Charitable Giving Responses to Education Budgets

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Abstract

Do changes in government spending affect voluntary contributions to those recipients? We examine how changes in K-12 education budgets impact donations to teachers using data from DonorsChoose.org, an online crowdfunding platform for public school teachers to raise money. We find a positive correlation between budgets and voluntary contributions when not accounting for their endogenous relationship. With instrumental variables, we find evidence for crowd-out of private giving, though the magnitudes are small relative to spending and do not meaningfully offset budget changes. These results are driven entirely by teachers' posting of requests.

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1 Introduction

The relationship between government funding and private contributions to public goods is of key importance in understanding the nature of altruism and policy towards charitable giving (Roberts, 1984; Warr, 1982; Bergstrom et al., 1986; Okten and Weisbrod, 2000; Hungerman, 2005; Gruber and Hungerman, 2007; De Wit and Bekkers, 2017). Increased government spending may lead donors to give less, viewing taxation as a substitute for voluntary contributions – "classic" crowd-out – but charities may pull back on their fundraising efforts when receiving government funds – "indirect" crowd-out (Andreoni and Payne, 2003, 2011). Government grants can also have crowd-in effects, generally by serving as a signal of quality (Vesterlund, 2003; Eckel et al., 2005; Heutel, 2014; Bekkers and De Wit, 2020). Further, local preferences and conditions influence spending by the government, charitable giving by individuals, and fundraising decisions by charities; the same people who elect policymakers or vote on budgets are those who make donations, making it difficult to determine the causal relationship (Payne, 1998). If crowd-out is significant in magnitude and primarily due to donors' responses, warm glow motivations may be less important (Andreoni, 1989, 1990; Ribar and Wilhelm, 2002).

We investigate the nature of crowd-out by examining how K-12 school budgets impact voluntary contributions to education. K-12 education in the United States is funded almost entirely through taxation and makes up a substantial portion of state and local budgets. Traditionally, fundraisers for schools have been local, generally organized by parent-led associations. As such, the relationship between these contributions and local education budgets is endogenous. These local donors often benefit directly from the contributions to the schools, as they are members of the community or have children in the school; the donations may be direct personal consumption rather than contributions to public goods. We address the endogeneity issues inherent in estimating these relationships using instrumental variables.

We construct a district-year panel by linking data from Donorschoose.org, an online crowdfunding platform for public school teachers to post projects for prospective donors, to data from the United States Department of Education on local school budgets. We examine the impact of changes in budgets on donations, as well as how teachers respond to those changes through their requests on the platform, allowing us to decompose crowd-out into its classic and indirect components. The primary concern for identification is that variations in school budgets, and charitable contributions are both affected by unobserved economic factors, which can also impact teachers' willingness to post requests.

We first address this problem by including state- or county-by-year fixed effects in addition to school district effects to control for shocks affecting a particular area in a given year. But these specifications may not fully account for district-year shocks that affect budgets, postings, and contributions, leading to spurious correlation. We instrument for per-pupil spending using the timing of school finance reforms (Jackson, Johnson, and Persico, 2016; Bayer, Blair, and Whaley, 2020) and a variable measuring the district's exposure to state funding similar to those used in a higher-education context by Dinerstein et al. (2015) and Deming and Walters (2017). There are tradeoffs to the instrumental variables approach, particularly in the inability to use geography-by-time fixed effects.

The DonorsChoose.org data has a number of advantages. Teachers' posts are easily linked to school districts, and the sample includes 1.5 million projects and 8.4 million donations. Donations go to a specific project, which is fulfilled only if the requested threshold is met. Expenditures on fundraising are not a component of this platform, which precludes measuring their effectiveness. But since donations can only be made when a project is posted, fundraising requests are observable, and there is a more direct link between the behavior of the recipient of the donation and the donor.[1] Moreover, charities' incentives to reduce administrative expenses lead to underreporting of fundraising expenditures in administrative data (Krishnan, Yetman, and Yetman, 2006; Mayo, 2021).

Our results follow a pattern that points to the importance of accounting for endogeneity. When including state-by-year fixed effects, we see evidence of crowd-in; that is, larger budgets are associated with more giving; stopping the analysis at this point would point to crowd-in. Controlling for conditions at a more local level with county-by-year fixed effects attenuates these results. With a full set of controls, there is no meaningful relationship between budgets and donations. The change in the results when including finer geographic controls suggests that local conditions play an important role in that relationship. And when instrumenting, there is a large and significant decrease in the likelihood of both receiving a donation and the amount given conditional on receiving at least one donation.

These conclusions, pointing to significant crowd-out, would be misleading without considering requests made by teachers. Larger budgets reduce both the likelihood of a DonorsChoose.org posting and the amount requested. Further, donations are very responsive to requests, demonstrating the "power of the ask" in charitable giving (Andreoni and Rao, 2011; Andreoni, Rao, and Trachtman, 2017; Meer and Rosen, 2011). The effectiveness of requests in this context suggests that teachers are leaving a significant amount of donations on the table.

Taken together, a 1 percent increase in elementary-secondary expenditures (about $340,000 for the average school district in our data) reduces donations by $410. But the amount requested by teachers is reduced by $603; applying our estimates of the efficacy of these requests suggests that this reduces donations by $546 – that is, the reduction in donations is driven by the endogenous response of teachers. This response seems trivial compared to the change in the budget. But most of these expenditures go to staff salaries and other operations that are not related to the sort of activities funded by DonorsChoose donations. A more meaningful comparison is the average teacher out-of-pocket spending of $479 (Kim, 2021). Even a large overall budget change may have a more muted impact on funding for which donations substitute. Further, we also only examine one source of education-related charitable giving – DonorsChoose.org – so the overall effects are larger if other potential recipients, like parent-teacher organizations, are also affected.

Recent evidence suggests that increases in education spending have positive effects on student outcomes, at least when that spending is reasonably well-targeted (Abott, Kogan,

[1] Crowdfunding platforms have been used to study the impact of social distance (Meer and Rigbi, 2013), the value of completing projects (Wash, 2013), competition among causes (Meer, 2017), donor distaste for overhead costs (Meer, 2014, 2023), the role of social networks and pressure (Castillo, Petrie, and Wardell, 2014, 2017), and other topics.

