaned Sample	174,828	29,138				
Private Donations			267	799	41	206
Government Grants			431	1296	0	241
Program Service Revenue			755	1833	117	562
Other Revenue			89	384	12	56
Fundraising Expenditures			21	103	0	4

Notes: Data are averaged over 1998-2003 in constant 2002 dollars. Private donations include direct and indirect public support. Other revenue includes interest, rents and sales.

Table 2

The Determinants of Private Donations[a]	(1)	(2)	(3)	(4)	(5)	(6)
Government Grants	0.154	0.00208	0.165	0.283***	0.211*	0.482
	(0.0941)	(0.182)	(0.107)	(0.0751)	(0.111)	(0.407)
Fundraising Expenditures	6.698	1.542	4.477	2.892	5.670*	-4.888
	(5.585)	(9.164)	(7.437)	(4.143)	(3.332)	(16.93)
Program Service Revenue	0.00640	-0.0209	0.0525	0.0377	-0.00312	0.106
	(0.0349)	(0.0328)	(0.0579)	(0.0267)	(0.0112)	(0.132)
Other Revenues	-0.0165	-0.0123	-0.0183	-0.0181	-0.0190	-0.0108
	(0.0141)	(0.0283)	(0.0184)	(0.0240)	(0.0147)	(0.0111)
Population	0.00263	0.00116	0.00560	0.00252	-0.000555	-0.00132
	(0.00410)	(0.00750)	(0.00765)	(0.00529)	(0.00119)	(0.000996)
Income	0.317	-0.136	-0.0225	-0.360	0.306	5.074
	(0.867)	(1.471)	(1.671)	(1.076)	(0.208)	(3.789)
Unemployment Rate	-4665	-2014	-2984	-1224	-1473	5251
	(4580)	(5099)	(7978)	(4811)	(1417)	(4383)
Percent Population > 65	-80565	-1169434	-807630	-1943548	354411	-1591628
	(1.60e+06)	(1.91e+06)	(2.90e+06)	(1.63e+06)	(444321)	(2.32e+06)
Number Dem Senators	-3244	-5964	-8585	-1954	2553*	659.6
	(4379)	(8327)	(6313)	(5363)	(1490)	(5500)
Percent Congress members Dem	12746	21424	11020	-9720	3601	-1442
	(20715)	(19608)	(32663)	(26427)	(7289)	(28046)
Indicator for Democratic governor	-7895	2353	-18864***	-8447	-2505	-8960*
	(5081)	(4863)	(6641)	(6348)	(1644)	(4849)
Observations	174828	145690	85764	111474	158016	264494
Number of Organizations	29138	29138	14300	18579	27187	52570
F-statistic on instruments for government grants in first-stage regression[b]	23.74	15.77	15.66	11.53	19.01	29.36
(p-value)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
F-statistic on instruments for fundraising expenditures in first-stage regression[c]	8.72	7.41	5.84	5.82	3.28	9.06

(p-value)	(0.000)	(0.000)	(0.000)	(0.000)	(0.011)	(0.000)
Hansen J-statistic	1.037	1.531	1.292	1.431	2.172	3.443
(p-value)	(0.595)	(0.465)	(0.524)	(0.489)	(0.338)	(0.179)
Cragg-Donald F-statistic	1.793	1.119	0.916	2.532	1.525	0.539
Lagged Endogenous Variable/Instrument?	No	Yes	No	No	No	No
Exclude Select Charities?[d]	No	No	Yes	Yes	Yes	No
Balanced Panel?	Yes	Yes	Yes	Yes	Yes	No

[a] Data are from 1998-2003 and only include those organizations that are in the panel for all six years (except column 6), whose reported categorical revenues sum up to reported total revenues, likewise for expenses, and who never report a negative amount in a revenue category. Charity-fixed-effects and year indicator variables are included in each regression. Heteroskedasticity and autocorrelation consistent standard errors are in parentheses.
[b] Instruments for government grants are the state-year total payments paid to individuals through SSI and the state-year payments paid to individuals through SSI for the aged.
[c] Instruments for fundraising expenditures are the charity's management expenditures and its total liabilities.
[d] Column 3 excludes charities that include "National" or "American" in their names, are classified as support organizations, or never have nonzero values for government grants or private donations. Column 4 excludes organizations classified as low-income and subsidized rental housing, senior citizens' housing and retirement communities, residential care and adult day programs, and centers to support the independence of specific populations. Column 5 excludes observations where the level of government grants or the level of private donations is in the top 5% among all observations.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 3

The Determinants of Government Grants[a]

