RESEARCH GRANTS CROWDING OUT AND CROWDING IN DONATIONS TO HIGHER EDUCATION

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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.

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1. 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 (NSF) and the National Institutes of Health (NIH). 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 composed 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 dataset, 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-out 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, for example, from Internal Revenue Service (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,[1] 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 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 NIH 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 seventy-four in the twelve weeks following the grant; a $1 million NSF grant increases that number by thirty-six. A large NSF grant decreases the average dollar amount per donation by $3 to $15 in the following twelve 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. These findings point to important implications for higher education development officers' strategy, including emphasizing the prestige of receiving NSF grants to amplify the extensive-margin crowding in, and reminding donors of the complementarity of research grants and individual donations to ameliorate the intensive-margin crowding out.

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, available separately online and can be accessed on *Education Finance and Policy*'s Web site at https://doi.org/10.1162/edfp_a_00381) 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

1. See for example Clotfelter (2003), Monks (2003), or Paarlberg et al. (2019).

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) estimate the effect of directed giving on donations to a university and find 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).[2] Levin et al. (2016) have access to a dataset 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 dataset 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.

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 and Sandler (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.[3] De Wit and Bekkers (2017) provide a meta-analysis of the literature and find that about two thirds of studies find evidence for crowding out while one third finds evidence for crowding in.

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 nonresearch universities and crowding in for research universities.

Our contribution to this literature lies in the use of our unique dataset 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

2. Related analyses include Ade et al. (1994), Okunade and Berl (1997), and Taylor and Martin (1995). Harrison (1995) and Harrison et al. (1995) also consider fundraising expenditures.
3. 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.

that have used similar administrative data (e.g., Hungerman and Ottoni-Wilhelm 2016; Levin et al. 2016), none have addressed the issues of crowding in or crowding out. A caveat of our dataset is that it does not contain any information on fundraising expenditure. We address this issue in the Alternate Specifications section below and argue that the other advantages of our dataset allow us to overcome this. In particular, because 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, because our data are 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.[4] 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.

2. DATA

We combine several datasets. First, we have a unique dataset containing the historical charitable donations to the university.[5] 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.[6]

We combine the donations dataset with the university's alumni database. For each alumnus 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

4. Svider et al. (2013) ask the same question, focusing specifically on the impact among academic otolaryngologists.
5. Taylor and Martin (1995) also use data from just one research university, but with a smaller sample size of just 371 alumni.
6. Later, we will examine issues of noisiness around the reported date that the donation is received.

Table 1. Summary Statistics of Alumni Database

	Non-Donors	Donors	Total
Observations	263,043	166,558	429,601
White	0.466	0.599	0.518
	(0.499)	(0.490)	(0.500)
	[144,334]	[92,878]	[237,212]
Female	0.507	0.451	0.485
	(0.500)	(0.498)	(0.500)
	[262,912]	[166,557]	[429,469]
Fraternity/Sorority	0.084	0.159	0.113
	(0.277)	(0.366)	(0.317)
	[263,043]	[166,558]	[429,601]
Ever married	0.198	0.538	0.330
	(0.398)	(0.499)	(0.470)
	[263,043]	[166,558]	[429,601]
Number of children	0.092	0.369	0.199
	(0.467)	(0.889)	(0.677)
	[263,043]	[166,558]	[429,601]
In-state resident	0.784	0.784	0.784
	(0.411)	(0.411)	(0.411)
	[220,391]	[154,889]	[375,280]
Birth year	1965	1957	1962
	(17)	(18)	(18)
	[223,341]	[154,820]	[378,161]
First degree year	1985	1981	1983
	(20)	(19)	(20)
	[263,043]	[166,558]	[429,601]

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.