Lavertu, and Peskowitz, 2020; Card and Payne, 2002; Jackson, Johnson, and Persico, 2016; Jackson, Wigger, and Xiong, 2021; Jackson, 2018; Lee and Polachek, 2018). Keppler et al. (2022) show that funding from DonorsChoose.org increases student performance at the lowest-income schools.

The evidence is mixed on the response of private funding to changes in public education budgets, with some finding little evidence of a response (Jones, 2015; Nelson and Gazley, 2014; Milton, 2017), while others do find crowd-out (Grosskopf et al., 2020; Hungerman et al., 2019). If voluntary contributions increase in response to budget cuts, then the effects of those cuts may be mitigated. However, depending on how those contributions are distributed, they may alleviate or exacerbate existing differences in resources; in that vein, Kim (2021) shows that teachers in schools with larger minority populations tend to spend more out-of-pocket.

In the paper most similar to ours, Andreoni and Payne (2011) use tax filings by charities to decompose total crowd-out into classic and indirect components by estimating the impact of government grants on donations and fundraising separately, instrumenting with a set of variables for the political affiliation of the governor and congressional delegation. They also estimate the impact of fundraising on donations, instrumenting with variables for the financial health of the nonprofit organization. They find significant crowd-out, with a $1000 grant reducing giving by over $700, but this is entirely due to reduced fundraising effort; fundraising expenditures themselves are effective at increasing donations. Our estimated effects, while leading to similar conclusions, are much smaller in magnitude. This difference is likely due to the different settings. Additional government funds directly granted to a charity are close substitutes for private contributions, while the sorts of activities that DonorsChoose.org contributions fund are a small part of a district's budget.

Differentiating between classic and indirect crowd-out demonstrates the importance of warm glow motivations in giving. Our contribution is to deploy data that are better-suited to answering this question and not subject to the issues with nonprofits' tax filings. While teachers are not nonprofits nor fundraisers, the behavior of those on the DonorsChoose.org platform provides insights that expand our understanding of the interaction between the supply and demand sides of the market for charitable giving.

2 DonorsChoose.org

2.1 Description of the Platform

DonorsChoose.org is an online platform for public school teachers to post projects and collect funding. Founded in 2000, more than 790,000 teachers have posted nearly 2.6 million projects for 40 million students on the site. The platform has attracted over $1 billion in donations from 5.7 million donors. Appendix Figure A2 presents data on the growth of the organization. Given the scope and broad use of DonorsChoose.org among low-income communities, DonorsChoose.org has been referred to as "the PTA Equalizer" (Rivero, 2018), providing fundraising opportunities to underserved communities that were previously only available to higher-income areas. The platform meets the criteria set by the National School Board Association for best-in-class

crowdfunding sites, such as financial transparency and accountability, privacy and safety, and integrity controls.[2] Teachers bear no fundraising costs apart from their time and effort in setting up a request. The accessibility and simplicity of working with this platform provide an opportunity for teachers to raise money for their classroom projects.

The data allow us to observe the demand for donations (as measured by projects posted by teachers) as well as the equilibrium outcome (projects funded and amounts donated). It is tempting to think of the amount donated as the supply of donations, but it is a function of both donors' intent and their opportunities – if there are no projects posted in a particular district, donors cannot give through the platform. By examining these outcomes separately, we can better determine whether teachers are responding to budget pressures separately from donors' behavior.

Of course, DonorsChoose.org is only one avenue for private contributions to education. Parent-teacher organizations raise significant amounts of money (Cope, 2019) and may serve as another conduit for funds. Many such organizations are below the Internal Revenue Service's $50,000 gross-revenue threshold for filing Form 990 and are less likely to file electronically and thus be included in publicly available databases. There is also evidence that charities manipulate their administrative expenses in response to incentives created by nonprofit ratings (Mayo, 2021). The DonorsChoose.org platform is by far the largest for crowdfunding in education. Its data structure and transparency, which allow us to examine teacher demand for financing and allow for donations from people not necessarily connected to the district, provide significant advantages in examining this question.

2.2 How does it work?

Teachers select supplies from lists provided by vendors and write a request that includes a discussion of student needs and the proposed use of the supply. Teachers also provide a photograph of their classroom. The request page includes information about the school (such as its location and poverty level) and the project (such as its subject matter and the number of students reached). The request includes an itemized list of the materials requested, their price and quantity, and any additional charges. These projects are screened by Donorschoose.org's staff and volunteers. Donors, whose gifts are tax-deductible, can search or browse projects. Appendix Figure A1 shows the page of a representative project; the layout of the web page has changed several times over the history of the organization.

If a project reaches its goal, DonorsChoose.org purchases the materials and ships them directly to the teacher. If the project expires prior to being funded, donors have the option to have the funds returned to their account to select another project or to have DonorsChoose.org select a project for them. Projects that do not reach their goal generally expire after four months.

[2]For more details, see https://help.donorschoose.org/hc/en-us/articles/360002942094-Resources-for-School-Board-Members.

3 Data and Empirical Strategy

3.1 Data

Data on projects posted at DonorsChoose.org include the U.s. Department of Education National Center for Education Statistics ID (NCESID) number for the school.[3] These consist of 1,715,764 projects posted by the end of 2018, of which 68.5% met their goal. The mean project amount requested (in 2017 dollars) is $791 with a median of $484. About 32 percent of projects request classroom supplies, with 18 percent requesting books and 30 percent requesting some form of technology. 83 percent of projects posted and 82 percent of dollars requested were from low-income schools, as defined by the percent qualifying for free and reduced-price lunch.

The data also include each project's posting date as well as the date of each donation to every project. We match these dates to each district's fiscal year, drawn from the Common Core of Data School Finance Survey. For most states, the fiscal year begins on July 1 and ends on June 30; Alabama, the District of Columbia, Nebraska, Texas, and Washington are exceptions (Cornman et al., 2020). Each project is assigned to a fiscal year based on its posting date, and all donations to that project are assigned to the fiscal year in which the project was posted. For example, a project posted on August 15, 2017 would be assigned to the 2017 fiscal year in Washington State, where the fiscal year begins on September 1, but to the 2018 fiscal year in California, where the fiscal year begins on July 1.

