Research Grants Crowding Out and Crowding In Donations to Higher Education

Grant Gannaway

University of Chicago

Garth Heutel

Georgia State University and NBER

Michael Price

University of Alabama and NBER

February 2021

Abstract

Using a dataset that includes every private donation made to a large public university from 1938 to 2012 and demographic information on all alumni, we examine the effects of public research funding on individual donations. Our dataset allows us to examine crowding effects on a small time scale and extensive donor characteristics. We estimate effects on the total number of donations (extensive margin) and on the average size of a donation (intensive margin). National Science Foundation research grants have a positive (crowd-in) effect on the extensive margin and a negative (crowd-out) effect on the intensive margin. We find no evidence of these effects from other sources of federal research funding. Previous donors and in-state residents respond differently to grants than do new donors and out-of-state residents, respectively.

We thank Kalee Burns, Mike Fosco, Bo Liu, and Xin Zhang for research assistance, and Scott Imberman, David Merriman, and participants at the National Tax Association annual conference for helpful comments.

I. Introduction

Higher education administrators and fundraisers seek charitable donations from alumni and community members. Strategies for soliciting donations, and research into what affects the number and size of donations, are important for these stakeholders. Universities also receive research grants, many of which come from federal agencies like the National Science Foundation and the National Institutes of Health. Research grants could potentially affect private donations. If potential donors see less of a need for supporting a university once it receives a large grant, then grants may crowd out private donations. If potential donors see research grants as signaling university quality, then grants may crowd in private donations. Either crowding effect may manifest itself on the extensive margin of the number of donations, or the intensive margin of the size of donations. Heterogeneity may exist among the population of potential donors; for example, alumni may respond differently than non-alumni, or in-state residents (for a public university) may respond differently than out-of-state residents. All of these factors are important for higher education stakeholders, especially those in development or fundraising, to understand. The purpose of this paper is to test for crowding out and crowding in of higher education donations by large government grants. We use a unique dataset comprised of observations not at the organization level but at the donation level. It contains every private donation in the nearly 80-year history of a large public university through 2012. We test whether donations respond, on either the intensive or extensive margin, to changes in federal research funding of the university, whether the responses differ by the demographics of the donor, and whether there is evidence of crowding between units within the university.

Our contribution lies in the use of this novel and exhaustive data set, which is proprietary and was accessed with participation from the university's advancement office. Previous studies have used relatively small datasets collected from laboratory or field experiments. Other studies have used large observational datasets that cover many nonprofits but with limited information about individual donations (for instance, publicly accessible tax return data from nonprofits' Form 990 filings). Our data only include one organization. However, we have an individual observation for each donation made to that organization. For each donation, we observe the date, amount, and target unit within the university (e.g., the medical school). The date of the donation allows us to examine time intervals shorter than one year, which allows us to plausibly identify causal effects even without data on potential confounders like fundraising effort. That is, endogenous fundraising responses to the university's grant receipts are unlikely to vary over such short time intervals. Understanding the crowding effects requires the use of granular data, since our identification is based on the immediate response of donors to large grants. Thus, our granular dataset is uniquely situated to measure crowd in or crowd effects. Furthermore, our data spans a long time frame, allowing us to measure the effects of many different grants.

For donations matched to alumni, we observe the donor's demographic information from the alumni database, including state of residency, race, and gender. An anonymous donor identification number allows us to observe the history of contributions of each donor, regardless of alumni status, so that we can separately examine gifts from previous donors and from new donors. This availability of donor demographic data is unavailable in studies using aggregate donation data, like from IRS Form 990 filings.

In summary, our dataset allows us to make two main contributions relative to the previous literature. First, we can exploit timing on a much finer scale than previous studies that rely on merely annual data, since we observe the day of the donation, allowing us to overcome potential sources of endogeneity. Second, we can study how the demographic characteristics of individual donors affect their crowding responses, which is not possible when using data that report just aggregate donation totals. Ours is not the only paper that examines differences across donor demographics, though we are able to examine some demographic variables that have not been examined before.

We supplement the donations data with two publicly available datasets on federal grants from the National Science Foundation (NSF) and other federal funding agencies. These datasets contain information on the recipients of the grants, the amount of the grant, and the date it was issued. The data on NSF grants are available for more years than are the data on funding from other agencies, which includes the National Institutes of Health and the Department of Defense.

We find that large NSF grants have a positive, crowd-in effect on the extensive margin (number of donations) but have a negative, crowd-out effect on the intensive margin (average dollar amount per donation). A $5 million NSF grant increases the average weekly number of donations by 74 in the 12 weeks following the grant; a $1 million NSF grant increases that number by 36. A large NSF grant decreases the average dollar amount per donation by $3 to $15 in the following 12 weeks, depending on the size of the grant. Overall, the extensive-margin crowd-in and the intensive-margin crowd-out roughly cancel each other out, and there is little consistent evidence of an effect on the total money raised (though for the largest NSF grants, there may be overall crowd-out). For other federal research grants, we do not see the same pattern; there is no consistent evidence of either crowd in or crowd out on either margin.

Our alumni demographic data allow us to explore whether these effects differ for different types of donors. Previous donors (the "hot list") show a larger extensive-margin crowd-out effect and a smaller intensive-margin crowd-in effect than do new donors (the "cold list"). This result is consistent with previous empirical findings. A novel result that we find based on our demographic data is that residents of the university's state, whose state taxes partially fund the university, also show larger effects on both margins than do out-of-state residents. This new finding is consistent with hypotheses from an analytical model (presented in the appendix) describing mechanisms behind crowding. Controlling for fundraising or media citations of grants in university press releases or the local daily newspaper does not change the results, though we find a large and significant effect of fundraising drives on the number of donations. We do not find any evidence from crowding in or crowding out across units of the university – for example, grants going to the medical school do not differentially affect donations to the law school.

There is a literature that examines private giving to universities and its determinants. Eckel et al. (2017) estimates the effect of directed giving on donations to a university and finds an effect on the intensive but not the extensive margin. Meer and Rosen (2009) test whether alumni giving to a university is related to the age of donors' children. Clotfelter (2003) examines the determinants of alumni donations to universities and finds that income, graduation, and degree of satisfaction all positively affect giving. In a similar analysis, Monks (2003) finds that satisfaction is the most important determinant of giving among young alumni, as does Gaier (2005).[1] Levin et al. (2016) have access to a data set similar to ours, and they use it to examine the determinants of giving among high-capacity donors. Hungerman and Ottoni-Wilhelm (2016) use a similar data set to estimate the tax-price elasticity of charitable giving. Another extensive literature examines the determinants of charitable giving more generally, not specifically giving to universities. For example, Auten et al. (2002) estimate price and income elasticities for charitable giving using variation in tax rates.

[1] Related analyses include Ade et al. (1994), Okunade et al. (1997), and Taylor and Martin (1995). Harrison (1995) and Harrison et al. (1995) also consider fundraising expenditures.

Another literature studies crowding out or crowding in in the nonprofit sector. The large bulk of this literature, including Okten and Weisbrod (2000) and Brooks (2003), looks at data across a large number of charities, for example, from the IRS Form 990s that 501(c)3 organizations are required to file. Khanna et al. (2000) use similar data but from UK charities. Some papers look at more specific types of charities, like public radio stations (Kingma 1989) or theatres (Borgonovi 2006). Several papers use field experiments to test hypotheses related to crowd out: Landry et al. (2010) test whether giving a small gift has any effect on donations, Kessler (2017) finds that announcements of support have a positive effect on others' giving, and Huck et al. (2015) test how different fundraising schemes affect donations. Andreoni and Payne (2003, 2011) extend the literature by examining whether government funding crowds out private giving or fundraising expenditures by nonprofits.[2]

Lastly, the crowding out literature that looks specifically at colleges and universities is smaller. Diamond (1999) studies federal funding of science, which includes but is not exclusively grants to universities. He finds no evidence that government funding crowds out private giving. Payne (2001) examines the relationship between private and public funding of universities and finds evidence of crowding out for non-research universities and crowding in for research universities.

Our contribution to this literature lies in the use of our unique data set that allows us to exploit the timing of individual donations down to the day and allows us to match individual donations with donor demographics, including alumni status. Of the papers that have used similar administrative data (e.g., Levin et al. 2016, Hungerman and Ottoni-Wilhelm 2016), none

[2] The crowding out phenomenon extends beyond just the response of charitable donations to government funding. Federal K-12 school funding may crowd out state and local funding (Gordon 2004), 401(k) savings may crowd out other savings (Poterba et al. 1995), and public health insurance may crowd out private insurance (Cutler and Gruber 1996). Meer (2017) explores whether matching grants crowd out giving to other (non-matching) charities.

have addressed the issues of crowding in or crowding out. A caveat of our data set is that it does not contain any information on fundraising expenditure. We address this issue in section III.C. below and argue that the other advantages of our data set allow us to overcome this. In particular, since our data are at the daily level, we include a set of year and week-of-year indicator variables that can control for variation in fundraising intensity, which is unlikely to vary substantially within these intervals. Furthermore, since our data is at the day level, we can observe effects of large donations or grants in the days and weeks immediately following the large donation or grant. This is beneficial in that it is unlikely the university can increase its fundraising efforts as a result of the large donation or grant in such a short time frame.

In addition to its contribution to the literature on crowding out and on the determinants of giving to universities and other nonprofits, our paper is related to a more general literature on the impact of research grants on a number of outcomes. Arora and Gambardella (2005) examine the impact of the receipt of NSF grants on individual researcher output, and Jacob and Lefgren (2011a, b) examine the same impact of NIH grants.[3] Bozeman and Gaughan (2007) estimate the effect of the receipt of a grant on academic researchers' interactions with industry. David et al. (2000) examine a related crowd out question: whether public R&D funding like research grants crowds out private R&D. They conclude the evidence is mixed. Jaffe (2002) discusses general difficulties with estimating the impacts of public research funding. To this general literature on the impacts of public research funding, we add one other specific impact: its effect on private support of research-intensive universities.

The rest of the paper proceeds as follows: section 2 describes the data used in more detail; section 3 lays out our empirical methodology and shows our results. Section 4 concludes.

[3] Svider et al. (2013) ask the same question, focusing specifically on the impact among academic otolaryngologists.

II. Data

We combine several datasets. First, we have a unique dataset containing the historical charitable donations to the university. [4] Each observation is a donation, complete with details about the time, amount, and donor-specified unit within the university that will receive the donation (e.g. law school or medical school). Notably, we observe the day that the donation is received, allowing us to examine crowding issues at a much finer time scale than previous studies that have used annual data.[5]

We combine the donations dataset with the university's alumni database. For each alumni graduating from the university, the alumni dataset contains several demographic variables, including the state of residence, gender, and race. We merge the alumni dataset and the donation dataset using the donor's identification number (created by the university). Not all donations match to an alumnus (since some donations are made by non-alumni), and not all alumni match to a donation (since some alumni never donate).

The giving dataset contains 1,905,455 total observations (donations) from 466,016 unique donors. The alumni dataset contains 429,601 observations (individual alumni). In total, the two datasets combined contain information from 729,059 unique individuals. Of those, 263,043 are alumni who have never donated (and thus do not appear in the donation dataset). The remaining 466,016 individuals are donors; 166,558 of them are alumni, and 299,458 of them are non-alumni. Therefore, only 36% of donors are alumni. Of the 429,601 individuals in the alumni dataset, only 39% have ever donated. Individuals can donate multiple times. Of the 1,905,455 observed donations, 58% of them come from alumni. Among alumni donors, the

[4] Taylor and Martin (1995) also use data from just one research university, but with a smaller sample size of just 371 alumni.

[5] Later, we will examine issues of noisiness around the reported date that the donation is received.

average number of donations is 6.6; among non-alumni donors, the average number is 2.7. About 0.6% of donations observed are duplicates (same donor, amount, and day); we drop these observations.

Table 1 presents summary statistics of several demographic variables included in the alumni database, separately for non-donors and donors. Donors are older and more likely to be white, male, formerly in a fraternity or sorority, married, and have children than non-donors. Table 2 presents summary statistics on the donations data, separately by time period and by targeted unit within the university. Only one percent of gifts occur before 1970 (the oldest observation is from 1938, but the second oldest is 1951). Deflating to year 2000 dollars using the Consumer Price Index, the median gift amount is around $50-$100, with a mean value more than 10 times higher, indicating substantial skew.

As mentioned above, a donor may select a unit within the university to receive their donation. We collapse the 24 units of gift targets into five broad categories: "general", "medical school", "liberal arts college", "athletics", and "other".[6] "General" gifts account for just under half of all donations. The largest single targeted unit is the medical school. The "other" category includes gifts to the law school, policy school, arts and architecture, and several others. There is substantial skew across all categories. Gifts to athletics are typically larger than others, with a median donation amount about four times higher than the other categories.

We use these gifts as left-hand-side variables, but we choose to focus only on modestly-sized donations. Our giving dataset includes donations as large as $200 million, which represent huge gifts. In our main analyses, we restrict ourselves to examining donations of less than

---

[6] The "General" category includes "Chancellor's Greatest Needs" and "General Campus" gifts. The "other" category includes all of the other units listed in Appendix Table A1, which lists the number of gifts, both below and above $1000, for each unit.

$1,000, and we also consider additional specifications where the donation cutoff is $500 or $10,000. There are two reasons for this. First, very large donations may be outliers that create noise biasing our results. Second, donors who make very large donations may behave differently than "ordinary" donors; for example, large donors may represent foundations that have more institutional knowledge. These small donations ($1,000 or less) account for the vast majority (93% on average across all weeks) of the total number of donations, but only a small fraction (15% average across all weeks) of the total dollar amount of donations, due to the large outliers.[7]

Figure 1 plots the weekly average number of donations (under $1,000) and the weekly average gift amount per small donation for each year between 1950 and 2012. Before the late 1980s, the average gift amount for small donations varied over a wide range from under $100 to over $300, but then, around 1985, the average gift amount steadied out at around $150. The average number of small donations per week steadily increased from around 1970 until about 2000, where it leveled out around 1,200 donations per week. The number of small donations before 1970 likely contributes to the high variation in donation size during that time period.[8]

We combine the alumni dataset and the donations dataset from the university with several additional data sources. First, we gather data on federal research grant funding to the university from the National Science Foundation (NSF). While this funding represents only a fraction of government support for the university, there are two major benefits to using this data as a measure of public grants. First, we can observe the day, rather than just the year, in which each

[7] Appendix Figures A1 and A2 plot the annual number of small donations (less than $1,000) and number of total donations, and the annual dollar amount of small and total donations, respectively. When the cutoff is $500, small donations account for 88% of all donations by count and 14% by dollars. When the cutoff is $10,000, small donations account for 99% of all donations by count and 41% by dollars.

[8] Appendix Figure A3 plots the average weekly total dollar amount received from small donations for each year between 1950 and 2012. This statistic closely follows the pattern of the number of weekly donations, increasing steadily between 1970 and 2000, with a tapering off at around $175,000 received per week from small donations. These two figures give an idea of a typical week in small donations around the recent peak-years: 1,200 small donations received; about $140 per donation; for a total of $168,000 received from small donations.

grant is awarded. Alternative measures like state funding or tuition revenues are typically available only at the annual level.[9] Second, NSF awards grants to specific faculty members, which allows us to determine the unit within the university that is receiving the grant. This setup allows us to create a difference-in-difference framework for both the large private donations and the public grants, comparing changes to units within the university. While NSF data are available starting in 1960, it is only starting in 1975 that we observe the day that the grant is awarded.