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 percent of donors are alumni. Of the 429,601 individuals in the alumni dataset, only 39 percent have ever donated. Individuals can donate multiple times. Of the 1,905,455 observed donations, 58 percent of them come from alumni. Among alumni donors, the average number of donations is 6.6; among non-alumni donors, the average number is 2.7. About 0.6 percent 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 1 percent of gifts occur before 1970 (the oldest observation is from 1938, but the second oldest is 1951). Deflating

Table 2. Summary Statistics of Gift Database

	Number of Gifts (% of total)	Mean Gift Amount (2000$)	Median Gift Amount (2000$)
		By Decade	
1938–69	24,490 (1%)	3,860	108
1970–79	162,307 (9%)	831	49
1980–89	360,957 (19%)	1,003	72
1990–99	537,730 (28%)	1,547	109
2000–09	653,949 (35%)	2,819	87
2010–12	153,862 (8%)	2,772	77
		By Gift Allocation Unit	
Undesignated	829,785 (44%)	393	62
Medical school	371,072 (20%)	4,529	76
Athletics	139,745 (7%)	1,614	331
Liberal arts college	103,188 (5%)	3,376	81
Other	449,504 (24%)	2,476	98

Notes: "Undesignated" includes the categories "Chancellor's greatest needs" and "general campus." "Other" includes all other units.

to year 2000 dollars using the Consumer Price Index, the median gift amount is around \$50 to \$100, with a mean value more than ten times higher, indicating substantial skew.

As mentioned above, a donor may select a unit within the university to receive the donation. We collapse the twenty-four units of gift targets into five broad categories: "undesignated," "medical school," "liberal arts college," "athletics," and "other."[7] "Undesignated" 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 \$1,000. 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 percent on average across all weeks) of the total number of donations, but only a small fraction (15 percent average across all weeks) of the total dollar amount of donations, due to the large outliers.[8]

7. The "undesignated" category includes "Chancellor's Greatest Needs" and "General Campus" gifts. The "other" category includes all of the other units. We are unable to observe whether the donation is restricted or unrestricted.
8. Online 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 percent of all donations by count and 14 percent by dollars. When the cutoff is \$10,000, small donations account for 99 percent of all donations by count and 41 percent by dollars.

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.

Figure 1. Donations Time Series

Thus, in robustness analysis, we will also report results with different donation cutoff values, of either $500 or $10,000, as well as results that do not use a cutoff value but run quantile regressions rather than least squares regressions.

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.[9]

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 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 grant starts. Alternative measures like state funding or tuition revenues are typically available only at the annual level.[10] Second, NSF awards grants to specific

9. Online 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.
10. 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/).

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 start date of the grant. The data include the start date and the end date of the grant, but we do not observe the date that the grant was announced or awarded. It is possible that the start date of the grant period could be quite a bit after it was awarded and announced, and therefore after it was publicized and had an effect on donors. If this is true, then the start date that we use is actually a lagged measure of the impact of the grant. This is partly addressed by using windows of various lengths after the grant start date (4 weeks, 12 weeks, or 26 weeks) to test for an effect. It could also be the case that research results or other outcomes from the grant are publicized during the grant period or after it has concluded, increasing donations. We would not be able to identify any effect on donations from such publicity. In this sense, our results are conservative in that they only measure the effects from the start date of the grant.

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 NIH and the Department of Defense. These data are available from two sources. From 2001 until the present, the data are available from the Web site USAspending.gov. The data on this Web site 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 percent of the observed grants. Most of HHS's grants are funded through the NIH. The two next most common grant-making agencies are the NSF (8 percent of grants) and the Department of Defense (4 percent 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.)

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.[11] 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

11. The keywords that we search for are "donation," "donates," "grant," and "gift."

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 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 ranges 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 1 January 1982 through 31 December 1988. The second ran from 1 January 1997 through 31 December 2005. We create an indicator variable equal to one for weeks during these fundraising drives.

3. 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 online appendix motivates these empirical questions and provides intuition for various effects that could explain both crowd-in and crowd-out.

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 \$1,000 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 1 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 online appendix tables.

Our estimating equation is

$$y_t = \beta_0 + \beta_1 LargeGrant_t + \beta_2 X_t + \varepsilon_t. \tag{1}$$

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 (all in levels, not logs). 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 1 if the week is within a twelve-week window after a large grant. The

Table 3. Response to Large National Science Foundation (NSF) Grants

	Number 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 1,939 for all regressions. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

control variables X_t include a set of year indicators and a set of week-of-year indicators.[12] 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 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. For our main results we estimate this equation using ordinary least squares, though we will also present other specifications with other estimators.