We aggregate the posting and donation data to the district-year level, summing the amounts requested and donated within each district and fiscal year. Our results are robust to assigning donations to the fiscal year in which they were made, as well as to excluding donations going to projects that were ultimately unsuccessful.

We link this to the Department of Education Common Core of Data (CCD), covering the 1995 to 2018 school years.[4] Ideally, we would match the school-level DonorsChoose.org data with school-level funding data; however, financial data are only available at the district level. The sample begins with 409,108 observations. We exclude districts with fewer than 50 students enrolled, as is standard in the literature (Cellini et al., 2010) and drop those with missing ID numbers, leaving 380,090 observations. Dropping observations with missing financial information leaves a final sample of 352,450 district-year observations representing 17,546 districts. Including all of the available data, 21.7 percent of observations have at least one project posted (31 percent from the start of the DonorsChoose.org data in 2003); 81.2 percent of districts ever have a project posted. The data represent 1,572,790 individual projects posted by 848,258 teachers, with 8,407,053 donations totaling 688.6 million dollars. Conditional on at least one project being posted in a district-year, the mean number of projects is 20.6, posted

[3]Each school's specific NCESID includes its district's unique Local Education Agency ID (LEAID). That identifier allows us to merge the DonorsChoose.org data with the U.S. Department of Education's Common Core of Data, which includes district-level financial information.

[4]Beginning in 2006, the Common Core of Data asks districts to report "gifts of cash or securities from private individuals or organizations." The accuracy of these data is unclear, though we report estimates using this outcome in Appendix Table A2. The combined estimate is positive but flips sign and becomes negative and statistically insignificant when including controls. Regardless, the lack of data on fundraising expenditures needed to compare classic and indirect crowd-out makes this variable ill-suited for our purposes.

by 11.1 teachers. The mean amount raised in a district year, conditional on any donations, is $9,558.54, with a median of $1,432.82. Nominal dollar amounts are adjusted to 2017 dollars. Table 1 reports summary statistics; due to missing observations for some demographic variables, the sample size changes depending on the specification.

Total expenditures include elementary-secondary expenditures (83.9 percent of the total), capital outlay expenditures (9.9 percent), payments to state or local governments, payments to different school systems, and interest paid. We focus on elementary-secondary expenditures because those directly affect the operation of the schools in the given school year. They include items such as salaries for school personnel, benefits, student transportation, books, and materials. Appendix Figure A3 shows total expenditures, elementary-secondary spending, and capital expenditures in school districts between 1995 and 2018. We also extract the number of teachers in the district, the share of children living in poverty from the U.S. Census Bureau's Small Area Income and Poverty Estimates program (SAIPE), and enrollment shares by race from the School Funding Fairness Database (Baker et al., 2016). Together, these variables are available for 268,854 observations.

3.2 Specification

We use a single-hurdle model to examine whether any project is posted (or receives a donation) in a given district year in the first stage. We then separately estimate the effects on the intensive margin (the amount requested or the amount received in donations) in the second stage for those district-year observations that clear the initial hurdle. This approach models the decision of whether or not any requests are posted, or any donations are made separately from the decision of how much to request or give. It also allows for control variables to have different effects on the two stages, which is often important in charitable giving contexts.[5] We then combine the results to find marginal effects on the unconditional means.

School spending is not randomly assigned. It is likely to be correlated with permanent and transitory economic conditions, as well as the underlying prosociality of a district's residents, which also impacts charitable giving. We include district fixed effects and school district demographics in our specifications to control for the factors that may confound the relationship between spending and donations. Macroeconomic conditions are known to have a significant impact on charitable giving (List and Peysakhovich, 2011; Meer et al., 2017); year fixed effects account for conditions that affect the entire country but do not account for time-varying shocks that affect only the region. For example, a localized recession could lead to both cuts in school spending and a reduction in donors' ability to make gifts. We include state-by-year

[5]See Huck and Rasul (2011) and Meer (2011) for further discussion on the use of this approach for charitable giving estimates. The Tobit is often used when there are many observations with outcomes equal to zero. However, this model suffers from tractability problems in the presence of fixed effects, is likely not appropriate when zeroes arise from corner solutions rather than true data censoring, and constrains the marginal effects on the extensive and intensive margins to be proportional to each other. This last issue is particularly problematic in the context of charitable giving. For example, income and gender have been shown to have very different effects on the extensive and intensive margins (Wiepking and Bekkers, 2012; Meer and Priday, 2021). In this case, per-pupil spending may have different effects on the likelihood of a request receiving a donation and the total amount received.

fixed effects to capture this variation. Shocks at a more local level could still leave spurious correlation. We also estimate specifications that include county-by-year fixed effects, but this approach does not fully account for time-specific factors within a district that could be driving the relationship between spending, fundraising requests, and donations. Below, we describe the set of instrumental variables we use to address this issue.

In the first stage, we examine whether any projects have been posted or if any donation is made, as shown in equation 1, which we estimate with a linear fixed effects model.

$$P(Y_{dst} > 0) = \alpha + \beta \cdot Log\ Exp_{dt} + \delta \cdot X_{dt} + \gamma_d + \mu_t + \eta_{st} + \epsilon_{dst} \quad (1)$$

Where d, s, and t index districts, states, and (fiscal) years, respectively. The outcome variable, $P(Y_{dst} > 0)$, is the probability of any giving or any posted project in district d at time t. $Log\ Exp_{dt}$ is the log total expenditures in district d and year t. We also include the log number of students, the share of children ages 5 to 17 in poverty, the log of the number of teachers in a district year, and enrollment shares by race in X_{dt}. γ_d, μ_t, and η_{st} are district fixed effects, year fixed effects, and state-year (or county-year) fixed effects, respectively. Year fixed effects are subsumed into the place-year fixed effects; as described below, the instrumental variables estimates do not include place-year effects. Standard errors are clustered at the district level.