Second, we supplement the NSF grant data with a broader set of federal public grants to the University from multiple federal grant-making agencies, including the National Institutes of Health (NIH) and the Department of Defense. These data are available from two sources. From 2001 until the present, the data are available from the website USAspending.gov. The data on this website are uploaded from more than 100 federal agencies' financial systems. We confine our search to just grants – excluding contracts, direct payments, loans, and other payments – made to the University before the end of 2012 (when our giving dataset ends). The second source for these data is the National Archives, which stores them from 1982 until 2000. We also search these archives for just grants, and just for those made to the University. In total, we collect 10,243 grant observations. For each grant, we observe the total funding amount, the start date, and the funding agency from which the grant is received. The mean grant amount is \$500,000 and the median is \$250,000. The vast majority of grants (and the highest total dollar value) come from the Department of Health and Human Services (HHS), which accounts for about 80% of the observed grants. Most of HHS's grants are funded through the National Institutes of Health (NIH). The two next most common grant-making agencies are the NSF (8% of grants) and the

[9] Data on total state funding to the university are available from the university's financial reports, and from the Integrated Postsecondary Education Data System (https://nces.ed.gov/ipeds/).

Department of Defense (4% of grants). While this dataset is more exhaustive than the NSF data in that it includes NSF grants along with grants from other agencies like HHS, the data are not available for as many years as are the NSF data. (NSF data go back to 1960, though the date is available only starting in 1975, while the USAspending.gov data go back only to 2001 and the National Archives data back to 1980.)

We create a weekly variable that measures the number of stories that week containing these keywords. These data are only available starting from 1997. From 1997-2012 (when the donation dataset ends), the number of articles per week that are about donations ranges from 0 to 7, with a median of one and a mean of 0.99. In addition to the university's press releases, we also search the online database of the large local daily newspaper in the city in which the university is located. We search for terms related to large public grants. These searches are only available at the monthly level, so we match the presence of these stories to the week.

Third, we use data on media citations of the receipt of large public and private grants by the university. We have two different sources of media citations. We search the university's online press releases for stories that contain several keywords related to private and public grants.[10] We create a weekly variable that measures the number of stories that week containing these keywords. These data are only available starting from 1997. From 1997-2012 (when the donation dataset ends), the number of articles per week that are about donations ranges from 0 to 7, with a median of one and a mean of 0.99. In addition to the university's press releases, we also search the online database of the large local daily newspaper in the city in which the university is located. We first limit this database to all articles that are tagged by the newspaper as relating to the university in any way. After downloading the titles and newspaper-generated

[10] The keywords that we search for are "donation", "donates", "grant", and "gift".

summaries of each article, we classify each article as dealing with a donation or a grant (separately) using keyword searches, just as in the university press release data. Then we create monthly counts of the number of articles that contain either the donation keywords or the grant keywords. We use the same keywords as in the university press release data. Donation coverage in the newspaper range from 0 to 4 articles in a month with a median of 0 and a mean of 0.19, while grant coverage ranges from 0 articles to 1 article per month with a mean and median of 0.04 and 0, respectively.

Fourth, we search for the history of large fundraising drives at the university. We find two major fundraising drives. The first ran from January 1, 1982, through December 31, 1988. The second ran from January 1, 1997, through December 31, 2005. We create an indicator variable equal to one for weeks during these fundraising drives.

III. Results

We use these data to explore several questions about how individual small donations respond to large public grants– with particular attention paid to whether they crowd out or crowd in individual donations on the extensive and/or intensive margins, whether there is a different response depending on the funding source, whether there is a different response based on the demographics of the giver, and whether there are unit-level crowding effects (between the different units within the university). The analytical model presented in the appendix motivates these empirical questions and provides intuition for various effects that could explain both crowd in and crowd out.

III.A. Response to Large Public Grants

We use our giving data to identify how small private donations are affected by large public grants. We consider three different specifications of what constitutes a "large grant" – either \$1 million or more, \$5 million or more, or \$10 million or more (all in 2000\$). For small private donations, we look at those gifts that are \$1000 or less. We aggregate our giving data to the weekly level in the base regressions reported, but we also consider daily and monthly aggregation. For each week, we define an indicator variable equal to one if that week is within a time window immediately after the receipt of a grant. In the base case, that time window is 12 weeks, though we also consider windows of 4 weeks and 26 weeks in appendix tables.

Our estimating equation is

$$y_t = \beta_0 + \beta_1 LargeGrant_t + \beta_2 X_t + \varepsilon_t \qquad (1)$$

The outcome y_t is either the total number of (small) donations in week t, the average dollar amount of (small) donations in week t, or the total dollar amount of (small) donations in week t. The first outcome represents an effect on the extensive margin, the second represents an effect on the intensive margin, and the third is the combination of both margins. The right-hand-side variable of interest $LargeGrant_t$ is an indicator equal to one if the week is within a 12-week window after a large grant. The control variables X_t include a set of year indicators and a set of week-of-year indicators.[11] These indicator variables help with identifying a causal effect in this context where the fundraising effect is unobservable and a potential confounder. With the fixed effects, we are exploiting variation within a given month, and it is unlikely that fundraising effort will vary dramatically or at all within such a short time period. Since the variable $LargeGrant_t$ is a binary indicator, we are not estimating the *magnitude* of the response (for instance, the

[11] Appendix Figures A4 and A5 plot the number of large NSF and federal grants, respectively, (for each of the three cutoff values for large donations) by week-of-year, aggregated across all years in the sample. These figures demonstrate that there is ample variation in the timing of receipt of these grants across the year, so that we are not artificially picking up timing effects in estimating equation 1.

percentage of crowding out), but rather merely trying to identify a response. We use both the NSF dataset and the USAspending.gov/National Archives dataset. For the NSF data, the regressions only include weeks from 1975 through 2012, since the daily NSF data are available only starting from 1975. The USAspending.gov and National Archives datasets include just weeks from 1982 through 2012.

Table 3 presents the regression results using the dataset on NSF grants. The first column shows evidence of a positive, crowd-in effect on the extensive margin, which is statistically significant when the large grants are defined based on either the $1 million or $5 million cutoffs. Being within 12 weeks of the receipt of a large NSF grant increases the number of small private donations received by 25 to 75 (compared to the mean value of about 450 donations per week). In the next column, the negative coefficients on the grants indicate crowding out on the intensive margin. Being within 12 weeks of the receipt of a large NSF grant decreases the average dollar value of each small private donation received by $3 to $14 (compared to the mean value of about $150 per donation). The effect is significant at the 10% level for all three large grant cutoff values, and significant at the 1% level for the $5 million and $10 million cutoffs. The third column represents the combined extensive and intensive margin effects, where the outcome is the total dollar amount of donations. Only for the largest, $10 million, cutoff value do we see a significant effect, and it is negative. The other two cutoffs yield effects of mixed sign, with neither being significant.

The results in Table 3 provide evidence that large private grants have two different effects on smaller private donations: crowding in on the extensive margin (increasing the number of donations) and crowding out on the intensive margin (reducing the average dollar amount per donation). The extensive margin crowding-in is consistent with the signaling theory presented in the appendix. There is little effect on the total dollar amount of donations, suggesting that these two crowding effects may roughly offset each other.

What explains the different effects on the extensive and intensive margins? The theoretical model presented in the appendix may shed some light on the mechanisms. In it, we demonstrate that receipt of a grant may create both a signaling effect, which crowds in donations, and a standard crowd-out effect. It is possible that the signaling effect dominates, and brings in more donors on the extensive margin. But since those donors are marginal, they are likely to make lower average donations, causing crowd-out on the intensive margin. The theoretical model also shows that there can be an income effect as well that reduces crowd-out. We are unable to disentangle all of the potential mechanisms.

Table 4 presents the results using the dataset on federal grants. In the first column, we see only weak evidence of extensive-margin crowding-in, as we saw with NSF grants in Table 3. Only when the cutoff for large federal grants is defined to be $5 million is there a significant crowding-in effect found, and it is about the same size (65 more donations per week) as in the corresponding column in Table 3. However, the intensive-margin crowding-out effect that we saw in Table 3 with the NSF grants is completely absent in Table 4 with the broader set of federal grants. Not only are all of the coefficients insignificant, but their magnitudes are about an order of magnitude lower than those from Table 3. Likewise, the third column shows only insignificant results. Together, these results suggest that donors respond differently to large NSF grants than they do to other large federal grants. It may also be the case that the broader federal grants database from USAspending.gov and the National Archives is less reliable than the data directly from the NSF website. Later, we will explore if there is any differential effect from different funding agencies within the broader federal grants database.

Appendix Tables A2 through A10 present alternative specifications of the regressions in Tables 3 and 4. Appendix Tables A2 and A3 replicate Tables 3 and 4, respectively, but consider two alternate time windows in which the effects of the large grants might be present: a 4-week window and a 26-week window (compared to the base case of a 12-week window). The extensive-margin crowd-in and the intensive-margin crowd-out from NSF grants are also found in Appendix Table A2 but only for the 26-week window. For the 4-week window, we see no significant results; this short of a window may be too little time for the diffusion of information about grant receipts that might inform and affect donors. Appendix Table A3 shows even more inconsistent results for the broader federal grants data – at the 26-week window, there is some significant evidence of crowding-out on the extensive margin and crowding-in on the intensive margin, the opposite of what we find for NSF grants. However, these results are generally inconsistent.

Appendix Tables A4 through A7 replicate Table 3, for the NSF grants, with different specifications.[12] In Appendix Tables A4 and A5, the cutoff size of the small donation (how the dependent variables are defined) is changed to either \$500 or \$10,000, compared to the \$1,000 cutoff used in the main specification. This change has no substantive impact on the results (except that the magnitude of the coefficients on average gift size change in an expected way as the donation size increases). In Appendix Table A6, we impose no cutoff and use all donations of any size. We find that the extensive-margin crowd-in effect is still present, but that the intensive-margin effects are no longer found, because of a small number of very large donations affecting the variable's values. In Appendix Table A7 we conduct the analysis at the daily level rather than the weekly level, and Appendix Table A8 does it at the monthly level. The daily

[12] Since the base-case results for the broader federal grants in Table 4 are insignificant, we do not report these alternate specifications for those data.

regressions include year and day-of-year fixed effects, and the post-donation window considered is the same length as in the main specification (expressed here in days: 84 days). Again, the results here are mainly the same as in the main specification in Table 3, except that the extensive-margin crowd-in effect is less significant. The results from the monthly level regressions in Appendix Table A8, which include year and month-of-year fixed effects, are consistent with the results in the main specification – there is evidence of crowding in on the extensive margin and crowding out on the intensive margin. The magnitude of the crowding in effect is larger though not quite significant.

A further concern is that individuals making small private donations may respond not only to the receipt of large federal grants, but also to the receipt of large private gifts. As described earlier, our dependent variables are based on what we define as small private donations, which are less than $1,000. But our private donation dataset also contains observations of larger private gifts, reaching into the millions of dollars each. In Appendix Tables A9 and A10 we explore whether or not individuals making small private donations respond to these large private gifts and whether controlling for the large private gifts affects the coefficients on the large federal grants.

We define large private gifts in the same way that we define large federal grants, using three different cutoff values: $10 million, $5 million, and $1 million. We again create indicator variables based on whether a week is within a 12-week window of the receipt of the large private gift. We perform the same regressions as in Tables 3 and 4 for NSF grants and other federal grants, respectively, but we also include the indicator variable for being with the 12-week window of the receipt of the large private gift. Appendix Tables A9 and A10 report the coefficients on both the large grant window indicator and the large private gift window indicator.

Appendix Table A9 shows that even when controlling for receipt of the large private gifts, the coefficients on the indicators for large NSF grants are relatively unchanged. The coefficients on the indicators for receipt of a large private gift are smaller and all insignificant. This indicates that small individual donors seem to respond to large NSF grants but not necessarily to large private gifts. Appendix Table A10, like Table 4, shows generally insignificant results for the response of donors to large federal grants, and the inclusion of the controls for large private gifts does not change this result substantially.

Finally, we explore issues related to the timing of the receipt of the donations. Our identification strategy rests on the fact that we observe the day of the donation, not merely the year, and we exploit within-year variance in receipt of grants and its effect on within-year variance of receipt of private donations. How accurate are the reported dates of the receipt of the donations from our donation database, and what exactly does "date received" mean? For example, is it the date when the donation is pledged, or when the check is written, or when the check is received in the mail, or when it is processed by the development office? For different types of donations (e.g. check vs. credit card), the answer to this question may differ. Unfortunately, we were not able to get clarity on the date received variable from the development office that provided the data, so we do not have an answer to this important question. We think that this does not create a serious problem for our analysis, because even the smallest window that we examine is four weeks, and it seems unlikely that for most donations any discrepancy across what could be meant by date received could be longer than that window.

To explore this issue further, given our data limitations, we can exploit a variable in the dataset listing the "payment type." For the vast majority of observations, the value of this variable is either "cash" (81.4%) or "credit card" (16.6%). [13] Notably, "check" is not a value, so we interpret the "cash" observations to include checks. Credit card payments are much more common in later years, though in all years cash/check payments are still the majority.[14] One might think that cash/check payments are more likely to suffer from issues of timing if it takes time for the check to be mailed or for the pledge to be fulfilled. Perhaps credit card payments are more likely to represent the actual date when the donor submitted the payment, if it was online. However, we do not observe whether credit card payments were made online or by mail.

We separately estimate the effect of grants on either cash/check donations or on credit card donations, and report the results in Appendix Table A11. For the cash/check donations, we find the same results as with the aggregate donations of extensive-margin crowd in and intensive-margin crowd out. Surprisingly, for credit card donations, we find different results. There is some evidence for extensive-margin crowd out, and no evidence for an intensive-margin effect. If we were confident that the credit card payments were recorded on the correct day that the donor made the payment and that the cash/check payments were not, then this finding may cast doubt on our main results reported earlier. But we have no reason to believe that this must be the case. Rather, while there is something different about cash/check vs. credit card donations, it is unclear how that is related to the issue of timing.

III. B. Comparison of Response based on Donor Demographics

[13] These percentages are of the observations with non-missing values for "payment type" (which is 77.8% of total observations). The remaining 2% are split amongst values including "gift in kind" or "securities."

[14] Again among observations with non-missing payment type, for the first 20 years in our main regression analysis (1975-1994), 97.2% of observations are cash and 1.31% are credit card. For the last 18 years (1995-2012), 69.1% are cash and 28.8% are credit card.

Next, we examine how the demographic characteristics of the donors affect their responses to large NSF grants.[15] As mentioned earlier, our unique dataset allows us to match individual donations to donor characteristics in a way that has not been done before in the literature, aside from relatively small field experiments. First, we compare donations from alumni to donations from non-alumni. We create an outcome variable for each set of donors; that is, one variable that measures the total dollar amount of small gifts from alumni in a week and one that measures the total dollar amount from non-alumni. We run two separate regressions and compare the responses of alumni to non-alumni. We present the results in the first two rows of Table 5.

We also consider the effect of demographic variables from the alumni database, including gender, race, and state of residency (comparing those who live in the university's state to those who do not). Our analysis on the state of residency is novel to the literature, and it ties to predictions from our theoretical model presented in the appendix about how crowding effects could differ depending on whether a donor's tax dollars fund the institution. For this analysis, we will only be able to use the donations from alumni for which we have demographic information. Fifty-eight percent of donations are from alumni linked in the database, and some of those alumni observations are missing demographic information.[16] We create a new outcome variable for several demographic groups. For instance, we create a total dollar amount of donations in a week from in-state residents, and the total amount from out-of-state residents. Lastly, we separately consider donations from previous donors and those from new donors. These include

[15] This analysis is related to the several papers cited earlier, including Clotfelter (2003) and Monks (2003), that estimate the demographic determinants of alumni giving. Here, though, we look instead for differential crowd out or crowd in by demographic group.
[16] See Table 1; most observations of donors contain gender, marital status, and age, but 45% of the observations are missing race.

donations from both alumni and non-alumni, since we have a unique donor identifier for both types of donors. We show the results in the remainder of Table 5. All the numbers reported are regression coefficients from estimating equation 1, using a 12-week window within a large ($5 million or more) NSF grant, and running the regression solely on the indicated subset of donors.