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 twenty-five to seventy-five (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 twelve 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 with the mean value of about $150 per donation). The effect is significant at the 10 percent level for all three large grant cutoff values, and significant at the 1 percent 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 cutoff value ($10 million) do we see a significant effect, and it is negative (the

12. Online 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.

Table 4. Response to Large Federal Grants

	Number 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 twelve-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 1,627 for all regressions. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

mean value of the total weekly dollar amount of donations is about $63,000). The other two cutoffs yield effects of mixed sign, with neither being significant.[13]

The results in table 3 provide evidence that large public 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 online 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 online 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 because 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 (sixty-five 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

13. The R^2 values for the regressions are almost identical across the three difference large grant cutoff values.

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.[14] Robustness checks are provided in online appendix tables A1 through A4.[15]

Outliers

Using any cutoff at all introduces some potential econometric issues. A donor might give below the threshold in one situation but move to giving above the threshold in another situation. To address this, in online appendix table A5, 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. The results in online appendix table A5 are striking, suggesting that additional NSF grants can substantially and significantly raise the overall total of private donations. However, we urge these results to be taken with a grain of salt, since they are most likely due to the presence of a small number of outliers. This is why large and significant coefficients are never found in any of the other regressions that impose a cutoff value for small donations.[16] Merely neglecting a cutoff value introduces issues due to outliers. Thus, we also present results where we do not impose any cutoff but we perform quantile regressions rather than least squares regressions. We perform regressions at the median as well as 25th and 75th quantiles. We report results from the 25th quantile regressions in online appendix table A6, which may better reflect the response of smaller donors, though the results from the median and 75th percentile regressions are available upon request. This table shows that the quantile regressions still yield both the extensive-margin crowd-in effect and the intensive-margin crowd-out effect at a significant level for most magnitudes of NSF grants.[17]

Alternate Specifications

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.

14. Table 4 uses just data starting in 1982, which is when the National Archives data are available. To more directly compare results from those data with those from the NSF data, we can also replicate table 3 using only the years for which the National Archives/USASpending.gov data are available. Doing so (results available upon request from the authors) yields results that are nearly identical to those in table 3.
15. Online appendix tables A1 and A2 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). Online appendix tables A3 through A6 replicate table 3, for the NSF grants, with different specifications. In online appendix tables A3 and A4, 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.
16. In unreported regressions available upon request from the authors, we also report regressions where we remove the top 5 percent or the top 1 percent of private donations by dollar amount, rather than by count. This eliminates a much smaller fraction of donations by count, and the results are consistent with those in online appendix table A5 with other cutoff values.
17. In online appendix table A7 we conduct the analysis at the daily level rather than the weekly level, and online appendix table A8 does it at the monthly level.

In online 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 twelve-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 twelve-week window of the receipt of the large private gift. In each regression, the cutoff value for the grant and the large gift is the same. Online appendix tables A9 and A10 report the coefficients on both the large grant window indicator and the large private gift window indicator. Online 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. Online appendix table A10, like table 4, shows generally insignificant results for the response of donors to large federal grants.

These results all use a binary indicator of being within the window of receipt of a large grant as the right-hand-side variable of interest. This specification thus ignores the magnitude of the grant itself. In online appendix table A11 we present regression results where the right-hand-side variable of interest is the total amount of grant funding received, in millions of dollars, within the twelve-week window that a large NSF grant or grants were received. In these regressions we still see the same qualitative patterns from the main specification in table 3: extensive-margin crowding in and intensive-margin crowding out. An additional $1 million of grant funding increases the number of small private donations by three to five donations, for grants at the $1 million or $5 million cutoff. An additional $1 million of grant funding reduces the average donation size by about 50 cents. The effect on total funding is small and only significant for the $10 million cutoff, where $1 million in grants reduces small donations by less than $1,000.

Because the left-hand-side variables are all censored at zero (they cannot be negative), we explore the importance of this feature by estimating the regression using a censored Tobit estimator. Online appendix table A12 presents these results for the NSF grants. The results from Tobit regressions are qualitatively identical to those from ordinary least squares regressions reported in table 3.

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 versus credit card), the answer to this question may differ. Unfortunately, we were not able to obtain 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%).[18] 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.[19] 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, especially if it was online (though 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 online appendix table A13. 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 do not believe that this must be the case. Rather, while there is something different about cash/check versus credit card donations, it is unclear how that is related to the issue of timing. As our online appendix model (and others in the literature) suggests, there should be no difference across payment type. One possible explanation for the difference is a behavioral/psychological explanation—perhaps donors engage in a different type of "mental accounting" for the two different payment types (Thaler 1999). Or, the crowding effects could differ over time, since credit card donations are more frequent in more recent years. This intriguing result warrants future research.