The second stage estimates the effects on the intensive margin. The outcomes of interest for this specification, in Equation 2, are the log of the amount requested and the log of the amount donated, $Log\ Y_{dst}$. We estimate this equation using a linear fixed effects model only on observations for which there is a nonzero outcome.[6]

$$Log\ Y_{dst} = \alpha + \theta \cdot Log\ Exp_{dt} + \delta \cdot X_{dt} + \gamma_d + \mu_t + \eta_{st} + \epsilon_{dst} \text{ if } Y_{dst} > 0 \quad (2)$$

The coefficients of the interest in Equations (1) and (2) are β and θ (respectively). The intensive margin effect cannot be taken as causal, though, because it reflects both a compositional change from the change in the sample due to the extensive margin effect as well as a behavioral effect on those whose extensive margin behavior does not change. That is, it consists of both a treatment effect and a change in the composition of the sample. However, these coefficients can be combined to find the marginal effect on the unconditional mean, with standard errors calculated using the delta method:

$$\frac{dLog\ Y_{dst}}{dLog\ Exp_{dst}} = \frac{dP(Y_{dst} > 0)}{dLog\ Exp_{dst}} \times E[Log\ Y_{dst} | Y_{dst} > 0] + P(Y_{dst} > 0) \times \frac{dE[Log\ Y_{dst} | Y_{dst} > 0]}{dLog\ Exp_{dst}} \quad (3)$$

For the relationship between the amount requested and the amount given, we estimate specifications conditional on a request. No donations can be given through DonorsChoose.org without a request. As such, there are no observations for which there are positive donations but no requests.

[6] 6.2% of district-year observations have a positive request amount but no donations. These observations are dropped when the log of the donation amount are taken. Adjusting the specification to include them, by adding one to donation amount prior to taking logs, does not meaningfully affect the estimates.

$$Log\ Donations_{dst} = \alpha + \rho \cdot Log\ Requests_{dst} + \delta \cdot X_{dt} + \gamma_d + \mu_t + \eta_{st} + \epsilon_{dst} \text{ if } Requests > 0 \quad (4)$$

3.3 Instrumental Variables

The set of controls we discuss in the previous section are an attempt to account for local conditions and factors that impact both giving and school expenditures. But it is possible that within a county, a school district's economic fortunes were trending downwards in a way that is not captured by those controls, leading to both lower expenditure and reduced giving by its residents. Or a shock to the district may lead to spurious correlation: for example, a natural disaster could lead to greater giving and changes in government spending. Districts with fewer resources may be more likely to hire young teachers, whose salaries are lower (Adamson and Darling-Hammond, 2012); these teachers may be more likely to be familiar with platforms like DonorsChoose.org.

It is difficult to rule out all such stories. But the use of instrumental variables which affect expenditures but are uncorrelated with district-specific shocks can assuage these concerns. We use versions of two sets of instrumental variables that have been used recently in the economics of education literature to instrument for per-pupil spending.[7]

First, we adapt the school finance reform instruments used in Jackson et al. (2016) and Bayer et al. (2020), who argue that judicially-imposed reforms are an exogenous source of variations, and which increase per-pupil spending by more in low-income districts than higher-income ones. The early reforms they study, beginning in the 1970s, are too far in the past to have appreciable impacts on our sample, yielding a weak first stage and imprecise and implausible estimates. We limited the sample to the seven reforms since 1995 (Vermont, Ohio, Michigan, Idaho, New York, South Carolina, and Oregon), interacted with base-year district spending quartile, and replicated those findings. Appendix Figure A4 shows an event study graph of the impact of these reforms on school expenditures in a regression that includes year and district-fixed effects.[8] The F-statistics for the first stages are 14 and 106 on the extensive margin for the specifications without and with additional controls, respectively, and 23 and 30 on the intensive margin.

We also follow Deming and Walters (2017), who use an instrument for higher education expenditures that interacts with an institution's appropriations revenue share in an initial year with the current year's total state appropriations (on a per-college-aged-population basis); this

[7] We considered using discontinuities around school budget votes as a source of identifying variation for changes in charitable giving, using data from New Jersey and New York. We found little impact on per-pupil spending and the results were sensitive to specification. We also follow Baron (2019), who finds that operational referenda in Wisconsin increase per-pupil expenditures, replicating his finding. However, the relatively small sample size of DonorsChoose.org projects posted in Wisconsin in the relevant time periods yields noisy estimates. We also replicated the results in Brunner et al. (2022), which use the construction of wind farms to proxy for increases in revenues. However, as Brunner et al. (2022) explain, these revenues are more likely to be used for capital expenditures (and, in some cases, are required to be used as such). As they did, we found little first-stage effect on elementary-secondary expenditures, making this approach unsuitable for our purposes.

[8] As there are 287 interaction terms, we follow Bayer et al. (2020) and present them graphically.

approach is a variation on that pioneered by Bartik (1991). In a similar vein, we interact with a district's share of its revenues coming from state appropriations in the first year it appears in our sample with current state appropriations divided by the number of children between the ages of 5 and 18, as shown below.

$$Z_{d,t} = \left(\frac{District's\ State\ Revenue_{d,t=1}}{District's\ Total\ Revenue_{d,t=1}}\right) \times \left(\frac{State\ Revenue_{s(d),t}}{Pop\ ages\ 5-18_{s(d),t}}\right) \tag{5}$$

$Z_{d,t}$ has two components: the reliance of the district on state funding in the initial year in the sample and the growth in overall per-pupil state revenue. If state appropriations increase, districts that are more reliant on state revenue in the baseline year are more likely to have revenue increases. State spending changes vary both within and across states during our sample period, with an interquartile range for all state-year observations of -1.1 to 4.5 percent. But changes in state appropriations are unlikely to be driven by the changes in an individual district's circumstances, thus creating exogenous variation in district-level spending. Recent work by Goldsmith-Pinkham et al. (2020) suggests that a shift-share approach is equivalent to using the initial shares as instruments, weighting by the overall shift over time. While we cannot directly verify that this exclusion restriction holds, the baseline year for most districts is eight years before the availability of DonorsChoose.org; as such, the shares are more likely to reflect these initial conditions and be excludable from the second stage. Since increases in state-level spending on education are expected to increase spending in districts that are more reliant on state aid, we expect this measure to have a positive coefficient in the first stage estimates. As shown in Columns 1 and 3 of Tables 4 and 5 – which also include the school finance reform indicators – it does, in both the extensive and intensive margins, and is precisely estimated.