As in the previous results that do not differentiate by demographic group (Table 3), we see that all demographic groups have a positive crowd-in effect on the extensive margin (number of donations), and a negative, crowd-out effect on the intensive margin (average dollars per donation). There is some evidence for different responses based on the demographics of the donors. On the extensive margin (number of donations), the response to large NSF grants is almost always positive, but there are some substantial differences in magnitude. Notably, the effect among in-state residents is twice as large as that of out-of-state residents (though it is insignificant), and the effect of previous donors is more than five times larger than that of new donors. The effect on alumni donors is slightly larger than the effect among non-alumni donors. Men and white donors show a slightly larger crowding-in effect than women and non-white donors, respectively. On the intensive margin (average dollars per donation), we see a negative (crowd out) coefficient for all subgroups. Alumni and men demonstrate a larger crowd-out effect than women and non-alumni, respectively. The largest difference is between previous donors and new donors; previous donors' crowd-out effect is twice as large as new donors'.

The result from the comparison of in-state to out-of-state residents is consistent with our theoretical model in the appendix, which predicts a larger crowd-out (or smaller crowd-in) effect in response to public funding from taxpayers. However, the public funding in the data is federal, not state, so the distinction between in-state and out-of-state residents may not be appropriate. However, the crucial determinant in this effect is the salience of public funding. In-state residents may see news stories or hear reports about public funding to the university more than out-of-state residents, and thus we would expect differences in giving patterns to the university.

The result on the differences between previous donors and new donors is analogous to previous literature that finds differences in responses between "warm list" and "cold list" donors (e.g., Landry et al. 2010). One might suspect that a signaling crowd-in effect will be weaker among previous donors, who are more knowledgeable about the university and therefore less likely to need an information signal. But, the larger extensive-margin crowd-in effect is consistent with findings from Levin et al. (2016), who find evidence for a quality signaling effect even among high-capacity previous donors. The larger intensive-margin crowd-out effect among previous donors could also reflect their increased knowledge about the university's resources and response to increased external funding, compared to new donors.

III. C. Control for Fundraisers and Media Citations

The associations we find above between large NSF grants and smaller donations may indicate crowding in or crowding out, but there may also be several confounding factors that do not allow us to identify causality. First, the university is not a passive receiver of donations; it engages in fundraising and conducts large fundraising drives. During drives, we might expect more grants and more small gifts, biasing the correlation between these two types of donations upwards.[17] Second, what may be more important than the receipt of large grants is the advertising of such receipts – if potential donors are unaware of these grants, they cannot respond to them.

[17] See for instance Scharf et al. (2017) on the effect of fundraising on the timing of donations.

Therefore, we include two additional sets of controls in our regressions. First, we create an indicator variable $Fundraiser_t$ that is equal to one if week t is during a large fundraising drive. Second, we create a variable $Media_t$ that equals the number of media stories that appear during week t that mention the public or private grants. We report regressions that control for these additional variables in Appendix Tables A12 and A13.

Appendix Table A12 adds an indicator variable equal to one for weeks during a university fundraising drive. Since both fundraising drives begin on January 1 and end on December 31, there is a multicollinearity issue with including this indicator as well as including the year-fixed effects that have been included in all previous regressions. Thus, the coefficients of interest in the regressions with and without the fundraising drive indicator are identical to each other (the regressions with the drive indicator omit an additional year indicator). This collinearity suggests, as argued earlier, that our controls for the year and week-of-year fixed effects are likely capturing much of the impact of fundraising drives in the other specifications. Nevertheless, the coefficient on the fundraising drive indicator is significantly positive in the number of donation regressions and the total dollar amount of donations regressions. Despite the collinearity of this indicator, reporting these results helps show the effect of fundraising drives. Being in a week during a fundraising drive increases the number of donations by 240-270 and increases the total dollar amount of donations by $55,000-$65,000. Fundraising drives may increase the average donation dollar amount, though the results are not as significant.

Appendix Table A13 replicates the regressions from Table 3, but it also adds controls for the number of media stories in the week that mention grants or gifts. There are two sources of media stories that we control for – those from the university's press releases, which are available starting in 1997, and those from the local daily newspaper, which are available starting in 1985.

The left column among each pair of columns does not include the media control, and thus it replicates the regressions from Table 3, except only for the years for which we have the media data. Due to the small number of observations, there is no statistical significance for the regressions in the top panel. In the second panel, using the daily newspaper data, we again see evidence of crowding in on the extensive margin and crowding out on the intensive margin, though the significance is somewhat less than it is in other regressions. Appendix Table A13 demonstrates that controlling for media citations (when we observe them) does not have a substantial impact on the previously estimated coefficients and does not affect outcomes.

Admittedly our fundraising control is coarse – it is merely a binary indicator equal to one during the years in which a large fundraising drive is going on, and there is no intra-year variation. It would be preferable to have more detailed fundraising data – for example, a measure of fundraising expenditures at the daily or weekly level. Then, we could control for fundraising like Andreoni and Payne (2003). Though we lack these data, we nonetheless argue that it does not present a problem for our empirical results. Our detailed, daily data combined with year-fixed effects and week-of-year-fixed effects allow us to make a plausible case that the fixed effects are picking up any variation in this unobserved confounder. If there is substantial variation in fundraising expenditure or effort even after controlling for these fixed effects, then our estimated relationship between large gifts and smaller donations may also be due in part to the mediating effect of fundraising. In any case, our estimated effects still have a valid interpretation as an effect on private donations *net of* any effect on fundraising.

An additional test that we perform to net out the effect that fundraising may have on expanding or contracting the donor pool is by isolating only the donations from a fixed pool of donors. If this pool is constant over the period of our sample, then by looking only at these donations, we do not merely pick up a change in the number of potential donors being solicited by fundraisers. We choose a pool to create a balanced panel of donors using only those donors who made at least one donation sometime between 1981 and 1985 and who were not reported as dying before the end of the sample period. Results from this regression are presented in Appendix Table A14. These results still show significant extensive-margin crowding in and intensive-margin crowding out, as do the main results. This suggests that these crowding effects are not merely artifacts of changes in fundraising intensity affecting the size of the donor pool.

III. D. Comparison of Response across Units of the University

Next, we exploit the fact that we can identify the unit within the university that the donor targets. Appendix Table A1 lists the 24 units to which donors target gifts; Table 2 collapses these into five groups and presents summary statistics. By identifying the unit within the university, we can test for crowding out or crowding in within or across units. For example, does a large grant to the medical school crowd out smaller donations to the engineering school?

We use a difference-in-differences strategy. We reshape the data so that each observation is a unit-week. Each unit-week observation contains the number of small donations, the total sum of money received in small donations, and the average size of small donations. We restrict the sample to only those weeks that are either within a specified time window before or after the large grant. We then define an indicator variable (*Same Unit*) that is equal to one if the unit is the same as the unit of the "local" grant ("local" meaning the grant in the time window). If there were multiple grants in the time window, we set the *Same Unit* variable equal to one if the unit is the same as the unit of any of the local grants. We define an indicator variable for whether the week occurred after the grant (*Post*) rather than before (within the specified time window).

Neither the NSF dataset nor the USAspending.gov/National Archives database indicates which unit receives the grant within the university. For the NSF grants, the NSF data provide us with the NSF organization awarding the grant, which we use to match the grant to the unit within the university. For example, we assign a grant from the NSF Division of Chemistry to the university's liberal arts college, which contains the chemistry department. We match all of the NSF grants to one of just three units: the liberal arts college, the engineering school, and the education school. The location of the NSF grant only matters when the location is known (or inferred) by the donors. NSF grants generally are not given to fine arts units, so the unit-level classification captures more narrow substitution than individual donors may actually be making. For the USAspending.gov and National Archives data, we observe the number assigned to the grant based on the Catalog of Federal Domestic Assistance (CFDA). We assign each CFDA number to a unit within the university by creating a cross-walk file, much in the same way we matched the NSF grants.

We run regressions controlling for unit, week-of-year, and year fixed effects. We include both the *SameUnit* indicator and the *Post* indicator, as well as the interaction term. Our estimating equation is

$$y_{i,t} = \beta_1 + \beta_2 Post_{i,t} + \beta_3 SameUnit_{i,t} + \beta_4 Post_{i,t} \times SameUnit_{i,t} + \beta_5 X_{i,t} + \varepsilon_{i,t}$$

We run this regression for each of the three large donation cutoff values and each of the three outcome variables. Table 6 presents the regression results from the NSF data, and Table 7 presents them using the broader federal grants database.

In order to infer causality from the difference-in-differences specification, we assume the trends in donations to each unit would be parallel over time, absent the grant. To verify this assumption, we take an event study approach, estimating the difference-in-differences specification with one modification: we replace the "after large grant" dummy in the interaction term with a set of dummies for "weeks since large grant". The coefficients in this event study specification give the effect of the grant in the referenced week since the grant. If the trends in donations to different units are parallel over time, this would be reflected in flat coefficients in the pre-period. We plot the coefficients on the interaction terms between the *SameUnit* indicator and the weeks-since dummies in Appendix Figures A6 through A8 for the three different outcome variables. The figures show that, as assumed, there are not significantly different trends in donations across units.

Unit-level crowd-in would imply that the coefficient on the interaction term is positive. In the first column of Table 6, we always find a positive coefficient on this interaction term, with a magnitude ranging from one to twelve donations per week, though it is never significant. The intensive-margin effect is mixed; two out of the three specifications find a negative sign (crowding out), while the other finds a positive sign (crowding in), though none are significant.

Table 7 shows evidence of crowding in on both the extensive and intensive margins for federal grants, though the only statistically significant coefficient is the intensive margin interaction effect for the $10 million large grant cutoff. Given that there was little evidence of any donor response to non-NSF federal grants overall (Table 4), it is not surprising that the evidence for unit-level crowding is also weak.

While the theory presented in the appendix provides some support for the hypothesis that crowding out or crowding in could be observed across units within the organization, we do not find evidence for either such effect in the data. This result could indicate that no such cross-unit crowding exists, or it could be due to the limitations of the data. In particular, the matching of grants to units within the university is likely noisy, and there is not much variation in grant receipts across units (most are going to the medical school or the liberal arts college).

III. E. Comparison of Response by Agency Type

The comparison of the results in Tables 3 and 4 suggests that donors react differently to NSF grants than they do to grants from other federal agencies. The USAspending.gov/National Archives data used in the regressions in Table 4 contain grants from the NSF as well as other federal agencies. The most common granting agency in that dataset by far is the Department of Health and Human Services (HHS), which accounts for about 80% of the observed grants. The two other most represented agencies are the Department of Defense (DOD) and the NSF. We further explore differences in responses to different grantmaking agencies by focusing just on the USAspending.gov/National Archives dataset, but separately look at grants from those three agencies, along with all other agencies lumped together as "Others." We present these results in Table 8.

The four panels of Table 8 each replicate the regressions in Table 4 but looking only at large grants to the DOD, HHS, NSF, and Other agencies, respectively. Regressions with the DOD grants show little evidence of crowding in either direction on either margin, although the coefficient on the grant window for the $5 million cutoff on the extensive margin (number of donations) regression is marginally significant. Likewise, the regressions using just the HHS grants, which account for the vast majority of all grants in the USAspending.gov/National Archives dataset, show little consistent results. On the extensive margin, using a $5 million cutoff provides significant evidence for crowding in, while using a $1 million cutoff provides significant evidence for crowding out. There is a similar inconsistency with the intensive margin effect.

Only in the third panel of Table 8, which examines NSF grants from the USAspending.gov/National Archives dataset, do we see results that are consistent with those from the NSF database – crowding in on the extensive margin and crowding out on the intensive margin. The magnitudes of these crowding effects are comparable to those found in the regressions with the NSF data in Table 3. In principle, the results from this panel and from Table 3 should be identical to each other if the USAspending.gov/National Archives dataset includes all of the NSF grants reported in the NSF dataset and vice versa. Since the datasets are not perfectly consistent with each other, the magnitudes of the regression results are not identical. Finally, the fourth panel in Table 8, which includes all of the other agency grants (accounting for just less than 5% of all of the grants) also shows no evidence for crowding effects.

Thus, Table 8 reinforces the findings from Tables 3 and 4 that donors respond differently to NSF grants than they do to other federal agency grants; this result is not a mere artifact of the two different data sources. One explanation for this finding could be that the university's fundraising program more heavily promotes the NSF grants than other types of grants. Our data from the university's press releases support this explanation – the number of press releases about HHS or NIH grants is about twice as high as the number of press releases about NSF grants, though the number of HHS or NIH grants is ten times as high as the number of NSF grants.[18] Another explanation is that donors interpret NSF funding as providing a more valuable quality signal than other funding sources. This explanation is explored more in our theoretical model presented in the appendix, which derives the magnitude of the signaling crowd-in effect.

[18] We search the text of the press release data, which does not contain the entire release but just the first sentence or two. We find 68 that mentioned "NSF" or "National Science Foundation," and 153 that mentioned "HHS", "Health and Human Services," "NIH," or "National Institutes of Health."

IV. Conclusion

Using a dataset that combines daily-level donation information with demographic information on donors, we estimate the determinants of private donations to a large university. In particular, we explore the extent to which federal research funding may crowd out or crowd in small private donations on either the extensive or the intensive margin. We find evidence of extensive margin crowding in and intensive margin crowding out from large federal NSF grants. For other types of federal grants, we find no consistent evidence for crowding in or crowding out on either margin. Some donor demographic characteristics affect the magnitude of the response to large NSF grants.

Our findings are directly relevant for stakeholders in the higher education sector, especially those in fundraising or development. Fundraisers want to know determinants of donations, how different types of alumni and non-alumni donors may act, and what issues that are either in or out of their control may affect donations. We find evidence that certain types of research grants (which are likely out of the control of development officers) can have important effects on the number and size of donations. Development officers may want to modify their strategies in light of these effects. More generally, our findings are related to the broad literature on the relationship between public and private funding of nonprofit organizations and whether there is crowd out or crowd in, and to the literature on the many effects of public research funding.

Our research is relevant to the literature examining crowd-in and crowd-out (Andreoni 1993, Landry et al. 2010). We use a unique dataset with observations at the individual donation level matched to donor characteristics, rather than aggregated annual data at the organization level or smaller samples of collected data (e.g. from field experiments). The limitation is that our data is just from one university. The advantage is that we have much richer information about the timing of donations and the donor, allowing us to overcome potential endogeneity bias from, for example, unobserved fundraising intensity.

Future research could make use of similar donation-level data sets from a broader range of universities across varying geographic areas as well as private versus public universities. This research is especially valuable to universities or other charitable organizations seeking to maximize revenue from fundraising.

References

Ade, Albert, Phanindra V. Wunnava, and Raymond Walsh Jr. "Charitable giving of alumni: micro-data evidence from a large public university." American Journal of Economics and Sociology (1994): 73-84.

Andreoni, J. "An experimental test of the public-goods crowding-out hypothesis." The American Economic Review 83, no. 5 (1993): 1317-1327.

Andreoni, James. "Leadership Giving in Charitable Fund-raising." Journal of Public Economic Theory 8, no. 1 (2006): 1-22.

Andreoni, James, and A. Abigail Payne. "Do government grants to private charities crowd out giving or fund-raising?" American Economic Review 93, no. 3 (2003): 792-812.

Andreoni, James, and A. Abigail Payne. "Is crowding out due entirely to fundraising? Evidence from a panel of charities." Journal of Public Economics 95, no. 5 (2011): 334-343.

Arora, Ashish, and Alfonso Gambardella. "The impact of NSF support for basic research in economics." *Annales d'Economie et de Statistique* (2005): 91-117.

Auten, Gerald E., Holger Sieg, and Charles T. Clotfelter. "Charitable giving, income, and taxes: An analysis of panel data." The American Economic Review 92, no. 1 (2002): 371-382.