Comparison of Response Based on Donor Demographics

Next, we examine how the demographic characteristics of the donors affect their responses to large NSF grants. 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.

18. These percentages are of the observations with non-missing values for "payment type" (which is 77.8 percent of total observations). The remaining 2 percent are split among values including "gift in kind" or "securities."
19. Again, among observations with non-missing payment type, for the first twenty years in our main regression analysis (1975–94), 97.2 percent of observations are cash and 1.31 percent are credit card. For the last eighteen years (1995–2012), 69.1 percent are cash and 28.8 percent are credit card.

Table 5. Comparison of Response to National Science Foundation (NSF) Grants Based on Donor Demographics

	Number of Donations	χ^2 Difference Test	Average $ per Donation	χ^2 Difference Test	Total $ of Donations	χ^2 Difference Test
Alumni	39.70*		−14.10***		−871.0	
	(20.68)		(3.646)		(3,569)	
Non-alumni	34.39**	0.11	−12.70***	0.30	258.5	0.25
	(14.38)	(0.74)	(3.341)	(0.59)	(2,279)	(0.62)
Men	21.20*		−15.41***		−1,133	
	(12.85)		(4.185)		(2,562)	
Women	18.50**	0.18	−10.97***	3.68*	261.8	0.67
	(8.311)	(0.67)	(3.146)	(0.06)	(1,108)	(0.41)
White	6.877		−11.67***		−1,015	
	(8.307)		(3.962)		(1,500)	
Non-white	−4.783	2.51	−11.78**	0.00	−938.2*	0.00
	(3.356)	(0.11)	(4.796)	(0.97)	(490.1)	(0.96)
In-state resident	23.92		−14.66***		−1,803	
	(16.06)		(3.880)		(2,939)	
Out-of-state residents	10.17**	0.86	−11.00***	2.22	650.7	0.80
	(4.349)	(0.35)	(3.663)	(0.14)	(691.9)	(0.37)
Previous donors	65.05**		−14.47***		−640.3	
	(26.92)		(3.582)		(4,944)	
New donors	9.043	3.42*	−7.881***	6.22***	27.74	0.02
	(9.563)	(0.06)	(3.045)	(0.01)	(1,046)	(0.90)

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) 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, 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 1,939 for all regressions. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

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 online 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 whom 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.[20] 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 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. We also include the χ^2 statistic and *p*-value from a Chow test of the significance of the difference of the coefficients across the two regressions.

20. See table 1; most observations of donors contain gender, marital status, and age, but 45 percent of the observations are missing race.

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, though generally these differences are not statistically significant. 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 the difference is insignificant), and the effect of previous donors is more than five times larger than that of new donors (significant at the 5 percent level). 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 and only significant 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 online appendix, which predicts a larger crowd-out (or smaller crowd-in) effect in response to public funding from taxpayers, though the difference is insignificant. 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 significant 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. This explanation is consistent with the theoretical model in the online appendix where cold list donors experience a stronger signal effect. But the larger extensive-margin crowd-in effect that we actually find in the data 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. Our theoretical model in online appendix A.I.b. allows for this possibility and could explain this empirical result.

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

Table 6. Control for Fundraisers

		Number of Donations		Average $ per Donation		Total $ of Donations	
$10 million cutoff	Grant window	25.94 (39.63)	25.94 (39.63)	-14.46^{***} (3.972)	-14.46^{***} (3.972)	$-15{,}502^{**}$ (6,902)	$-15{,}502^{**}$ (6,902)
	Drive window		263.1^{**} (104.0)		19.94^{*} (10.42)		$67{,}151^{***}$ (18,112)
$5 million cutoff	Grant window	74.09^{**} (31.47)	74.09^{**} (31.47)	-12.04^{***} (3.157)	-12.04^{***} (3.157)	−612.5 (5,495)	−612.5 (5,495)
	Drive window		238.7^{**} (104.3)		21.90^{**} (10.47)		$64{,}353^{***}$ (18,218)
$1 million cutoff	Grant window	36.46^{**} (18.52)	36.46^{**} (18.52)	-3.151^{*} (1.863)	-3.151^{*} (1.863)	2,345 (3,232)	2,345 (3,232)
	Drive window		269.6^{***} (103.9)		14.36 (10.46)		$55{,}375^{***}$ (18,140)

Notes: This table presents the estimated coefficient (and standard error) on the indicator for being within a twelve-week window of a large public National Science Foundation 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 1,939 for all regressions. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

between these two types of donations upwards.[21] 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. Therefore, we include two additional sets of controls in our regressions. First, we create an indicator variable $Drive_t$ that is equal to 1 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 tables 6 and 7.