We modify the specification described in the previous section by estimating an instrumental variables model for each stage separately, using the cmp module developed by Roodman (2011). The coefficients of interest are again combined to estimate the marginal effects on the unconditional mean. Using these instruments in our specifications for donations and requests comes at a cost. Both are determined at the state-year level. The school finance reform variables are a function of a district-specific factor (the district's resource quartile) multiplied by a state-year function. The state-funding exposure instrument is similarly composed of a district-level factor (reliance on state revenue in the baseline year) multiplied by a state-year function. As such, including state- or county-by-year effects in the instrumented specifications leaves little identifying variation. These specifications, therefore, only include year and district effects.

In terms of the effects of requests on donations, the primary concern regarding endogeneity is a shock that affects both donor desire and teachers' requests, such as a spike in local need, leading to spurious correlation. It is difficult to envision an instrument that affects requests without also potentially affecting donations. We experimented with the amount and number of projects posted by neighboring school districts in the previous year, positing that knowledge of DonorsChoose.org might spread. As seen in Table A1, these instruments tend to be statistically significant. However, there are reasons to be skeptical of these instruments; competition from neighboring districts in the previous year may directly affect the amount given this year, though Meer (2017) shows that such longer-run negative spillovers are unlikely. Ultimately, the instru-

mented results are nearly identical to the uninstrumented ones, suggesting that endogeneity is not a major concern for this specification.

4 Results

4.1 Baseline Specifications

4.1.1 Donations

We begin with the effect of K-12 elementary-secondary expenditures on donations in Table 2. Panel A reports the estimates on the likelihood that any donations are made, while Panel B shows the intensive margin effect on the amount donated. Panel C combines the effects. In Column (1), we report the results of the simplest specification, with no controls other than state-by-year fixed effects. These are positive and statistically significant on both the extensive and intensive margins, with a combined effect – essentially, the elasticity of donations with respect to school expenditures – of 0.58 (s.e. = 0.03). This estimate diminishes slightly to 0.52 (s.e. = 0.11) in Column (2) when adding controls such as the district's enrollment, number of teachers, racial composition, and the share of children in poverty. These estimates would indicate the presence of crowd-in, with larger school budgets leading to *more* funding.

But the addition of county-by-year fixed effects reduces the effect further. Column (3), without controls, shows a combined effect of 0.18 (s.e. = 0.03), while the inclusion of controls reduces the effect to an economically and statistically insignificant 0.04 (s.e. = 0.12).[9] These finer-grained geographic effects are more likely to account for local preferences and time-varying local conditions. Indeed, this reduction suggests the presence of omitted variables that impact both donors' willingness to give and the size of school budgets.

4.1.2 Teacher Postings

But simply examining the relationship between budgets and donations is insufficient to draw conclusions about the nature of crowd-out, even without endogeneity concerns. Changes in expenditures are generally more salient to teachers than to donors. Further, teachers can post a request irrespective of the desire to donate. This response, therefore, gives a measure of the need perceived by teachers.[10]

Columns (5) and (6) of Table 2 show a similar pattern of results, with an elasticity of requests with respect to expenditures of 0.47 (s.e. = 0.11) when controls are included. That is, these results suggest that larger budgets lead teachers to post more. But once again, adding county-by-year fixed effects in Columns (7) and (8) reduces the effect, with an estimated elasticity is -0.05 (s.e. = 0.13) in Column (8).

[9]The change between Columns (3) and (4) is driven by the inclusion of the controls. Estimating the more parsimonious specification on the limited sample in Columns (4) yields results similar to those in (3) and (2).

[10]Of course, we cannot reject the possibility that teachers are responding to a stated desire to give by potential donors; for example, a parent may suggest to his or her child's teacher that the teacher post a request to allow for tax-deductible directed giving to that classroom. Note that donations can come from anywhere. Meer (2017) shows that general geographic proximity has an effect on donor preferences, but many donations are given to schools outside of the area in which the donor lives.

4.1.3 Effects of Requests on Donations

Finally, we estimate the impact of requests on donations. This specification differs from those above since donations can only be made in response to a request. Table 3 shows similar results across all the columns, with a 10 percent increase in the amount requested associated with a roughly 9 percent increase in donations. While this is not directly comparable to the effect of fundraising expenditures in other work, it is in line with the findings that charities are not revenue maximizers – that is, it appears that teachers could raise more funds by asking for more, conditional on asking. The inclusion of geography-specific time effects does not alter the coefficients in a meaningful way, suggesting that unobserved local shocks are less of a concern for these estimates.

Taken together, the results in this section suggest that endogeneity that leads to spurious positive correlations between government spending and donations is likely present. An analysis that stopped with the simplest specification and focused only on donations would conclude incorrectly that government spending leads to more donations. The addition of the results on requests indicates that teachers' responses may play a role. But with finer geographic controls, the effects diminish and become both small and statistically insignificant – an increase in spending leads to a negligible change in donations. Yet these controls may not fully account for the opaque relationship between government expenditures, fundraising, and private contributions. We therefore turn to specifications using instrumental variables.

4.2 Instrumented Specifications

4.2.1 Donations

We begin again with the effect of education expenditures on donations in Table 4. The instrumented specifications include year and district-fixed effects since the variation in the instruments is at the state-year level. The effects on both the extensive (Panel A) and intensive margins (Panel B) are negative and statistically significant. Panel C combines these estimates; with no controls, the estimated elasticity is -2.17 (s.e. = 0.47). With controls, it increases in absolute value to -4.29 (s.e. = 0.37). This estimate appears quite large, perhaps implausibly so, but it compares a district's total expenditures to DonorsChoose.org donations, which are orders of magnitude smaller. We benchmark the estimates below for a more clear interpretation. But compared to the results without instruments, we might now conclude that there is significant crowd-out when we account for endogeneity. Without considering the effect on requests for funding, though, we do not know whether this is a classic or indirect crowd-out.