Borgonovi, Francesca. "Do public grants to American theatres crowd-out private donations?." Public Choice 126, no. 3-4 (2006): 429-451.

Bozeman, Barry, and Monica Gaughan. "Impacts of grants and contracts on academic researchers' interactions with industry." *Research policy* 36, no. 5 (2007): 694-707.

Brooks, Arthur C. "Do government subsidies to nonprofits crowd out donations or donors?." Public Finance Review 31, no. 2 (2003): 166-179.

Clotfelter, Charles T. "Alumni giving to elite private colleges and universities." Economics of Education Review 22, no. 2 (2003): 109-120.

Cutler, David M., and Jonathan Gruber. "Does public insurance crowd out private insurance?." The Quarterly Journal of Economics 111, no. 2 (1996): 391-430.

David, Paul A., Bronwyn H. Hall, and Andrew A. Toole. "Is public R&D a complement or substitute for private R&D? A review of the econometric evidence." *Research policy* 29, no. 4-5 (2000): 497-529.

Diamond Jr, Arthur M. "Does federal funding" crowd in" private funding of science?." Contemporary Economic Policy 17, no. 4 (1999): 423.

Eckel, Catherine C., David H. Herberich, and Jonathan Meer. "A field experiment on directed giving at a public university." Journal of behavioral and experimental economics 66 (2017): 66-71.

Gaier, Scott. "Alumni satisfaction with their undergraduate academic experience and the impact on alumni giving and participation." International Journal of Educational Advancement 5, no. 4 (2005): 279-288.

Gordon, Nora. "Do federal grants boost school spending? Evidence from Title I." Journal of Public Economics 88, no. 9 (2004): 1771-1792.

Harrison, William B. "College relations and fund-raising expenditures: Influencing the probability of alumni giving to higher education." Economics of Education Review 14, no. 1 (1995): 73-84.

Harrison, Willian B., Shannon K. Mitchell, and Steven P. Peterson. "Alumni donations and colleges' development expenditures: Does spending matter?." American Journal of Economics and Sociology 54, no. 4 (1995): 397-412.

Heutel, Garth. "Crowding Out and Crowding In of Private Donations and Government Grants." NBER Working Paper #15004, 2009.

Huck, Steffen, Imran Rasul, and Andrew Shephard. "Comparing Charitable Fundraising Schemes: Evidence from a Natural Field Experiment and a Structural Model." American Economic Journal: Economic Policy, 7, no. 2 (2015): 326-69.

Hungerman, Daniel, and Mark Ottoni-Wilhelm. "What is the Price Elasticity of Charitable Giving? Toward a Reconciliation of Disparate Estimates," Working Paper, 2016.

Jacob, Brian A., and Lars Lefgren. "The impact of research grant funding on scientific productivity." *Journal of public economics* 95, no. 9-10 (2011a): 1168-1177.

Jacob, Brian A., and Lars Lefgren. "The impact of NIH postdoctoral training grants on scientific productivity." *Research Policy* 40, no. 6 (2011b): 864-874.

Jaffe, Adam B. "Building programme evaluation into the design of public research-support programmes." *Oxford Review of Economic Policy* 18, no. 1 (2002): 22-34.

Khanna, Jyoti, and Todd Sandler. "Partners in giving : The crowding-in effects of UK government grants." European Economic Review 44, no. 8 (2000): 1543-1556.

Kessler, Judd B. "Announcements of Support and Public Good Provision." American Economic Review, 107, no. 12 (2017): 3760-87.

Kingma, B. R. "An accurate measurement of the crowd-out effect, income effect, and price effect for charitable contributions." The Journal of Political Economy 97, no. 5 (1989): 1197-1207.

Landry, C. E., Lange, A., List, J., Price, M. K., & Rupp, N. G. "Is a donor in hand better than two in the bush? Evidence from a natural field experiment." American Economic Review, 100, no. 3 (2010): 958-83.

Levin, Tova, Steven D. Levitt, and John A. List. "A Glimpse into the World of High Capacity Givers: Experimental Evidence from a University Capital Campaign." NBER Working Paper #22099, 2016.

Meer, Jonathan. "Does fundraising create new giving?." Journal of Public Economics 145 (2017): 82-93.

Meer, Jonathan, and Harvey S. Rosen. "Altruism and the child cycle of alumni donations." American Economic Journal: Economic Policy 1, no. 1 (2009): 258-86.

Monks, James. "Patterns of giving to one’s alma mater among young graduates from selective institutions." Economics of Education review 22, no. 2 (2003): 121-130.

Okten, Cagla, and Burton A. Weisbrod. "Determinants of donations in private nonprofit markets." Journal of Public Economics 75, no. 2 (2000): 255-272.

Okunade, Albert A., and Robert L. Berl. "Determinants of charitable giving of business school alumni." Research in Higher Education 38, no. 2 (1997): 201-214.

Payne, A. Abigail. "Measuring the effect of federal research funding on private donations at research universities: is federal research funding more than a substitute for private donations?." International Tax and Public Finance 8, no. 5-6 (2001): 731-751.

Poterba, James M., Steven F. Venti, and David A. Wise. "Do 401 (k) contributions crowd out other personal saving?." Journal of Public Economics 58, no. 1 (1995): 1-32.

Roberts, Russell. "A Positive Model of Private Charity and Public Transfer." Journal of Political Economy 92, no. 1 (1984): 136-148.

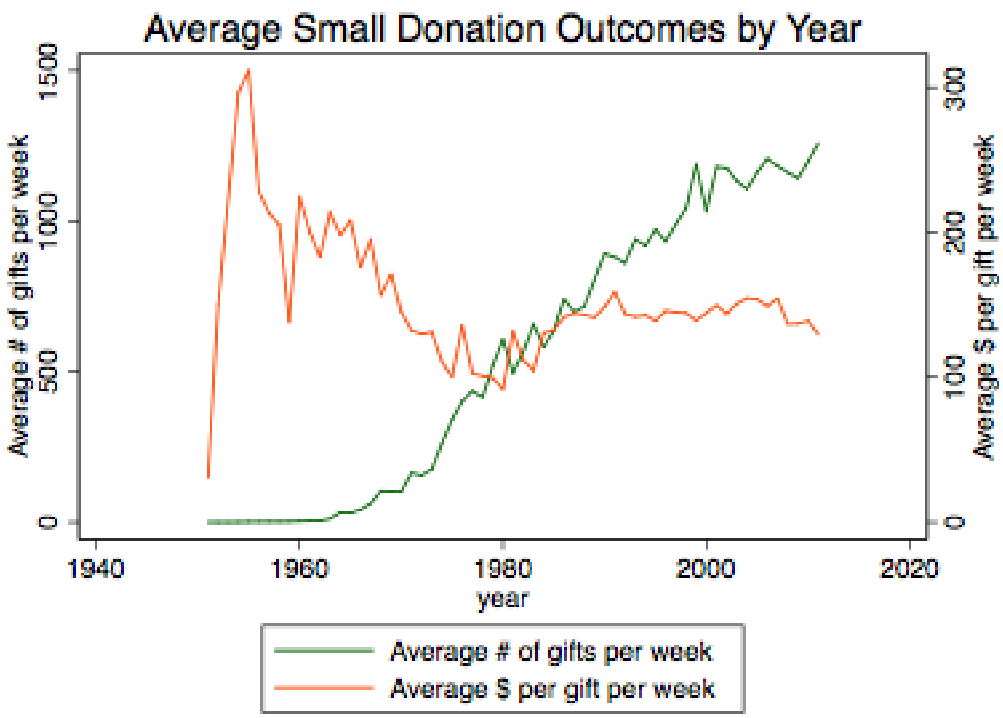
Scharf, Kimberley A., Sarah Smith, and Mark Wilhelm. "Lift and shift: the effect of fundraising interventions in charity space and time." CEPR Discussion Paper # DP12338 (2017).

Svider, Peter F., Kevin M. Mauro, Saurin Sanghvi, Michael Setzen, Soly Baredes, and Jean Anderson Eloy. "Is NIH funding predictive of greater research productivity and impact among academic otolaryngologists?." *The Laryngoscope* 123, no. 1 (2013): 118-122.

Taylor, Alton L., and Joseph C. Martin Jr. "Characteristics of alumni donors and nondonors at a research I, public university." Research in Higher Education 36, no. 3 (1995): 283-302.

Warr, Peter. "Pareto Optimal Redistribution and Private Charity." Journal of Public Economics 19, no. 1 (1982): 131-138.

Figure 1: Donations Time Series



Notes: This figure shows the average number of donations (under $1,000) per week (left axis) and the average amount per donation per week (right axis) over time.

Table 1: Summary statistics of Alumni Database

	Non-Donors	Donors	Total
Observations	263043	166558	429601
White	0.466	0.599	0.518
	(0.499)	(0.490)	(0.500)
	[144334]	[92878]	[237212]
Female	0.507	0.451	0.485
	(0.500)	(0.498)	(0.500)
	[262912]	[166557]	[429469]
Fraternity/Sorority	0.084	0.159	0.113
	(0.277)	(0.366)	(0.317)
	[263043]	[166558]	[429601]
Ever Married	0.198	0.538	0.330
	(0.398)	(0.499)	(0.470)
	[263043]	[166558]	[429601]
Number of Children	0.092	0.369	0.199
	(0.467)	(0.889)	(0.677)
	[263043]	[166558]	[429601]
In-state Resident	0.784	0.784	0.784
	(0.411)	(0.411)	(0.411)
	[220391]	[154889]	[375280]
Birth Year	1965	1957	1962
	(17)	(18)	(18)
	[223341]	[154820]	[378161]
First Degree Year	1985	1981	1983
	(20)	(19)	(20)
	[263043]	[166558]	[429601]

Notes: Table displays the mean value, the standard deviation (in parentheses), and the number of non-missing observations [in square brackets]. All variables are binary indicators except for birth year and first degree year.

Table 2: Summary Statistics of Gift Database

	Number of gifts (% of total)	Mean Gift Amount (2000$)	Median Gift Amount (2000$)
		By Decade	
1938-1969	24490 (1%)	3860	108
1970-1979	162307 (9%)	831	49
1980-1989	360957 (19%)	1003	72
1990-1999	537730 (28%)	1547	109
2000-2009	653949 (35%)	2819	87
2010-2012	153862 (8%)	2772	77
		By Gift Allocation Unit	
General	829785 (44%)	393	62
Medical School	371072 (20%)	4529	76
Athletics	139745 (7%)	1614	331
Liberal Arts College	103188 (5%)	3376	81
Other	449504 (24%)	2476	98

Notes: "General" includes the categories "Chancellor's Greatest Needs" and "General Campus". "Other" includes all other units listed in Appendix Table A1.

Table 3: Response to Large NSF Grants

	# of donations	Average $ per donation	Total $ of donations
$10 million cutoff	25.94	-14.46***	-15,502**
	(39.63)	(3.972)	(6,902)
$5 million cutoff	74.09**	-12.04***	-612.5
	(31.47)	(3.157)	(5,495)
$1 million cutoff	36.46**	-3.151*	2,345
	(18.52)	(1.863)	(3,232)

Notes: This table presents the estimated coefficient (and standard error) on the indicator for being within a 12-week window of a large public NSF grant, in regressions where the dependent variable is either the number of private donations, the average dollar amount per donation, or the total dollar amount of donations. Regressions also include year indicators and week-of-year indicators, and a constant. Regressions are at the weekly level and include just the years 1975-2012. The number of observations is 1939 for all regressions. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 4: Response to Large Federal Grants

	# of donations	Average $ per donation	Total $ of donations
$10 million cutoff	3.131	3.651	-2,467
	(32.29)	(2.802)	(5,685)
$5 million cutoff	65.52**	-1.285	4,363
	(27.09)	(2.356)	(4,776)
$1 million cutoff	-22.97	-0.413	-4,959
	(33.47)	(2.906)	(5,891)

Notes: This table presents the estimated coefficient (and standard error) on the indicator for being within a 12-week window of a large public federal grant, in regressions where the dependent variable is either the number of private donations, the average dollar amount per donation, or the total dollar amount of donations. Regressions also include year indicators and week-of-year indicators, and a constant. Regressions are at the weekly level and include just the years 1982-2012. The number of observations is 1627 for all regressions. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 5: Comparison of Response to NSF Grants based on Donor Demographics

	# of donations	Average $ per donation	Total $ of donations
Alumni	39.70*	-14.10***	-871.0
	(20.68)	(3.646)	(3,569)
Non-alumni	34.39**	-12.70***	258.5
	(14.38)	(3.341)	(2,279)
Men	21.20*	-15.41***	-1,133
	(12.85)	(4.185)	(2,562)
Women	18.50**	-10.97***	261.8
	(8.311)	(3.146)	(1,108)
Whites	6.877	-11.67***	-1,015
	(8.307)	(3.962)	(1,500)
Non-whites	-4.783	-11.78**	-938.2*
	(3.356)	(4.796)	(490.1)
In-state Resident	23.92	-14.66***	-1,803
	(16.06)	(3.880)	(2,939)
Out-of-state Residents	10.17**	-11.00***	650.7
	(4.349)	(3.663)	(691.9)
Previous Donors	65.05**	-14.47***	-640.3
	(26.92)	(3.582)	(4,944)
New Donors	9.043	-7.881***	27.74
	(9.563)	(3.045)	(1,046)

Notes: This table presents the estimated coefficients (and standard errors) on the indicators for being within a 12-week window of a large ($5 million or more) NSFgrant, in regressions where the dependent variable is either the number of private donations, the average dollar amount per donation, or the total dollar amount of donations, just from the specified demographic groups. Regressions also include year indicators and week-of-year indicators, and a constant. Regressions are at the weekly level and include just the years 1975-2012. The number of observations is 1939 for all regressions. *** p<0.01, ** p<0.05, * p<0.1

Table 6: Unit-Level, Difference-in-differences – Large NSF Grants

		# of donations	Average $ per donation	Total $ of donations
$10 million cutoff	After	-5.022	-2.763	-1,305
		(4.202)	(7.712)	(1,295)
	Same Unit	-7.408	1.746	-2,106
		(7.580)	(11.98)	(2,336)
	Interaction	12.74	-4.279	4,406
		(9.238)	(14.57)	(2,847)
$5 million cutoff	After	0.195	-10.45**	-652.1
		(2.290)	(4.697)	(722.6)
	Same Unit	-13.68**	2.196	-1,772
		(5.823)	(9.938)	(1,837)
	Interaction	7.793	8.509	1,765
		(6.884)	(11.79)	(2,172)
$1 million cutoff	After	1.514*	-1.658	14.27
		(0.821)	(1.792)	(254.8)
	Same Unit	-1.974	-1.211	-1,834*
		(3.350)	(6.052)	(1,040)
	Interaction	1.133	-7.910	228.4
		(3.242)	(5.854)	(1,006)

Notes: This table presents the estimated coefficients (and standard errors) for three indicators variables 12 weeks after a large NSF grant (but still in the listed time window), donations made to the same unit as the large grant that occurred in the same time window, and an interaction between the two; in regressions where the dependent variable is either the number of private donations, the average dollar amount per donation, or the total dollar amount of donations. When there were multiple large grants in the same window, the "Same Unit" indicator is equal to one if the unit is equal to the unit of any of the large grants in the time window. If weeks were both before and after a large grant, but in the time window for both, we set the "After" indicator to one. Regressions also include year indicators, week-of-year indicators, unit indicators, and a constant. Regressions are at the donation-week level, and include just the years 1950-2012. We only include observations if they are within the specified time window distance either before or after a large grant. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 7: Unit-Level, Difference-in-differences – Large Federal Grants