Table 6 adds an indicator variable equal to one for weeks during a university fundraising drive. Both fundraising drives begin on January 1 and end on December 31. This creates a multicollinearity issue when including this indicator alongside 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. This collinearity suggests 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. Fundraising drives may increase the average donation dollar amount, though the results are not as significant.

Table 7 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

21. See, for instance, Scharf et al. (2017) on the effect of fundraising on the timing of donations.

Table 7. Control for Media Citations

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

Notes: This table presents the estimated coefficient (and standard error) on the indicator for being within a twelve-week window of a large public National Science Foundation 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. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

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.

One issue with the interpretation of these regressions is whether fundraising and media citations should be interpreted as confounders or as mediators of the relationship between grants and private donations. If the interpretation is more as a mediator, then a compelling regression specification is one in which they are outcome variables rather than additional controls in the main regression specification. We present results from these specifications in online appendix table A14. In column 1, the dependent variable is the indicator for being in a fundraising year. Because these fundraising windows are collinear with calendar years, we cannot also include year fixed effects here, so instead we include decade fixed effects. The second and third columns are from regressions where the dependent variables are university press releases and local daily newspaper stories, and year fixed effects are again included. There is not much evidence of grant receipts having an effect on the media stories. For the fundraising drive, though, there is a significant positive correlation between being within a $10 million or $5 million grant and being in a fundraising drive year in the regression with decade fixed effects.

Admittedly our fundraising control is coarse—it is merely a binary indicator equal to 1 during the years in which a large fundraising drive is going on. 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, including any effect that operates through fundraising.[22]

Online appendix section A.II presents results from additional specifications.

4. 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. An NSF research grant is correlated with an increase of twenty-five to seventy-five donations and a decrease of $3–$15 per donation. 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 NSF 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. Specifically, because we find that the receipt of NSF grants has a positive effect on the extensive margin of giving, development officers may want to play up the prestige of winning such a grant, to further increase this crowding-in effect. Because NSF grants have a negative effect on

22. An additional test that we perform to remove 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. 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 online appendix table A15. Results still show significant extensive-margin crowding in and intensive-margin crowding out, as do the main results.

the intensive margin (crowding out), development officers may be able to respond to this by emphasizing to experienced donors the importance of the research work being done by the university and the complementary nature of NSF grants with individual donations. 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 are 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 datasets from a broader range of universities across varying geographic areas as well as private versus public universities. It could also work to address some other limitations of our work or unexplained results. For example, though we find generally consistent results for large NSF grants, there are some discrepancies, like when using smaller time windows or cutoff values for donations. We also find differing results for the size of the grant. Future research could explore in more depth the cause behind the differential results for NSF grants compared with other government grants, or the different results for credit card donations. Nonetheless, our research is especially valuable to universities or other charitable organizations seeking to maximize revenue from fundraising.

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REFERENCES

Ade, Albert, Phanindra V. Wunnava, and Raymond Walsh, Jr. 1994. Charitable giving of alumni: Micro-data evidence from a large public university. *American Journal of Economics and Sociology* 53(1): 73–84. 10.1111/j.1536-7150.1994.tb02674.x

Andreoni, James. 1993. An experimental test of the public-goods crowding-out hypothesis. *American Economic Review* 83(5): 1317–1327.

Andreoni, James. 2006. Leadership giving in charitable fund-raising. *Journal of Public Economic Theory* 8(1): 1–22. 10.1111/j.1467-9779.2006.00250.x

Andreoni, James, and A. Abigail Payne. 2003. Do government grants to private charities crowd out giving or fund-raising? *American Economic Review* 93(3): 792–812. 10.1257/000282803322157098

Andreoni, James, and A. Abigail Payne. 2011. Is crowding out due entirely to fundraising? Evidence from a panel of charities. *Journal of Public Economics* 95(5): 334–343. 10.1016/j.jpubeco.2010.11.011

Arora, Ashish, and Alfonso Gambardella. 2005. The impact of NSF support for basic research in economics. *Annales d'Economie et de Statistique* 2005(79–80): 91–117.