4.2.2 Teacher Postings

We turn to the demand side, examining the effect on teacher postings. The estimates mirror those for donations, with negative and statistically significant effects on both the extensive and intensive margins in Table 5. Without controls, the unconditional elasticity is -2.31 (s.e. = 0.50). Adding controls yields an elasticity of -4.76 (s.e. = 0.38). We can conclude that teachers are responsive to changes in educational budgets; they reduce their efforts to raise external

funds in the face of higher budgets. These results are similar in spirit to those in Andreoni and Payne (2003) and Andreoni and Payne (2011), who find a significant reduction in fundraising expenditures in response to government grants. That these results are similar in magnitude to those for donations further suggests that the reduction in giving is driven by the reduction in requests.

4.2.3 Effects of Requests on Donations

For completeness, we report instrumented results for the effect of requests on donations in Table A1, despite the doubts we detail above regarding their value. In practice, the coefficients do not change much when these finer controls are included. Much like the uninstrumented estimates, the elasticity of donations with respect to requests is close to 1, suggesting that teachers could raise more money by asking for more, conditional on asking at all.

4.2.4 Estimates of Classic and Indirect Crowd-Out

Using these results, we decompose total crowd-out into the classic and indirect effects. A 1 percent increase in elementary-secondary expenditures (about $340,000 for the average school district in our data) reduces donations by $410. But the amount requested by teachers is reduced by $603. This reduction in postings can be combined with the estimates from Table A1 on the effects of requests on donations to determine the change in donations driven by the change in postings. We estimate the reduced postings lead to a $546 reduction in donations. That is, the entirety of the reduction in donations is driven by the endogenous response of teachers. This response is quite small compared to the budget itself. But DonorsChoose.org donations do not substitute for most of a district's expenditures, but rather the sorts of additional activities that may be funded by a principal's discretionary budget or a teacher's out-of-pocket spending. The relevant margin is likely much smaller than a percentage of the budget in its entirety.

4.3 Additional Results

4.3.1 Donor Location

Examining the response of local and non-local donors to changes in changes in elementary-secondary expenditures provides suggestive evidence of the degree to which shocks to local preferences that affect both giving behavior and K-12 funding is a concern. About 85 percent of the dollars donated are associated with observations that have the donor's state available. ZIP postal codes are specific to smaller geographies but available for far fewer observations, so we focus on the state. In-state donors are somewhat more responsive to changes in expenditures than out-of-state donors, with an instrumented elasticity of -3.9 (s.e. = 0.32) as compared to -3.44 (s.e. = 0.33).

However, this finding should not be taken as definitive. Expenditures are likely more salient to locals, but states are fairly large geographic areas. And ultimately, given the evidence that changes to teachers' posting behavior drive the results – and the small role that classic crowd out plays – this is not surprising.

4.4 Project Subject and Resource Type

We examine how the responsiveness to teachers' requests for funds varies by subject and resource type. Each project is assigned one of 31 categories as their primary subject matter, such as "Mathematics," "Literature & Writing," "Mental Health," " Special Needs," and so on. We classify these as "Academic," "Enrichment/Extracurricular," "Support," and "Other." Further, projects are assigned to one of 18 categories of resource types, such as "Art Supplies," "Books," "Food, Clothing, & Hygiene," and "Musical Instruments." We classify these as "Classroom Supplies," "Enrichment," "Technology," and "Basic Needs/Other." We then estimate our instrumented specification separately for each category type.

Requests for and donations to projects focusing on Academic subjects and Classroom Supplies and Technology resources are the most responsive to changes in budgets. Enrichment (both in terms of subject and resources) and other types of projects tend to be less responsive. The results are in Appendix Tables A3 and A4. Without making too much of these patterns, they suggest that teachers are funding core needs through DonorsChoose.org. That is, the results are consistent with enrichment-type activities being less affected by marginal changes in budgets and more often in need of external support. Further suggestive evidence for this hypothesis is seen when we use the share of projects that are funded successfully in a given district year, conditional on any postings. In the instrumented specifications, including controls, the unconditional elasticity is -0.97 (s.e. = 0.10), from a baseline of about 64 percent.[11] Since the results above show that the denominator (posted projects) is reduced, it must be that the numerator (funded projects) falls by more. It is possible that teachers are posting more marginal projects that are less likely to be funded in the presence of higher budgets, though other responses – like reduced donor interest or teacher fundraising efforts – could also play a role.

5 Discussion & Conclusion

We examine how K-12 education budgets impact private giving to education using rich data from DonorsChoose.org. We show that the estimates that do not account for endogeneity suggest crowd-in, with higher spending leading to more donations. These estimates become smaller when finer geographic controls are included, and then negative when we account for endogeneity using instrumental variables. But the reduction in donations is driven by a reduction in the amount requested by teachers. Without accounting for endogeneity or examining the response by teachers, one would draw incorrect conclusions about the relationship between education budgets and donations.

Our empirical analysis is limited, of course, since we are only examining one form of voluntary contributions to schools. Giving through a crowdfunding platform may also be different than giving through other methods. And the nature of requests on DonorsChoose.org does not necessarily lend itself to direct comparisons with more traditional fundraising methods.

[11] This figure does not precisely match the 68.5 percent success rate reported in the Introduction because the unit of observation here is a district-year rather than an individual project.

While we show that private contributions can counteract changes in government spending if charities respond by changing their fundraising effort, the magnitudes we find are small relative to overall education spending. Policymakers cannot necessarily rely on voluntary contributions to make up large reductions in government spending. Our results on the effects of requests on donations do suggest that teachers could attract more contributions by requesting more funds.

That indirect crowd-out rather than the "classic" variety is at work is perhaps unsurprising. After all, prospective donors are less likely to be well-informed about budgeting for the sorts of activities for which DonorsChoose.org funds are substitutes. But this reflects the reality of the fundraising landscape. By examining the impact of expenditures on teachers' requests and of requests on donations themselves, we show that this effect is entirely driven by endogenous responses on the part of the teachers. This shows the importance of considering the interaction between different agents in the market for charitable giving.