		# of donations	Average $ per donation	Total $ of donations
$10 million cutoff	After	-2.001	-3.446	-787.3
		(1.500)	(2.912)	(490.6)
	Same Unit	-0.258	-16.09	-2,688
		(6.957)	(12.06)	(2,275)
	Interaction	0.474	27.25*	2,730
		(7.988)	(14.04)	(2,612)
$5 million cutoff	After	1.935	-3.860	258.2
		(1.236)	(2.520)	(395.9)
	Same Unit	5.870	-1.972	145.7
		(6.014)	(11.24)	(1,927)
	Interaction	3.264	12.89	553.6
		(6.495)	(12.14)	(2,081)
$1 million cutoff	After	-0.982	-4.392	-592.9
		(1.329)	(2.712)	(428.3)
	Same Unit	5.773	-32.35	-10,400
		(37.24)	(109.1)	(12,003)
	Interaction	7.775	35.82	10,558
		(37.25)	(109.1)	(12,007)

Notes: This table presents the estimated coefficients (and standard errors) for three indicators variables 12 weeks after a large federal grant (but still in the listed time window), donations made to the same unit as the large grant that occurred in the same time window, and an interaction between the two; in regressions where the dependent variable is either the number of private donations, the average dollar amount per donation, or the total dollar amount of donations. When there were multiple large grants in the same window, the "Same Unit" indicator is equal to one if the unit is equal to the unit of any of the large grants in the time window. If weeks were both before and after a large grant, but in the time window for both, we set the "After" indicator to one. Regressions also include year indicators, week-of-year indicators, unit indicators, and a constant. Regressions are at the donation-week level, and include just the years 1950-2012. We only include observations if they are within the specified time window distance either before or after a large grant. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 8: Response to Large Federal Grants by Agency

	# of donations	Average $ per donation	Total $ of donations
		Agency: DOD	
$10 million cutoff	-121.4	3.210	-17,949
	(120.9)	(10.50)	(21,285)
$5 million cutoff	135.5*	7.739	22,568
	(78.51)	(6.821)	(13,822)
$1 million cutoff	5.803	2.813	1,300
	(35.42)	(3.075)	(6,235)
		Agency: HHS	
$10 million cutoff	1.999	2.229	-5,116
	(33.11)	(2.874)	(5,827)
$5 million cutoff	75.16**	-5.778**	-2,191
	(29.79)	(2.587)	(5,254)
$1 million cutoff	-94.50**	4.469	-13,685**
	(38.79)	(3.372)	(6,832)
		Agency: NSF	
$10 million cutoff	33.20	-11.99**	-13,610
	(54.86)	(4.754)	(9,652)
$5 million cutoff	49.49	-5.702	-877.3
	(43.21)	(3.751)	(7,610)
$1 million cutoff	136.1***	-7.487**	10,782
	(39.51)	(3.438)	(6,977)
		Agency: Others	
$10 million cutoff	-46.85	4.663	-3,353
	(51.80)	(4.497)	(9,120)
$5 million cutoff	26.46	1.707	4,425
	(28.93)	(2.512)	(5,093)
$1 million cutoff	21.03	0.793	2,267
	(24.88)	(2.160)	(4,380)

Notes: This table presents the estimated coefficient (and standard error) on the indicator for being within a 12-week window of a large public federal grant, in regressions where the dependent variable is either the number of private donations, the average dollar amount per donation, or the total dollar amount of donations. We separately examine grants from DOD, HHS, the NSF, and all other agencies in the USAspending.gov/National Archives database. Regressions also include year indicators and week-of-year indicators, and a constant. Regressions are at the weekly level and include just the years 1982-2012. The number of observations is 1627 for all regressions. *** p<0.01, ** p<0.05, * p<0.1

Appendix – For Online Publication Only

A.I. Model

Here we present a simple model of crowd out and crowd in to frame some of the empirical analyses of the paper. This model shares many features with previous models in the literature. Though we do not attempt to structurally estimate this model, the model nonetheless provides a helpful framework for interpreting the reduced-form regression results in the paper.

We consider how government grants to an organization affect a donor's level of giving. We allow for the quality of the organization to be uncertain, so that large grants may serve as quality signals. We also model different organizations (or for different units within an organization).

A.I.a. Base-case, one-charity model

Consider a representative consumer endowed with income y who is deciding over how much to donate to a single charity, d, and how much to spend on the composite consumption good, c. She faces a tax imposed by a government, τ. The consumer's budget constraint is $y \geq c + d + \tau$.

The consumer has preferences over consumption and over the level of charitable activity G. The quality of the charity is α; a higher value of α indicates a higher-quality charity. The consumer's utility is $U(c, G; \alpha)$. Assume that utility from consumption is separable from utility from the charity, as in Andreoni (2006): $U(c, G; \alpha) = u(c) + v(G, \alpha)$, with $u' > 0, u'' < 0, v_G > 0, v_{GG} < 0, v_\alpha > 0$, and $v_{G\alpha} > 0$. This last inequality ensures that the marginal utility of charitable activity is increasing in charity quality.

The consumer does not observe α but has a belief μ that describes her assessment of the probability distribution of α. Suppose that α can take only one of two values: α_L or α_H, with $\alpha_L < \alpha_H$. Let μ denote the consumer's belief that $\alpha = \alpha_H$. The consumer maximizes expected utility: $u(c) + \mu v(G, \alpha_H) + (1 - \mu) v(G, \alpha_L)$.

The total level of charitable activity G is determined by four sources: the consumer's voluntary contribution d, the consumer's tax payment τ (all of which goes to the charity), an exogenous level of public contributions g_{pub} (not including the consumer's tax payment), and an exogenous level of private contributions g_{priv}. Thus $G = d + \tau + g_{pub} + g_{priv}$.

The consumer does not directly observe α, but she does observe total private gifts g_{priv} and total public grants $g_{pub} + \tau$. Her beliefs about charity quality may be determined by the level of public or private grants that she sees the charity receiving: $\mu = \mu(g_{pub} + \tau, g_{priv})$. Public and private grants may have differential signaling effects.[19]

The consumer's decision can be written as

$$\max_{d \geq 0} u(y - d - \tau) + \mu\left(g_{pub} + \tau, g_{priv}\right) \cdot v\left(\tau + d + g_{pub} + g_{priv}, \alpha_H\right) + \left(1 - \mu\left(g_{pub} + \tau, g_{priv}\right)\right) \cdot v\left(\tau + d + g_{pub} + g_{priv}, \alpha_L\right)$$

Assuming an interior solution, this yields a first-order condition of:

$$-u'(y - d - \tau) + \mu\left(g_{pub} + \tau, g_{priv}\right) \cdot v_G\left(\tau + d + g_{pub} + g_{priv}, \alpha_H\right) + \left(1 - \mu\left(g_{pub} + \tau, g_{priv}\right)\right) \cdot v_G\left(\tau + d + g_{pub} + g_{priv}, \alpha_L\right) = 0$$

We can use this first-order condition for comparative statics. In particular, how does a change in the tax imposed on the consumer affect her donation? The implicit function theorem shows that

$$\frac{dd}{d\tau} = -1 + \frac{d\mu}{d\tau} \cdot \frac{v_G(G, \alpha_H) - v_G(G, \alpha_L)}{-u''(c) - E[v_{GG}(G)]} \tag{1}$$

Here $E[v_{GG}(G)] = \mu v_{GG}(G, \alpha_H) + (1 - \mu) v_{GG}(G, \alpha_L)$ is the expected value of the second derivative of the subutility from the charitable good. If a consumer's belief about charity quality is independent of the tax $(d\mu/d\tau = 0)$, then this derivative is -1. In other words, absent any signaling effect, an increased government contribution to the charity is perfectly crowded out by a decreased private contribution. This result is originally found in Warr (1982) and Roberts (1984).

The remainder of the expression represents a signaling effect. It is of the same sign as $d\mu/d\tau$ (the denominator is positive from the concavity of u and v, and the numerator is positive from the assumption on the cross-partial derivative of v). If a higher level of government grants from τ signals to the consumer that the charity is more likely to be high quality, then the signaling effect will lead her to increase her contributions. The magnitude of this depends on parameters, including how much the signal affects her beliefs. This positive

[19] The belief function is exogenous; for a more general treatment in which beliefs are derived from donors' actions in a Bayesian equilibrium see Heutel (2009).

signaling effect may or may not dominate the negative crowd-out effect. This signaling effect is found also in the model in Payne (2001).

The classic one-for-one crowd out result was replicated when the increase in government funding of the charity came directly from the consumer, via τ. Consider an increase instead in g_{pub}, the exogenous level of government grants (i.e. not funding coming directly from the consumer).

$$\frac{dd}{dg_{pub}} = -1 + \frac{d\mu}{dg_{pub}} \cdot \frac{v_G(G, \alpha_H) - v_G(G, \alpha_L)}{-u''(c) - E[v_{GG}(G)]} + \frac{u''(c)}{u''(c) + E[v_{GG}(G)]} \tag{2}$$

The first term (classic crowd-out) and second term (signaling) are identical to the two respective terms in equation 1 for $\frac{dd}{d\tau}$ (since beliefs μ are affected by g_{pub} or by τ in the same way). The third term is an income effect, and it is positive but less than one. An exogenous increase in government funding increases the utility that the consumer gets from the charity at no cost to the consumer; therefore, she will reallocate more of her income from charitable donations to private consumption. If there is no signaling effect (second term), then the net derivative is strictly between -1 and 0: there is crowding-out but less than one-for-one.

The distinction between $dd/d\tau$ and dd/dg_{pub} depends on this income effect. In practice, the relevant question is whether or not the increase in government funding is directly tied to a decrease in the consumer's wealth via a tax, and whether the consumer recognizes this. For instance, if a consumer learns that a charity's government grants increase, he may infer (perhaps correctly) that the increased funding came not from increased taxes but rather from a reallocation of government expenditures from something that he did not care for to something that he does. In this instance, the increased government funding will create an additional income effect that will not be present if the consumer infers that the increased government grant is being paid for by him.

The last comparative static result from this one-period, one-charity model is the effect on donations of a change in private grants:

$$\frac{dd}{dg_{priv}} = -1 + \frac{d\mu}{dg_{priv}} \cdot \frac{v_G(G, \alpha_H) - v_G(G, \alpha_L)}{-u''(c) - E[v_{GG}(G)]} + \frac{u''(c)}{u''(c) + E[v_{GG}(G)]} \tag{3}$$

As in equation 2, here there are three terms: the first representing one-for-one crowding-out, the second signaling, and the third an income effect. The crowd-out effect and the income effect are identical to the analogous terms in equation 2 for the expression for dd/dg_{pub}. The signaling effect only differs in that it depends on $\frac{d\mu}{dg_{priv}}$. Thus, if a consumer's beliefs are affected differentially by public vs. private grants, then these signaling effects may differ. For example, a consumer may hold more faith in a private foundation's assessment of a charity's quality than in the government's assessment, and thus the impact of g_{priv} on μ is greater than the effect of g_{pub} on μ.

To summarize, contributions to a charity create a negative crowding out effect and a positive signaling effect, and the net magnitude and sign of the response are ambiguous. Furthermore, there are two reasons why a donor's response to government funding may differ from her response to private funding. First, the signaling effect of those two types of funding may differ from one another (the second terms in equations 2 and 3). Second, while private funding creates an income effect, public funding will not if the funding comes from the donor's taxes.

A.I.b. Multiple Charities

Suppose now that there exist two charities, with a total charitable output of G_1 and G_2, respectively. In our empirical setting, one can think of this as two units within an organization, e.g., two different colleges within a university. The consumer chooses among composite consumption c and donations to either charity d_1 and d_2. The consumer knows how her tax payment is allocated across charities: $\tau = \tau_1 + \tau_2$. Public and private grants can go to either of the two charities: $g_{pub1}, g_{pub2}, g_{priv1}$, and g_{priv2}. Each charity can have one of two quality levels, α_H or α_L. The consumer's beliefs about quality may differ between the two charities. Assume that μ_1, the consumer's belief that charity 1 is high-quality, depends only on contributions to charity 1: $\mu_1 = \mu_1(\tau_1 + g_{pub1}, g_{priv1})$. Similarly, $\mu_2 = \mu_2(\tau_2 + g_{pub2}, g_{priv2})$. The consumer's utility function is $u(c) + E[v(G_1)] + E[v(G_2)]$.

The consumer's problem is

$$\max_{d_1, d_2 \geq 0} u(y - d_1 - d_2 - \tau_1 - \tau_2) + \sum_{j=1}^{2} \mu_j\left(g_{pubj} + \tau_j, g_{privj}\right) \cdot v\left(\tau_j + d_j + g_{pubj} + g_{privj}, \alpha_H\right) + \left(1 - \mu_j\left(g_{pubj} + \tau_j, g_{privj}\right)\right) \cdot v\left(\tau_j + d_j + g_{pubj} + g_{privj}, \alpha_L\right)$$

The consumer's first-order condition for the choice of d_j, assuming an interior solution, is

$$-u'(y - d_1 - d_2 - \tau_1 - \tau_2) + \mu_j(g_{pubj} + \tau_j, g_{privj}) \cdot v_G(\tau_j + d_j + g_{pubj} + g_{privj}, \alpha_H) + \left(1 - \mu_j(g_{pubj} + \tau_j, g_{privj})\right) \cdot v_G(\tau_j + d_j + g_{pubj} + g_{privj}, \alpha_L) = 0$$

We perform comparative statics using these first-order conditions. First consider the impact of a change in the consumer's tax revenue going towards charity 1.

$$\frac{dd_1}{d\tau_1} = -1 + \frac{d\mu_1}{d\tau_1} \cdot \frac{(v_G(G_1, \alpha_H) - v_G(G_1, \alpha_L)) \cdot (-u''(c) - E[v_{GG}(G_2)])}{D} \tag{4}$$

The denominator $D \equiv u''(c) \cdot (E[v_{GG}(G_1)] + E[v_{GG}(G_2)]) + E[v_{GG}(G_1)] \cdot E[v_{GG}(G_2)]$ is positive. The first term is the crowd-out effect, and it is again –1. The second term is the signaling effect. It is the same sign as $d\mu_1/d\tau_1$. As before, if increased government funding via τ_1 increases the consumer's belief that the charity is high quality, this effect increases her voluntary contributions.

What effect does a change in τ_1 have on d_2?

$$\frac{dd_2}{d\tau_1} = \frac{d\mu_1}{d\tau_1} \cdot \frac{(v_G(G_1, \alpha_H) - v_G(G_1, \alpha_L)) \cdot u''(c)}{D} \tag{5}$$

There is no crowd-out effect, only a signaling effect. The signaling effect exists even though contributions to charity 1 (τ_1) do not affect the consumer's belief about the quality of charity 2 (μ_2). Rather, there is an effect on the belief about the quality of charity 1 (μ_1), and that may cause a shift from giving between the two charities. The signaling effect is of the opposite sign of $d\mu_1/d\tau_1$. If a higher government contribution via τ_1 signals higher quality, then the consumer will divert donations away from charity 2 and towards charity 1. With no signaling, a change in τ_1 has no effect on d_2.

Next, consider the effects of a change in the level of private contributions to charity 1, g_{priv1}. The effect on donations to charity 1 can be decomposed into three terms:

$$\frac{dd_1}{dg_{priv1}} = -1 + \frac{d\mu_1}{dg_{priv1}} \cdot \frac{v_G(G_1, \alpha_H) - v_G(G_1, \alpha_L)}{D} \cdot u''(c) \cdot E[v_{GG}(G_2)] + \frac{u''(c) \cdot E[v_{GG}(G_2)]}{D} \tag{6}$$

These three terms are analogous to the three terms in dd/dg_{priv} in the one-charity case (equation 2). The first term is the crowd-out effect (one-for-one); the second term is the signaling effect (the same sign as $d\mu_1/dg_{priv1}$); the third term is the income effect (positive and less than one).