Auten, Gerald E., Holger Sieg, and Charles T. Clotfelter. 2002. Charitable giving, income, and taxes: An analysis of panel data. *American Economic Review* 92(1): 371–382. 10.1257/000282802760015793

Borgonovi, Francesca. 2006. Do public grants to American theatres crowd-out private donations? *Public Choice* 126(3-4): 429–451. 10.1007/s11127-006-3887-z

Bozeman, Barry, and Monica Gaughan. 2007. Impacts of grants and contracts on academic researchers' interactions with industry. *Research Policy* 36(5): 694–707. 10.1016/j.respol.2007.01.007

Brooks, Arthur C. 2003. Do government subsidies to nonprofits crowd out donations or donors? *Public Finance Review* 31(2): 166–179. 10.1177/1091142102250328

Clotfelter, Charles T. 2003. Alumni giving to elite private colleges and universities. *Economics of Education Review* 22(2): 109–120. 10.1016/S0272-7757(02)00028-6

Cutler, David M., and Jonathan Gruber. 1996. Does public insurance crowd out private insurance? *Quarterly Journal of Economics* 111(2): 391–430. 10.2307/2946683

David, Paul A., Bronwyn H. Hall, and Andrew A. Toole. 2000. Is public R&D a complement or substitute for private R&D? A review of the econometric evidence. *Research Policy* 29(4–5): 497–529. 10.1016/S0048-7333(99)00087-6

De Wit, Arjen, and René Bekkers. 2017. Government support and charitable donations: A meta-analysis of the crowding-out hypothesis. *Journal of Public Administration Research and Theory* 27(2): 301–319.

Diamond, Arthur M., Jr. 1999. Does federal funding crowd in private funding of science? *Contemporary Economic Policy* 17(4): 423. 10.1111/j.1465-7287.1999.tb00694.x

Eckel, Catherine C., David H. Herberich, and Jonathan Meer. 2017. A field experiment on directed giving at a public university. *Journal of Behavioral and Experimental Economics* 66:66–71. 10.1016/j.socec.2016.04.007

Gaier, Scott. 2005. Alumni satisfaction with their undergraduate academic experience and the impact on alumni giving and participation. *International Journal of Educational Advancement* 5(4): 279–288. 10.1057/palgrave.ijea.2140220

Gordon, Nora. 2004. Do federal grants boost school spending? Evidence from Title I. *Journal of Public Economics* 88(9): 1771–1792. 10.1016/j.jpubeco.2003.09.002

Harrison, William B. 1995. College relations and fund-raising expenditures: Influencing the probability of alumni giving to higher education. *Economics of Education Review* 14(1): 73–84. 10.1016/0272-7757(94)00035-5

Harrison, Willian B., Shannon K. Mitchell, and Steven P. Peterson. 1995. Alumni donations and colleges' development expenditures: Does spending matter? *American Journal of Economics and Sociology* 54(4): 397–412. 10.1111/j.1536-7150.1995.tb03243.x

Huck, Steffen, Imran Rasul, and Andrew Shephard. 2015. Comparing charitable fundraising schemes: Evidence from a natural field experiment and a structural model. *American Economic Journal: Economic Policy* 7(2): 326–369. 10.1257/pol.20120312

Hungerman, Daniel, and Mark Ottoni-Wilhelm. 2016. *What is the price elasticity of charitable giving? Toward a reconciliation of disparate estimates*. Artefactual Field Experiments 00557, The Field Experiments Web site. Available https://ideas.repec.org/p/feb/artefa/00557.html.