Table 1: Summary statistics

Panel A - unconditional				
District Demographics	Mean	Std. Dev.	Median	Observations
Fall Enrollment	3254.77	14137.26	1012.00	352523
Total Teachers	199.79	807.88	68.67	347634
Frac. White Enrollment	0.73	0.29	0.86	352981
Frac. Black Enrollment	0.10	0.21	0.01	350136
Frac. Hispanic Enrollment	0.12	0.20	0.03	351996
Frac. Children In Poverty (Ages 5 to 17)	0.16	0.10	0.15	276526
Any Project Posted	0.21	0.41	0.00	365434
Any Donation Received	0.20	0.40	0.00	365434
Number of Schools with Posted Projects	0.87	6.67	0.00	365434
District Finance Data in Million Dollars ($2017)				
Total Revenues	39.98	223.83	12.13	365434
Total Expenditures	40.49	237.97	12.04	365434
Elementary-Secondary Expenditures	33.94	195.47	10.24	365434
Capital Expenditures	4.02	27.20	0.48	365434
Teacher Salaries Expenditures	14.17	84.37	4.13	365434
Private Contributions to Districts	0.07	0.63	0.00	208994
Panel B - conditional on any posting				
Posting ($2017)	Mean	Std. Dev.	Median	Observations
Number of Teachers with Posted Projects	11.05	62.88	2.00	76884
Number of Posted Projects	20.48	137.03	3.00	76884
Amount Requested by Teachers	12651.14	89426.06	2008.66	76884
Panel C - conditional on any donation				
Donations ($2017)	Mean	Std. Dev.	Median	Observations
Number of Complete Projects	14.86	99.40	2.00	72129
Number of Donations	116.71	1070.06	18.00	72129
Amount Donated	9558.54	67736.75	1432.82	72129
Amount Donated within the Same State	3542.08	32043.09	475.09	72129
Amount Donated by a Different State	4693.73	32545.12	609.11	72129

Table 2: Impact of elementary-secondary expenditures

	Donations				Postings			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Extensive Margin	Any Giving				Any Posted Project			
Log elementary-secondary spending	0.07	0.06	0.02	-0.0001	0.08	0.05	0.03	-0.01
	(0.004)	(0.01)	(0.004)	(0.02)	(0.004)	(0.01)	(0.004)	(0.02)
N	365434	265586	340228	242367	365434	265586	340228	242367
Panel B: Intensive Margin	Log Amount Received				Log Requested Amount			
Log elementary-secondary spending	0.19	0.47	0.05	0.17	0.14	0.37	-0.01	0.09
	(0.06)	(0.12)	(0.06)	(0.15)	(0.04)	(0.10)	(0.05)	(0.13)
N	70248	59685	56730	45704	75186	63899	61422	49646
Panel C: Combined Effects	Panel A and B				Panel A and B			
Log elementary-secondary spending	0.58	0.52	0.18	0.04	0.62	0.47	0.20	-0.05
	(0.03)	(0.11)	(0.03)	(0.12)	(0.03)	(0.11)	(0.03)	(0.13)
N	365434	265586	340228	242367	365434	265586	340228	242367
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes	No	Yes
State-Year FE	Yes	Yes	No	No	Yes	Yes	No	No
County-Year FE	No	No	Yes	Yes	No	No	Yes	Yes

Standard errors in parentheses.

This table shows the impact of elementary-secondary expenditures on project postings and donations for years 1995-2018. Expenditures and amount requested (received) are in constant 2017 dollars. Panel A shows the results for the extensive margin (if a project posted and if a project receives any donation), while Panel B shows the intensive margins (amount requested and donated). Panel C provides the marginal effect of unconditional mean for the associated specifications. We show results for donation outcomes in columns 1-4 and posting in columns 5-6. Columns 1, 3, 5, and 7 show the results including no controls, while columns 2, 4, 6, and 8 include covariates as log number of students, share of children in poverty, enrollment shares by race, and log number of teachers. We include state-year FEs in columns 1, 2, 5, and 6, while other columns include county-year FEs.

Table 3: Impact of fundraising effort on donations

	(1)	(2)	(3)	(4)
	Log amount received			
Log amount requested	0.92	0.92	0.91	0.90
	(0.004)	(0.005)	(0.005)	(0.006)
N	71946	59839	58494	45864
District FE	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes
State-Year FE	Yes	Yes	No	No
County-Year FE	No	No	Yes	Yes

Standard errors in parentheses.

This table shows the impact of fundraising effort on donations for years 1995-2018. Donations and requests are in constant 2017 dollars. Columns 1 and 3 show the results including no controls, while columns 2 and 4 includes covariates as log number of students, a share of children in poverty, enrollment shares by race, and log number of teachers. Columns 1 and 2 include state-year FEs while we include county-year FEs in columns 3 and 4.

Table 4: Two-stage least squares estimates of the effects of elementary-secondary spending on donations

	First stage	Second stage	First stage	Second stage
Panel A: Extensive Margin	Log spending	Any giving	Log spending	Any giving
	(1)	(2)	(3)	(4)
Budget shock instrument	0.03		0.06	
	(0.003)		(0.002)	
Log spending		-0.17		-0.49
		(0.04)		(0.04)
F-statistic for instruments	14.29		119.05	
N	348801	348801	265503	265503
Panel B: Intensive Margin	Log spending	Log amount received	Log spending	Log amount received
Budget shock instrument	0.07		0.09	
	(0.003)		(0.002)	
Log spending		-1.18		-1.58
		(0.29)		(0.31)
F-statistic for instruments	18.88		42.52	
N	68572	68572	59666	59666
Panel C: Combined Effects		Panel A and B		Panel A and B
Log spending		-2.17		-4.29
		(0.47)		(0.37)
N		348801		265503
Year and District FE	Yes	Yes	Yes	Yes
Controls	No	No	Yes	Yes

Standard errors in parentheses.

This table reports two-stage least squares estimates of the impact of elementary-secondary expenditures on donations for years 1995-2018. In the first stage, we regress each district's log elementary-secondary spending on the budget shock (shift-share instrument) and school finance reforms after 1995, following (Bayer et al., 2020). The second stage regresses donations on predicated spending from the first stage. Expenditures and amount donated are in constant 2017 dollars. Panel A shows the results for the extensive margin (if a project receives any donation), while Panel B shows the intensive margin (amount donated). Panel C presents the marginal effect of unconditional mean for the associated specifications. Columns 1 and 2 show the results including no controls, while columns 3 and 4 include the log number of students, share of children in poverty, enrollment shares by race, and log number of teachers. All columns include year fixed effects and district fixed effects.