The effect on donations to the *other* charity is

$$\frac{dd_2}{dg_{priv1}} = \frac{d\mu_1}{dg_{priv1}} \cdot \frac{v_G(G_1, \alpha_H) - v_G(G_1, \alpha_L)}{D} \cdot u''(c) + \frac{u''(c) \cdot E[v_{GG}(G_1)]}{D} \tag{7}$$

This contains two effects: a signaling effect that is of the opposite sign of $d\mu_1/dg_{priv1}$ (identical to the signaling effect in the expression for $dd_2/d\tau_1$), and an income effect that is positive but less than one (almost identical to the income effect in the second term of the previous expression, but replacing G_2 with G_1).

The effects on d_1 and d_2 from a change in g_{priv1} are analogous to the two expressions above, except replacing $d\mu_1/dg_{priv1}$ with $d\mu_1/dg_{pub1}$. They differ if the consumer infers different information about charity quality from government grants vs. private gifts.

To summarize, contributions to one charity cause two offsetting effects on donations to the other charity. There is a negative signaling effect (a grant to charity 1 signals high quality for charity 1 leading to less donated to charity 2) and a positive income effect, though the income effect exists only for government funding, not private funding.

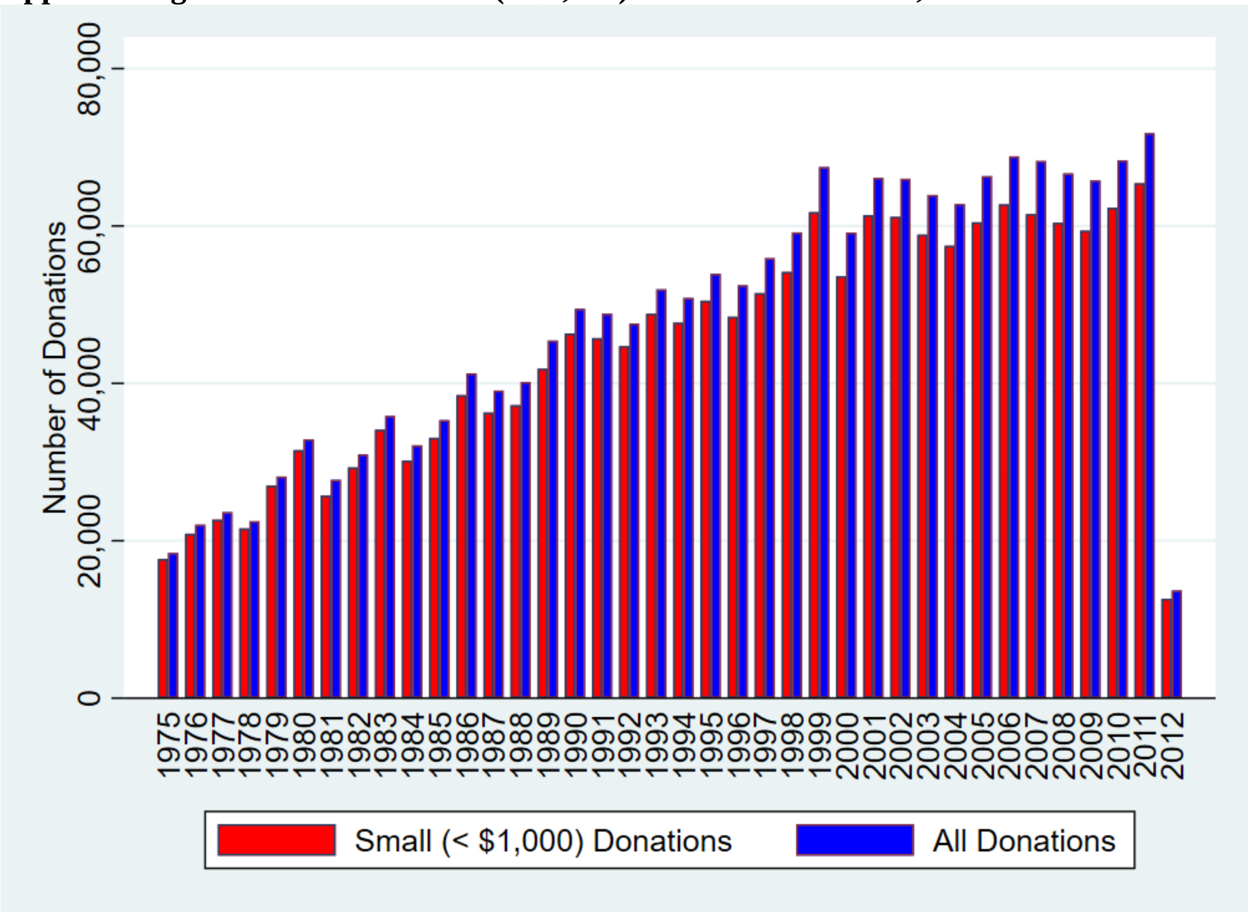
A.I.c. Empirical Questions

Motivated by the model, we use our dataset to answer several questions:

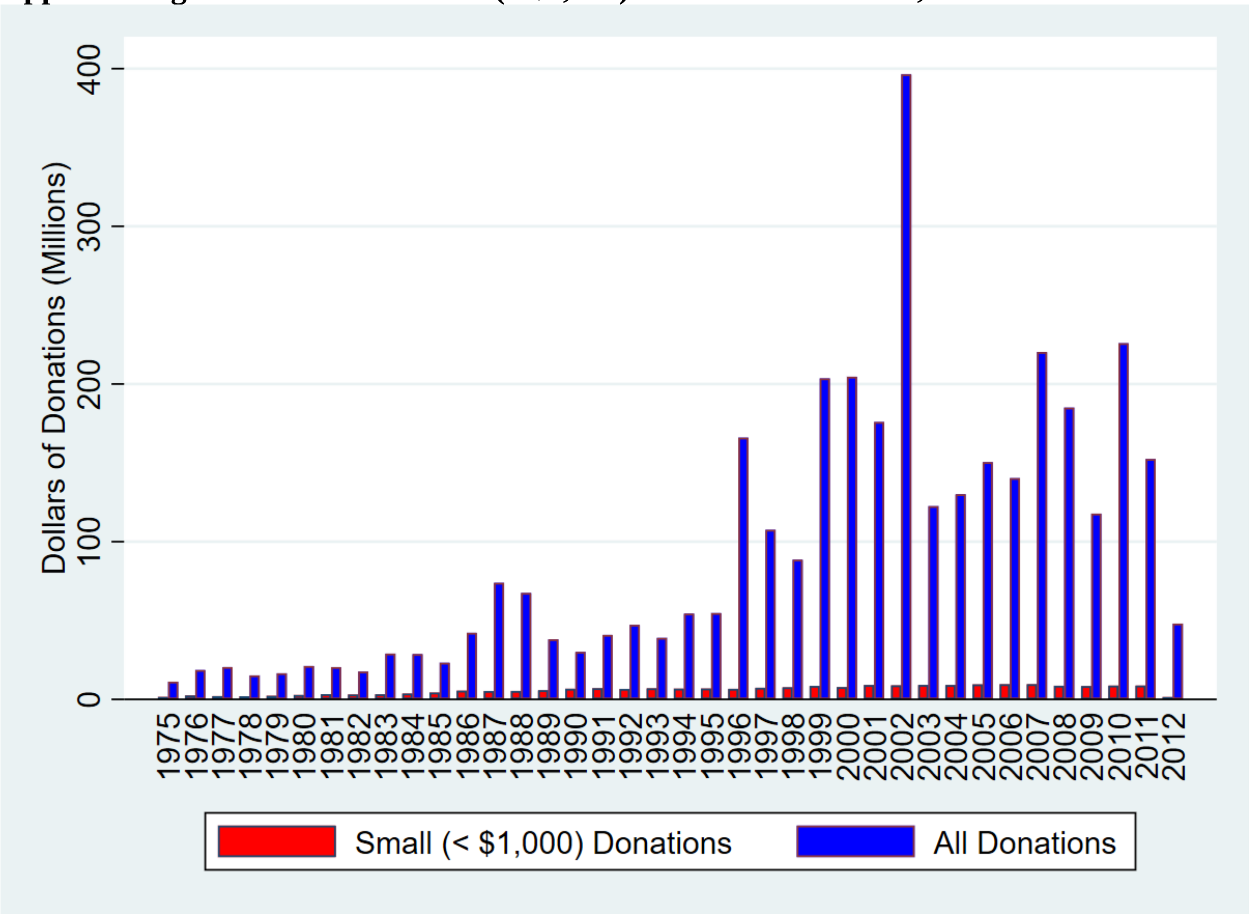
- Is there crowding in or crowding out of private donations by large public grants?
- Do private donations respond differently to different funding sources that may potentially have different signaling effects?
- Does giving to one unit of the university crowd out or crowd in giving to another unit?

Our model is very simple and omits several relevant features. Notably, because the comparative statics rely on interior solutions, the model does not address the distinction between effects on giving on the extensive margin (whether or not one gives) vs. on the intensive margin (how much one gives).

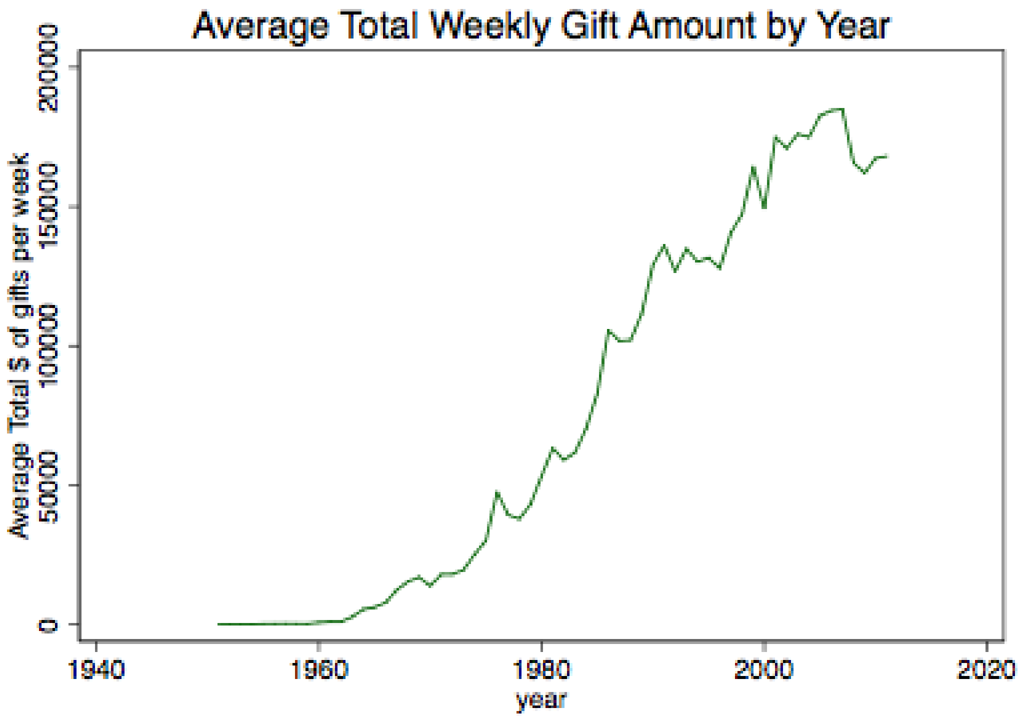
Appendix Figure A1: Annual Small (< $1,000) and Total Donations, Count



Appendix Figure A2: Annual Small (< $1,000) and Total Donations, Dollar Amount

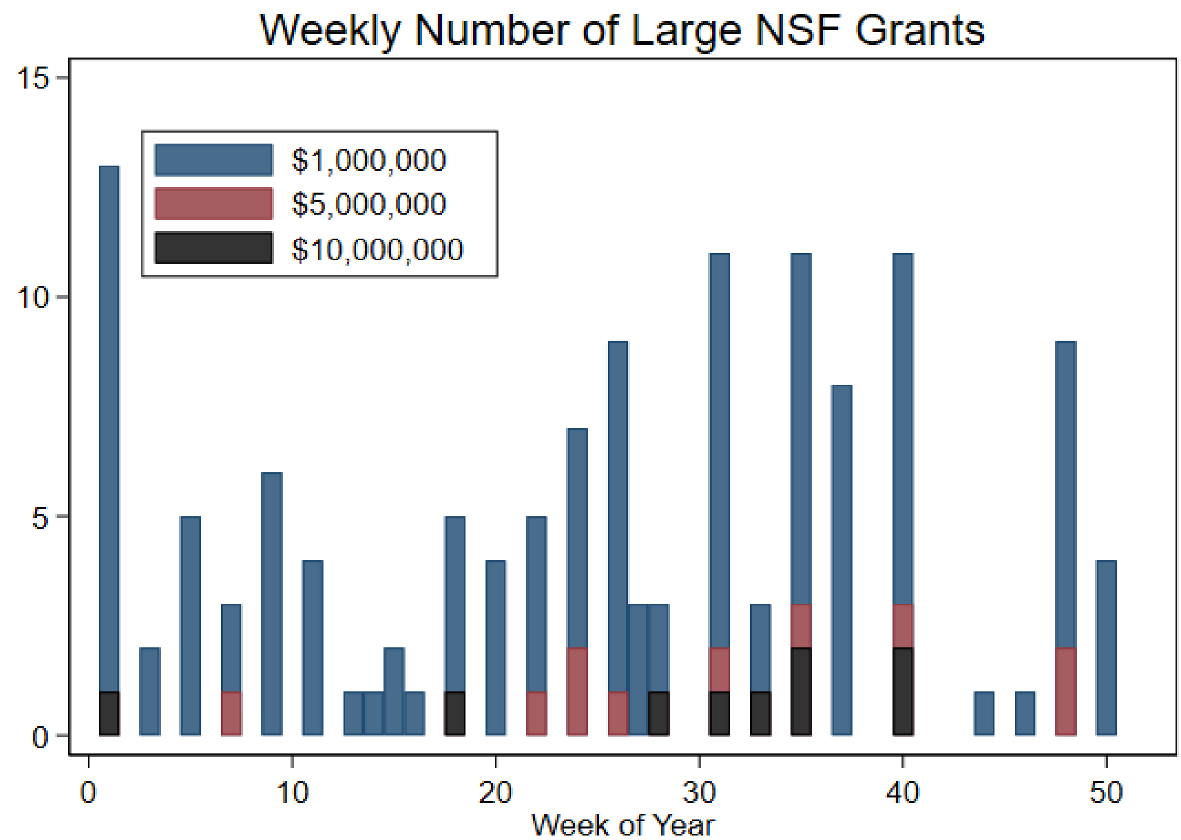


Appendix Figure A3: Average Gift Size Time Series



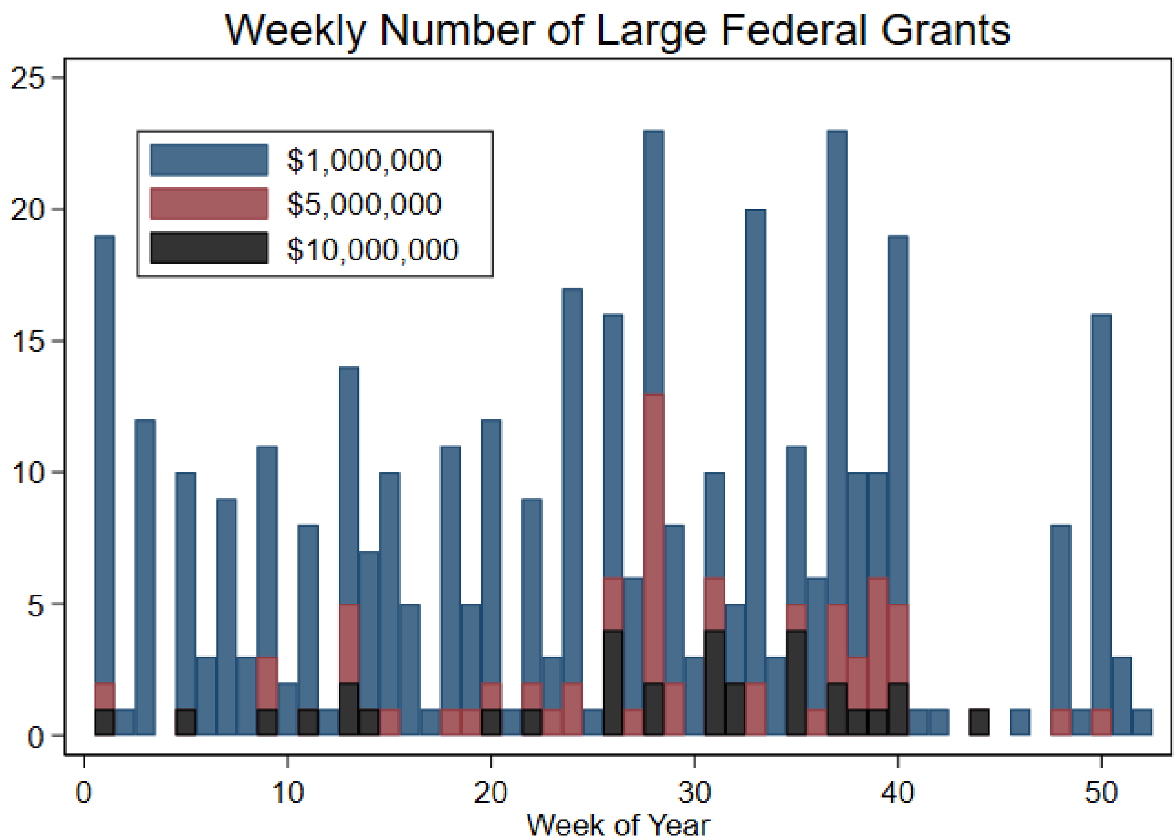
Notes: This figure shows the weekly average of the total amount received of small donations each week, from 1950 to 2012.