Jacob, Brian A., and Lars Lefgren. 2011a. The impact of research grant funding on scientific productivity. *Journal of Public Economics* 95(9–10): 1168–1177. 10.1016/j.jpubeco.2011.05.005

Jacob, Brian A., and Lars Lefgren. 2011b. The impact of NIH postdoctoral training grants on scientific productivity. *Research Policy* 40(6): 864–874. 10.1016/j.respol.2011.04.003

Jaffe, Adam B. 2002. Building programme evaluation into the design of public research-support programmes. *Oxford Review of Economic Policy* 18(1): 22–34. 10.1093/oxrep/18.1.22

Khanna, Jyoti, and Todd Sandler. 2000. Partners in giving: The crowding-in effects of UK government grants. *European Economic Review* 44(8): 1543–1556. 10.1016/S0014-2921(99)00007-0

Kessler, Judd B. 2017. Announcements of support and public good provision. *American Economic Review* 107(12): 3760–3787. 10.1257/aer.20130711

Kingma, B. R. 1989. An accurate measurement of the crowd-out effect, income effect, and price effect for charitable contributions. *Journal of Political Economy* 97(5): 1197–1207. 10.1086/261649

Landry, C. E., Lange, A., List, J., Price, M. K., and Rupp, N. G. 2010. Is a donor in hand better than two in the bush? Evidence from a natural field experiment. *American Economic Review* 100(3): 958–983. 10.1257/aer.100.3.958

Levin, Tova, Steven D. Levitt, and John A. List. 2016. A glimpse into the world of high capacity givers: Experimental evidence from a university capital campaign. NBER Working Paper No. 22099.

Meer, Jonathan. 2017. Does fundraising create new giving? *Journal of Public Economics* 145:82–93. 10.1016/j.jpubeco.2016.11.009

Meer, Jonathan, and Harvey S. Rosen. 2009. Altruism and the child cycle of alumni donations. *American Economic Journal: Economic Policy* 1(1): 258–286. 10.1257/pol.1.1.258

Monks, James. 2003. Patterns of giving to one's alma mater among young graduates from selective institutions. *Economics of Education Review* 22(2): 121–130. 10.1016/S0272-7757(02)00036-5

Okten, Cagla, and Burton A. Weisbrod. 2000. Determinants of donations in private nonprofit markets. *Journal of Public Economics* 75(2): 255–272. 10.1016/S0047-2727(99)00066-3

Okunade, Albert A., and Robert L. Berl. 1997. Determinants of charitable giving of business school alumni. *Research in Higher Education* 38(2): 201–214. 10.1023/A:1024933720131

Paarlberg, Laurie E., Rebecca Nesbit, Richard M. Clerkin, and Robert K. Christensen. 2019. The politics of donations: Are red counties more donative than blue counties? *Nonprofit and Voluntary Sector Quarterly* 48(2): 283–308. 10.1177/0899764018804088

Payne, A. Abigail. 2001. 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(5–6): 731–751. 10.1023/A:1012843227003

Poterba, James M., Steven F. Venti, and David A. Wise. 1995. Do 401(k) contributions crowd out other personal saving? *Journal of Public Economics* 58(1): 1–32. 10.1016/0047-2727(94)01462-W

Roberts, Russell. 1984. A positive model of private charity and public transfer. *Journal of Political Economy* 92(1): 136–148. 10.1086/261212

Rose-Ackerman, Susan. 1981. Do government grants to charity reduce private donations. In *Nonprofit firms in a three sector economy*, edited by M. White. Washington, DC: Urban Institute Press.

Scharf, Kimberley A., Sarah Smith, and Mark Wilhelm. 2017. Lift and shift: The effect of fundraising interventions in charity space and time. CEPR Discussion Paper No. DP12338.

Svider, Peter F., Kevin M. Mauro, Saurin Sanghvi, Michael Setzen, Soly Baredes, and Jean Anderson Eloy. 2013. Is NIH funding predictive of greater research productivity and impact among academic otolaryngologists? *Laryngoscope* 123(1): 118–122. 10.1002/lary.23659

Taylor, Alton L., and Joseph C. Martin, Jr. 1995. Characteristics of alumni donors and nondonors at a research I public university. *Research in Higher Education* 36(3): 283–302. 10.1007/BF02208312

Thaler, Richard H. 1999. Mental accounting matters. *Journal of Behavioral Decision Making* 12(3): 183–206. 10.1002/(SICI)1099-0771(199909)12:3⟨183::AID-BDM318⟩3.0.CO;2-F

Warr, Peter. 1982. Pareto optimal redistribution and private charity. *Journal of Public Economics* 19(1): 131–138. 10.1016/0047-2727(82)90056-1