	(1)	(2)	(3)	(4)	(5)	(6)
Private Donations	-0.700	-1.143	-1.931	-1.123	0.665*	-0.307
	(1.165)	(1.212)	(2.667)	(1.334)	(0.342)	(0.923)
Program Service Revenue	-0.279***	-0.279***	-0.498***	-0.289***	-0.0422***	-0.253***
	(0.0308)	(0.0304)	(0.0466)	(0.0522)	(0.00513)	(0.0234)
Other Revenues	-0.0327	-0.0197	-0.0468	-0.0143	-0.00427	-0.00526
	(0.0293)	(0.0231)	(0.0641)	(0.0287)	(0.00396)	(0.0134)
Population	0.00789	-0.000255	0.0258	0.0126	0.000182	0.00209***
	(0.00695)	(0.00554)	(0.0269)	(0.00945)	(0.00176)	(0.000796)
Income	-1.356	-1.127	-4.438	-1.879	-0.488**	-4.388*
	(0.938)	(1.186)	(4.416)	(1.834)	(0.230)	(2.550)
Unemployment Rate	-2276	1910	-3170	-4788	-1404*	-11528***
	(1921)	(5441)	(5064)	(3142)	(754.3)	(2611)
Percent Population > 65	-2171059	-3317986	-9332267	-2355580	-125400	-904656
	(2.45e+06)	(3.20e+06)	(8.83e+06)	(3.77e+06)	(277585)	(1.13e+06)
Number Dem Senators	4118	-1281	-10013	2025	-2201	4587
	(4682)	(14177)	(21595)	(7926)	(1549)	(3302)
Percent Congress members Dem	54497*	124182*	204517*	72447*	9239	20125
	(33102)	(73427)	(115870)	(40320)	(7931)	(18596)
Indicator for Dem governor	10200	20923***	7014	17028*	3959**	11030*
	(7092)	(7514)	(30070)	(8749)	(1987)	(6283)
Observations	174828	145690	85764	111474	158016	265105
Number of Organizations	29138	29138	14300	18579	27187	52689
F-statistic on instruments in first-stage regression[b]	4.88	4.30	2.10	4.60	8.99	5.92
(p-value)	(0.027)	(0.038)	(0.147)	(0.032)	(0.003)	(0.015)
Cragg-Donald F-statistic	60.78	33.86	33.08	55.61	29.70	63.41
Lagged Endogenous Variable/Instrument?	No	Yes	No	No	No	No
Exclude Select Charities?[c]	No	No	Yes	Yes	Yes	No
Balanced Panel?	Yes	Yes	Yes	Yes	Yes	No

[a] Data are from 1998-2003 and only include those organizations that are in the panel for all six years (except column 6), whose reported categorical revenues sum up to reported total revenues, likewise for expenses, and who never report a negative amount in a revenue category. Charity-fixed-effects and year indicator variables are included in each regression. Heteroskedasticity and autocorrelation consistent standard errors are in parentheses.
[b] Instrument for private donations is the level of dues collected by the charity.
[c] Column 3 excludes charities that include "National" or "American" in their names, are classified as support organizations, or never have nonzero values for government grants or private donations. Column 4 excludes organizations classified as low-income and subsidized rental housing, senior citizens' housing and retirement communities, residential care and adult day programs, and centers to support the independence of specific populations. Column 5 excludes observations where the level of government grants or the level of private donations is in the top 5% among all observations.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 4

The Effect of Age on Crowding In

	(1)	(2)	(3)	(4)	(5)
Government Grants	0.959***	0.153	0.825**	1.283***	1.278***
	(0.366)	(0.211)	(0.345)	(0.375)	(0.334)
Charity Age	8461	2513	10137	13862	5609
	(9471)	(7762)	(13055)	(9782)	(4456)
Age*Grants	-0.0254***	-0.00359*	-0.0207***	-0.0320***	-0.0421***
	(0.00877)	(0.00215)	(0.00735)	(0.00961)	(0.0101)
Observations	159912	133260	78621	102024	144351
Number of Organizations	26652	26652	13108	17004	24837
F-statistic on instruments for government grants in first-stage regression	13.65	10.23	8.34	8.00	8.42
(p-value)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Hansen J-statistic	1.704	0.544	0.530	1.653	0.0650
(p-value)	(0.426)	(0.762)	(0.767)	(0.438)	(0.968)
Cragg-Donald F-statistic	0.912	1.174	0.847	2.552	0.578
Lagged Endogenous Variable/Instrument?	No	Yes	No	No	No
Exclude Select Charities?[b]	No	No	Yes	Yes	Yes

[a] Data are from 1998-2003 and only include those organizations that are in the panel for all six years (except column 6), whose reported categorical revenues sum up to reported total revenues, likewise for expenses, and who never report a negative amount in a revenue category. Only those charities with a consistent value for age are included. Instruments and control variables from Table 2 all appear in these regressions, though not reported. Heteroskedasticity and autocorrelation consistent standard errors are in parentheses.

[b] Column 3 excludes charities that include "National" or "American" in their names, are classified as support organizations, or never have nonzero values for government grants or private donations. Column 4 excludes organizations classified as low-income and subsidized rental housing, senior citizens' housing and retirement communities, residential care and adult day programs, and centers to support the independence of specific populations. Column 5 excludes observations where the level of government grants or the level of private donations is in the top 5% among all observations.

*** p<0.01, ** p<0.05, * p<0.1

Table 5

Contemporaneous and Cumulative Grants[a]	(1)	(2)	(3)
Government Grants	0.208***	0.167***	0.263***
	(0.0400)	(0.0420)	(0.0594)
Cumulative Government Grants	-0.00224	-0.000931	-0.00429
	(0.00197)	(0.00230)	(0.00294)
Observations	145690	71472	92895
Number of Observations	29138	14300	18579
F-statistic on instruments in first-stage regression	36.63	43.03	22.04
(p-value)	(0.000)	(0.000)	(0.000)
Hansen J-statistic	6.625	11.96	7.487
(p-value)	(0.0848)	(0.00752)	(0.0579)
Cragg-Donald F-statistic	816.3	717.2	458.0
Exclude Select Charities?[b]	No	Yes	Yes

[a] Data are from 1998-2003 and only include those organizations that are in the panel for all six years (except column 6), whose reported categorical revenues sum up to reported total revenues, likewise for expenses, and who never report a negative amount in a revenue category. Instruments and control variables from Table 2 all appear in these regressions, though not reported. Heteroskedasticity and autocorrelation consistent standard errors are in parentheses.

[b] Column 2 excludes charities that include "National" or "American" in their names, are classified as support organizations, or never have nonzero values for government grants or private donations. Column 3 excludes organizations classified as low-income and subsidized rental housing, senior citizens' housing and retirement communities, residential care and adult day programs, and centers to support the independence of specific populations.

*** $p<0.01$, ** $p<0.05$, * $p<0.1$