Appendix Figure A4: Large NSF Grant Time Series by Week of Year



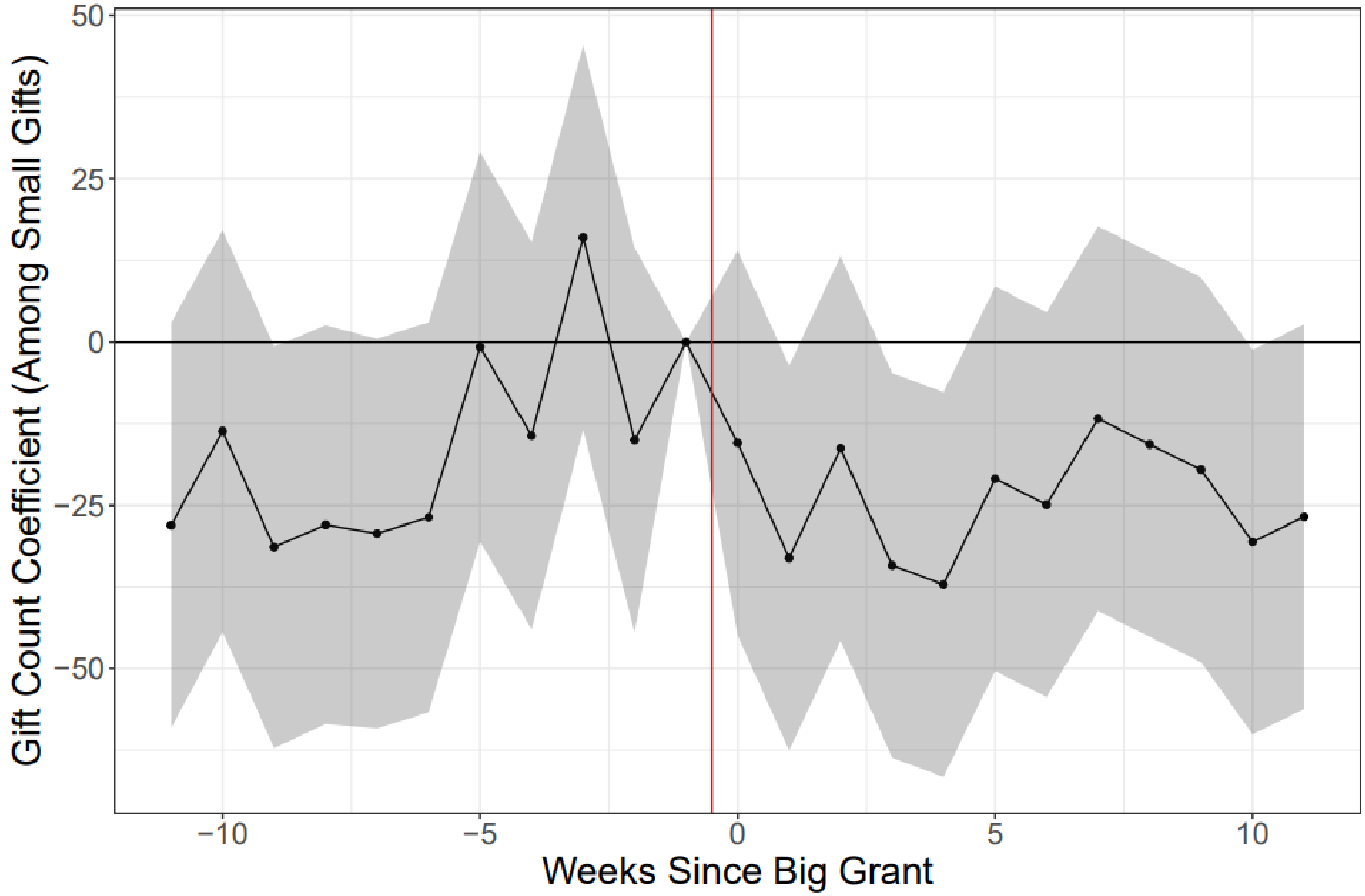
Notes: This figure shows the mean number of large NSF grants by the week of the year, for each cutoff level of large grants.

Appendix Figure A5: Large Federal Grant Time Series by Week of Year



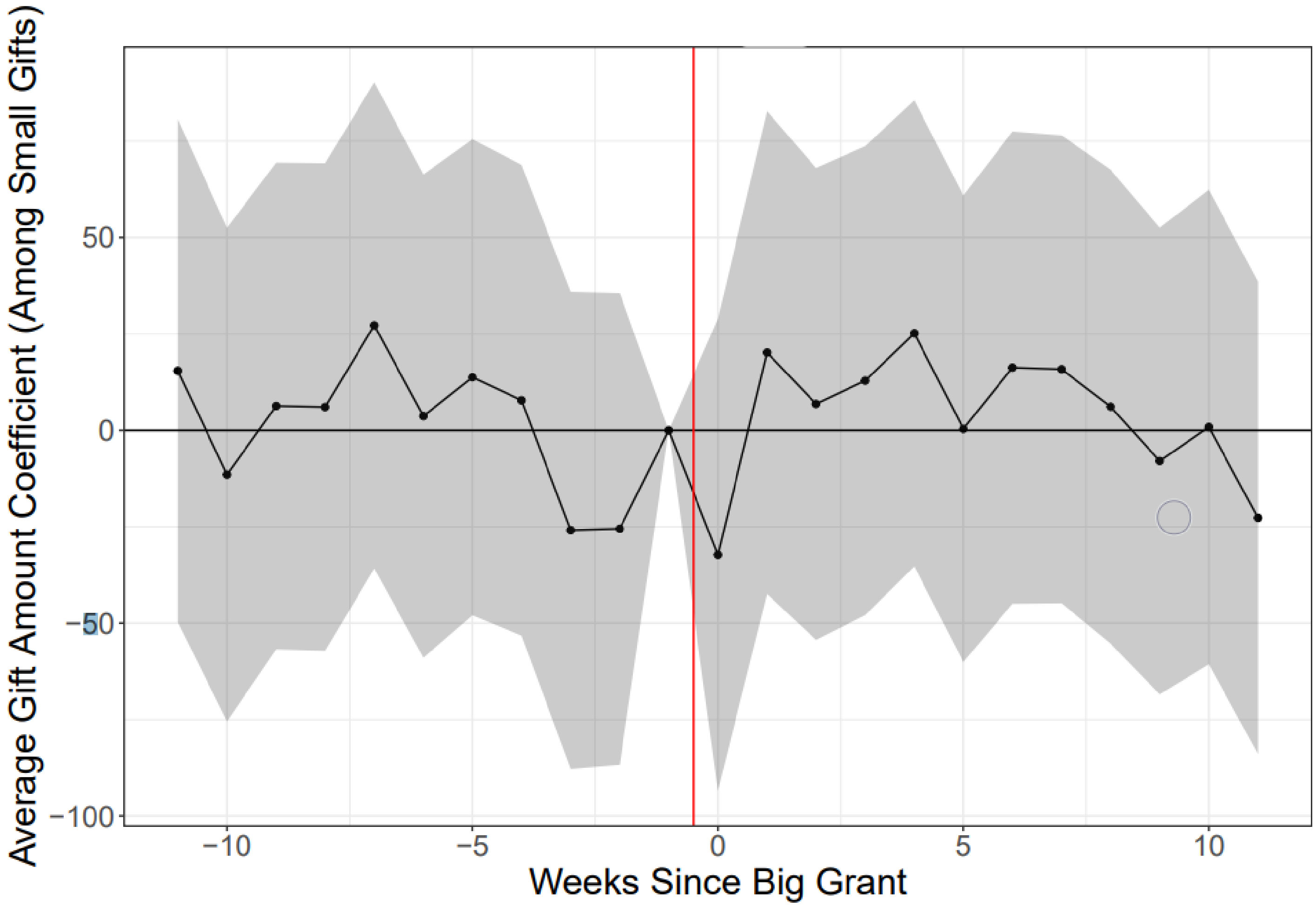
Notes: This figure shows the mean number of large federal grants by the week of the year, for each cutoff level of large grants.

Appendix Figure A6: Event Study, Number of Donations



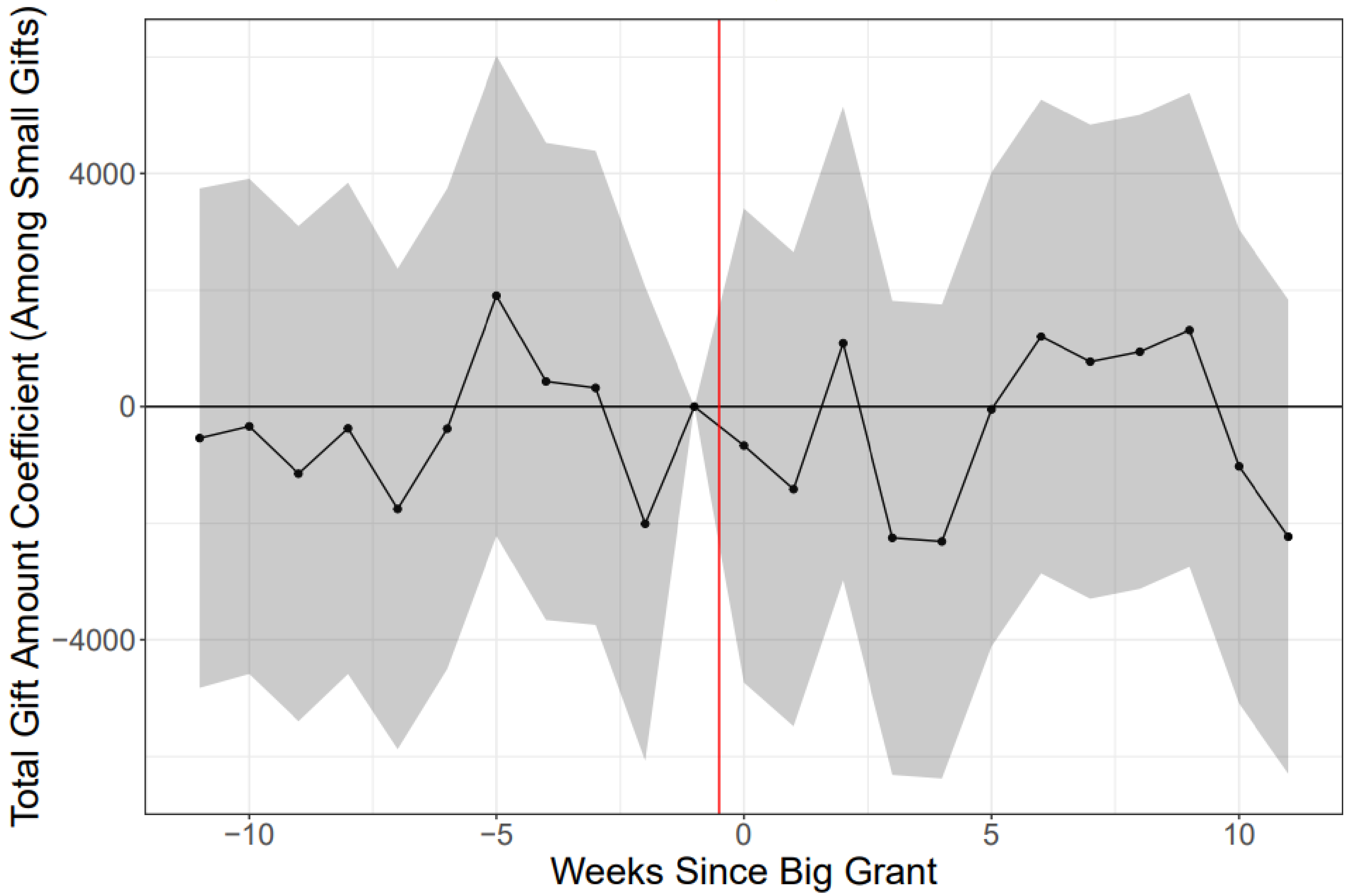
Notes: This figure presents the estimated coefficients on the interaction terms between the *SameUnit* indicator and an indicator for a grant being within a given window in weeks, when the outcome variable is the number of small donations.

Appendix Figure A7: Event Study, Average $ per Donation



Notes: This figure presents the estimated coefficients on the interaction terms between the *SameUnit* indicator and an indicator for a grant being within a given window in weeks, when the outcome variable is the average dollars per small donation.

Appendix Figure A8: Event Study, Total $ of Donations



Notes: This figure presents the estimated coefficients on the interaction terms between the *SameUnit* indicator and an indicator for a grant being within a given window in weeks, when the outcome variable is the total dollars from small donations.

Appendix Table A1 – Gift Count by Destination

Unit	Gifts below $1000	Gifts above $1000	Total
Business	64,547	7,004	71,551
Arch & Urban Plan	3,169	328	3,497
Arts and Architecture	73,927	10,597	84,524
Chancellor's Greatest Needs	713,490	28,017	741,507
College of L&S	90,125	9,423	99,548
Medical School	322,755	33,821	356,576
Dentistry	20,405	1,509	21,914
School of Public Health	14,971	1,140	16,111
Fine Arts & Perf. Arts	1,297	85	1,382
Education	40,910	2,476	43,386
General Campus	78,425	2,722	81,147
Graduate Program	862	49	911
Engineering	38,259	1,910	40,169
Independent Organized Units	1	1	2
Intercollegiate Athletics	109,021	25,562	134,583
International Institute	443	102	545
Law	64,921	5,226	70,147
School of Public Affairs	5,556	378	5,934
Nursing	17,710	452	18,162
Other Health Sciences	0	1	1
Student Affairs	16,073	1,107	17,180
Theatre, Film, and Television	11,239	3,420	14,659
Extension	4,617	335	4,952
Library	18,838	4,363	23,201
Total	1,711,561	140,028	1,851,589

Appendix Table A2: Response to Large NSF Grants – Alternate Time Windows

	# of donations	Average $ per donation	Total $ of donations
		4-week window	
$10 million cutoff	-72.41	-5.295	-19,224*
	(61.96)	(6.233)	(10,798)
$5 million cutoff	-21.56	-6.618	-6,978
	(45.04)	(4.528)	(7,853)
$1 million cutoff	-9.822	0.411	-1,772
	(21.18)	(2.130)	(3,692)
		26-week window	
	# of donations	Average $ per donation	Total $ of donations
$10 million cutoff	57.23*	-12.80***	-4,052
	(30.54)	(3.060)	(5,329)
$5 million cutoff	57.33**	-12.65***	-1,683
	(27.20)	(2.723)	(4,748)
$1 million cutoff	7.569	-11.03***	-3,783
	(23.05)	(2.304)	(4,018)

Notes: This table presents the estimated coefficient (and standard error) on the indicator for being within a 4-week or 26-week window of a large public NSF grant, in regressions where the dependent variable is either the number of private donations, the average dollar amount per donation, or the total dollar amount of donations. Regressions also include year indicators and week-of-year indicators, and a constant. Regressions are at the weekly level and include just the years 1975-2012. The number of observations is 1939 for all regressions. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Appendix Table A3: Response to Large Federal Grants – Alternate Time Windows

	# of donations	Average $ per donation	Total $ of donations
	4-week window		
	# of donations	Average $ per donation	Total $ of donations
$10 million cutoff	-23.46	-0.583	-8,919
	(38.35)	(3.331)	(6,749)
$5 million cutoff	29.10	0.779	1,161
	(28.89)	(2.509)	(5,087)
$1 million cutoff	-35.17	3.037	-7,243
	(26.03)	(2.260)	(4,582)
	26-week window		
	# of donations	Average $ per donation	Total $ of donations
$10 million cutoff	36.62	6.472**	10,820*
	(36.33)	(3.151)	(6,391)
$5 million cutoff	-54.55*	-1.052	-11,070**
	(30.88)	(2.684)	(5,434)
$1 million cutoff	-59.89	2.125	-11,808
	(44.30)	(3.849)	(7,798)

Notes: This table presents the estimated coefficient (and standard error) on the indicator for being within a 4-week or 26-week window of a large public federal grant, in regressions where the dependent variable is either the number of private donations, the average dollar amount per donation, or the total dollar amount of donations. Regressions also include year indicators and week-of-year indicators, and a constant. Regressions are at the weekly level and include just the years 1982-2012. The number of observations is 1627 for all regressions. *** p<0.01, ** p<0.05, * p<0.

Appendix Table A4: Response to Large NSF Grants - $500 Small Donation Cutoff

	# of donations	Average $ per donation	Total $ of donations
$10 million cutoff	39.90	-7.730***	-3,825
	(37.57)	(2.005)	(4,379)
$5 million cutoff	76.24**	-5.490***	3,289
	(32.50)	(1.739)	(3,792)
$1 million cutoff	19.86	-3.609***	-1,908
	(21.30)	(1.138)	(2,482)

Notes: This table presents the estimated coefficient (and standard error) on the indicator for being within a 12-week window of a large public NSF award, in regressions where the dependent variable is either the number of private donations, the average dollar amount per donation, or the total dollar amount of donations. The cutoff value for a small donation is $500 (compared to $1,000 in the main text results). Regressions also include year indicators and week-of-year indicators, and a constant. Regressions are at the weekly level and include just the years 1975-2012. The number of observations is 1939 for all regressions. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Appendix Table A5: Response to Large NSF Grants - $10,000 Small Donation Cutoff

	# of donations	Average $ per donation	Total $ of donations
$10 million cutoff	10.20	-48.92***	-67,180***
	(42.32)	(11.19)	(19,675)
$5 million cutoff	63.68*	-37.67***	-20,690
	(36.62)	(9.700)	(17,087)
$1 million cutoff	14.62	-18.52***	-17,568
	(23.99)	(6.360)	(11,180)

Notes: This table presents the estimated coefficient (and standard error) on the indicator for being within a 12-week window of a large public NSF grant, in regressions where the dependent variable is either the number of private donations, the average dollar amount per donation, or the total dollar amount of donations. The cutoff value for a small donation is $10,000 (compared to $1,000 in the main text results). Regressions also include year indicators and week-of-year indicators, and a constant. Regressions are at the weekly level and include just the years 1975-2012. The number of observations is 1939 for all regressions. *** p<0.01, ** p<0.05, * p<0.1

Appendix Table A6: Response to Large NSF Grants - No Small Donation Cutoff

	# of donations	Average $ per donation	Total $ of donations
$10 million cutoff	56.58*	3,181	3,175,435***
	(31.75)	(3,793)	(425,539)
$5 million cutoff	22.84	5,016*	1,957,861***
	(21.96)	(2,621)	(294,717)
$1 million cutoff	21.09	10,467*	491,647***
	(20.3)	(2,468)	(274,201)

Notes: This table presents the estimated coefficient (and standard error) on the indicator for being within a 12-week window of a large public NSF grant, in regressions where the dependent variable is either the number of private donations, the average dollar amount per donation, or the total dollar amount of donations. There is no cutoff value for a small donation (compared to $1,000 in the main text results). Regressions also include year indicators and week-of-year indicators, and a constant. Regressions are at the weekly level and include just the years 1975-2012. The number of observations is 1939 for all regressions. *** p<0.01, ** p<0.05, * p<0.1

Appendix Table A7: Response to Large NSF Grants – Daily Regressions

	# of donations	Average $ per donation	Total $ of donations
$10 million cutoff	3.900	-11.44***	-2,281**
	(5.548)	(2.698)	(956.9)
$5 million cutoff	9.028*	-10.35***	-470.1
	(4.820)	(2.356)	(831.6)
$1 million cutoff	1.910	-2.377	-657.5
	(3.138)	(1.580)	(541.3)

Notes: This table presents the estimated coefficient (and standard error) on the indicator for being within a 84-day window of a large public NSF award, in regressions where the dependent variable is either the number of private donations, the average dollar amount per donation, or the total dollar amount of donations. Regressions also include year indicators and day-of-year indicators, and a constant. Regressions are at the daily level and include just the years 1975-2012. The number of observations is 13615 for the # of donations and total $ of donations regressions, and it is 11718 for the average $ per donation regressions. *** p<0.01, ** p<0.05, * p<0.1

Appendix Table A8: Response to Large NSF Grants – Monthly Regressions

	# of donations	Average $ per donation	Total $ of donations
$10 million cutoff	115.3	-15.32**	-62,326
	(237.3)	(6.411)	(40,293)
$5 million cutoff	317.3	-12.20**	-2,456
	(208.0)	(5.641)	(35,514)
$1 million cutoff	191.1	-5.918	-393.3
	(139.9)	(3.803)	(23,876)

Notes: This table presents the estimated coefficient (and standard error) on the indicator for being within a 3-month window of a large public NSF award, in regressions where the dependent variable is either the number of private donations, the average dollar amount per donation, or the total dollar amount of donations. Regressions also include year indicators and month-of-year indicators, and a constant. Regressions are at the monthly level and include just the years 1975-2012. The number of observations is 448 for all regressions. *** p<0.01, ** p<0.05, * p<0.1

Appendix Table A9: Response to Large NSF Grants, Controlling for Large Private Gifts

		# of donations	Average $ per donation	Total $ of donations
$10 million cutoff	Grant Window	26.48	-14.31***	-15,100**
		(39.67)	(3.975)	(6,904)
	Gift Window	11.96	3.401	8,955
		(33.14)	(3.321)	(5,767)
$5 million cutoff	Grant Window	73.34**	-12.06***	-763.2
		(31.49)	(3.160)	(5,498)
	Gift Window	18.33	0.454	3,663
		(23.79)	(2.387)	(4,154)
$1 million cutoff	Grant Window	36.42**	-3.150*	2,338
		(18.52)	(1.864)	(3,233)
	Gift Window	14.20	-0.550	2,261
		(25.51)	(2.566)	(4,452)

Notes: This table presents the estimated coefficients (and standard errors) on the indicators for being within a 12-week window of a large public NSF grant and for being within a 12-week window of a large private gift, in regressions where the dependent variable is either the number of private donations, the average dollar amount per donation, or the total dollar amount of donations. Regressions also include year indicators and week-of-year indicators, and a constant. Regressions are at the weekly level and include just the years 1975-2012. The number of observations is 1939 for all regressions. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Appendix Table A10: Response to Large Federal Grants, Controlling for Large Private Gifts

		# of donations	Average $ per donation	Total $ of donations
$10 million cutoff	Grant Window	4.175	3.920	-1,601
		(32.61)	(2.829)	(5,738)
	Gift Window	8.099	2.085	6,719
		(34.54)	(2.997)	(6,078)
$5 million cutoff	Grant Window	68.70**	-1.136	4,850
		(27.27)	(2.373)	(4,809)
	Gift Window	25.32	1.189	3,877
		(25.17)	(2.190)	(4,438)
$1 million cutoff	Grant Window	-21.92	0.0389	-4,688
		(33.71)	(2.925)	(5,933)
	Gift Window	8.612	3.732	2,235
		(32.40)	(2.812)	(5,703)

Notes: This table presents the estimated coefficients (and standard errors) on the indicators for being within a 12-week window of a large public federal grant and for being within a 12-week window of a large private gift, in regressions where the dependent variable is either the number of private donations, the average dollar amount per donation, or the total dollar amount of donations. Regressions also include year indicators and week-of-year indicators, and a constant. Regressions are at the weekly level and include just the years 1982-2012. The number of observations is 1627 for all regressions. *** p<0.01, ** p<0.05, * p<0.1

Appendix Table A11: Cash/Check vs. Credit Card Donations

		# of donations	Average $ per donation	Total $ of donations
$10 million cutoff	Cash/Check Donations	47.50	-14.50***	–4,385
		(29.35)	(4.297)	(4,276)
	Credit Card Donations	-51.56***	5.778	-11,040***
		(11.23)	(9.047)	(2,395)
$5 million cutoff	Cash/Check Donations	73.12***	-12.78***	3,918
		(23.29)	(3.413)	(3,399)
	Credit Card Donations	-24.51**	2.143	-5,632***
		(9.578)	(7.756)	(2,042)
$1 million cutoff	Cash/Check Donations	31.56**	-4.850**	447.9
		(13.72)	(2.012)	(2,000)
	Credit Card Donations	-1.936	2.823	-1,423
		(6.333)	(5.511)	(1,350)

Notes: This table presents the estimated coefficients (and standard errors) on the indicators for being within a 12-week window of a large public NSF grant, in regressions where the dependent variable is either the number of private donations, the average dollar amount per donation, or the total dollar amount of donations, separately for donations by cash or check and donations by credit card. Regressions also include year indicators and week-of-year indicators, and a constant. Regressions are at the weekly level and include just the years 1975-2012. The number of observations is 1939 for all regressions. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Appendix Table A12: Control for Fundraisers

		# of donations		Average $ per donation		Total $ of donations	
$10 million cutoff	Grant Window	25.94	25.94	-14.46***	-14.46***	-15,502**	-15,502**
		(39.63)	(39.63)	(3.972)	(3.972)	(6,902)	(6,902)
	Drive Window		-201.9*		10.23		-13,750
			(104.0)		(10.42)		(18,112)
$5 million cutoff	Grant Window	74.09**	74.09**	-12.04***	-12.04***	-612.5	-612.5
		(31.47)	(31.47)	(3.157)	(3.157)	(5,495)	(5,495)
	Drive Window		238.7**		21.90**		64,353***
			(104.3)		(10.47)		(18,218)
$1 million cutoff	Grant Window	36.46**	36.46**	-3.151*	-3.151*	2,345	2,345
		(18.52)	(18.52)	(1.863)	(1.863)	(3,232)	(3,232)
	Drive Window		269.6***		14.36		55,375***
			(103.9)		(10.46)		(18,140)

Notes: This table presents the estimated coefficient (and standard error) on the indicator for being within a 12-week window of a large public NSF grant, along with the coefficient (and standard error) on an indicator for being within a large fundraising drive, in regressions where the dependent variable is either the number of private donations, the average dollar amount per donation, or the total dollar amount of donations. Regressions also include year indicators and week-of-year indicators, and a constant. Regressions are at the weekly level and include just the years 1975-2012. The number of observations is 1939 for all regressions. *** p<0.01, ** p<0.05, * p<0.1

Appendix Table A13: Control for Media Citations

		# of donations		Average $ per donation		Total $ of donations	
		University Press Releases – 1997-2012					
$10 million cutoff	Grants	-56.08	-52.74	-4.962	-5.005	-15,344*	-14,774*
		(47.76)	(46.89)	(3.276)	(3.290)	(8,315)	(8,168)
	Media		11.76		0.420		1,811
			(14.01)		(0.983)		(2,440)
$5 million cutoff	Grants	-9.796	-0.356	-4.567	-4.768*	-5,702	-4,508
		(40.68)	(40.24)	(2.787)	(2.820)	(7,090)	(7,018)
	Media		11.82		0.378		1,783
			(14.02)		(0.983)		(2,445)
$1 million cutoff	Grants	-30.25	-40.39	-3.007	-3.183	-7,178	-8,838
		(37.49)	(37.01)	(2.572)	(2.598)	(6,533)	(6,453)
	Media		12.44		0.475		1,964
			(14.02)		(0.984)		(2,444)
		Local Daily Newspaper – 1985-2012					
$10 million cutoff	Grants	5.020	5.987	-5.901*	-5.906*	-12,604*	-12,219
		(42.12)	(42.52)	(3.309)	(3.283)	(7,531)	(7,606)
	Media		-67.03		2.067		-10,315
			(55.66)		(4.298)		(9,957)
$5 million cutoff	Grants	48.10	48.23	-4.352	-4.334	-690.9	-515.8
		(36.48)	(36.83)	(2.868)	(2.847)	(6,533)	(6,599)
	Media		-65.71		1.981		-10,256
			(55.63)		(4.301)		(9,969)
$1 million cutoff	Grants	14.66	7.006	0.152	0.252	-196.5	-1,914
		(24.12)	(25.29)	(1.897)	(1.956)	(4,318)	(4,529)
	Media		-64.68		2.188		-10,894
			(56.32)		(4.355)		(10,085)

Notes: This table presents the estimated coefficient (and standard error) on the indicator for being within a 12-week window of a large public NSF grant, along with the coefficient (and standard error) on the number of media stories about large grants, in regressions where the dependent variable is either the number of private donations, the average dollar amount per donation, or the total dollar amount of donations. The top panel controls for stories from the university press releases and uses data from 1997-2012, and the bottom panel controls for stories from the local daily newspaper and uses data from 1985-2012. Regressions also include year indicators and week-of-year indicators, and a constant. Regressions are at the weekly level. *** p<0.01, ** p<0.05, * p<0.1

Appendix Table A14: Response to Large NSF Grants, Balanced Panel

	# of donations	Average $ per donation	Total $ of donations
$10 million cutoff	44.30***	-15.24***	242.3
	(16.70)	(4.317)	(2,608)
$5 million cutoff	32.38**	-13.17***	1,269
	(13.90)	(3.589)	(2,169)
$1 million cutoff	16.76*	-2.579	187.5
	(8.617)	(2.232)	(1,344)

Notes: This table presents the estimated coefficients (and standard errors) on the indicators for being within a 12-week window of a large NSF grant and, in regressions where the dependent variable is either the number of private donations, the average dollar amount per donation, or the total dollar amount of donations. Regressions also include year indicators and week-of-year indicators, and a constant. The dependent variables are generated only from the balanced panel of donors who gave at least once between 1981 and 1985 and who are not reported to have died before the end of the panel (2012). Regressions are at the weekly level and include just the years 1980-2012. The number of observations is 1627 for all regressions. *** $p<0.01$, ** $p<0.05$, * $p<0.1$