Table 5: Two-stage least squares estimates of the effects of elementary-secondary spending on project postings

	First stage	Second stage	First stage	Second stage
Panel A: Extensive Margin	Log spending	Any posted project	Log spending	Any posted project
	(1)	(2)	(3)	(4)
Budget shock instrument	0.03		0.06	
	(0.003)		(0.002)	
Log elm-sec spending		-0.19		-0.53
		(0.04)		(0.04)
F-statistic	14.29		119.05	
N	348801	348801	265503	265503
Panel B: Intensive Margin	Log spending	Log requested amount	Log spending	Log requested amount
Budget shock instrument	0.07		0.08	
	(0.003)		(0.002)	
Log elm-sec spending		-0.40		-0.89
		(0.23)		(0.25)
F-statistic	19.22		43.78	
N	73398	73398	63878	63878
Panel C: Combined Effects		Panel A and B		Panel A and B
Log elm-sec spending		-2.31		-4.76
		(0.50)		(0.38)
N		348801		265503
Year and District FE	Yes	Yes	Yes	Yes
Controls	No	No	Yes	Yes

Standard errors in parentheses.

This table reports two-stage least squares estimates of the impact of elementary-secondary expenditures on project postings for years 1995-2018. In the first stage, we regress each district's log elementary-secondary spending on the budget shock (shift-share instrument) and school finance reforms after 1995, following (Bayer et al., 2020). The second stage regresses posting outcomes on predicted spending from the first stage. Expenditures and amount requested are in constant 2017 dollars. Panel A shows the results for the extensive margin (if any projects are posted), while Panel B shows the intensive margin (amount requested). Panel C presents the marginal effect of unconditional mean for the associated specifications. Columns 1 and 2 show the results including no controls, while columns 3 and 4 include the log number of students, share of children in poverty, enrollment shares by race, and log number of teachers. All columns include year fixed effects and district fixed effects.

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A Appendix

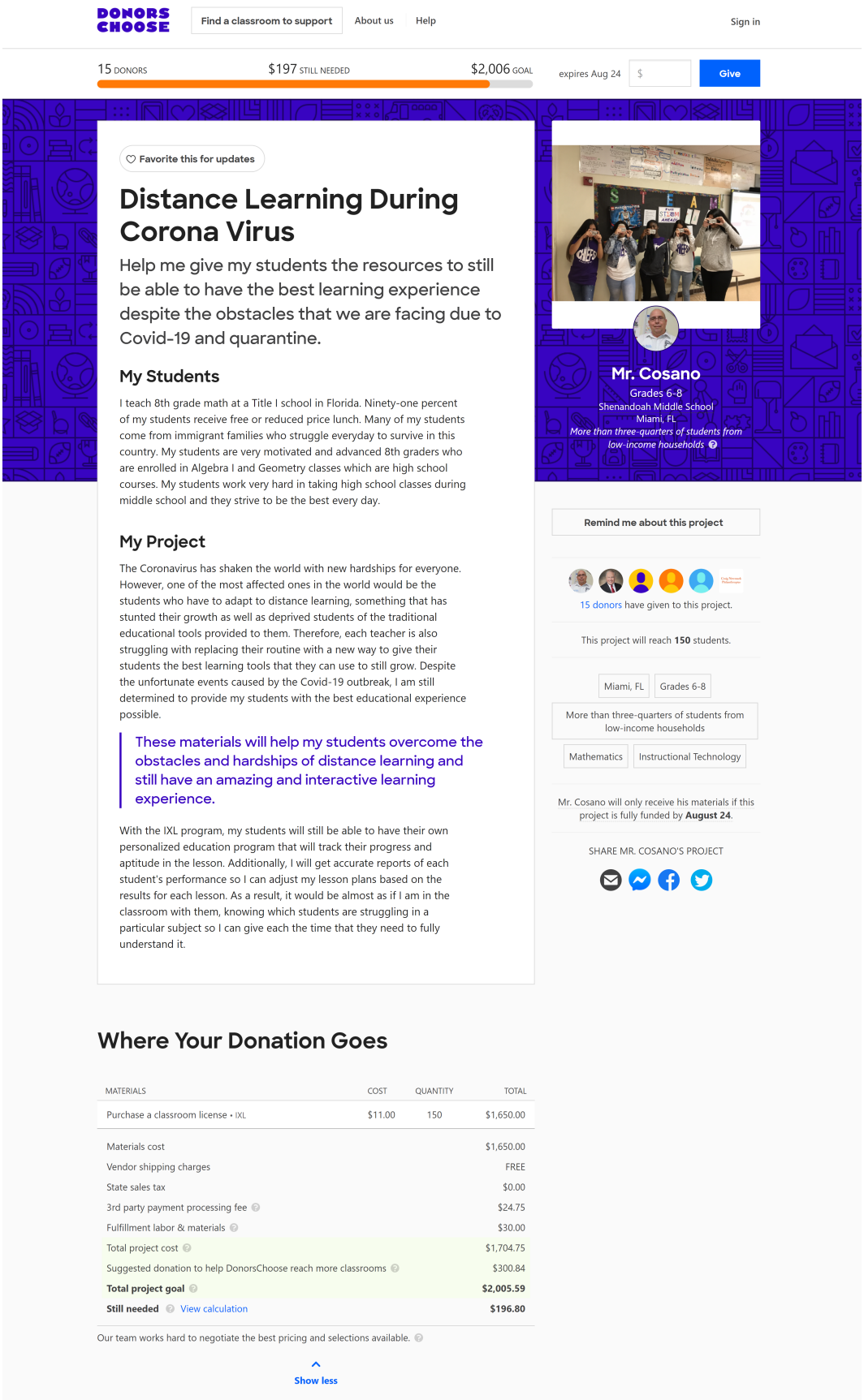

Figure A1: Sample DonorsChoose.org project posting.

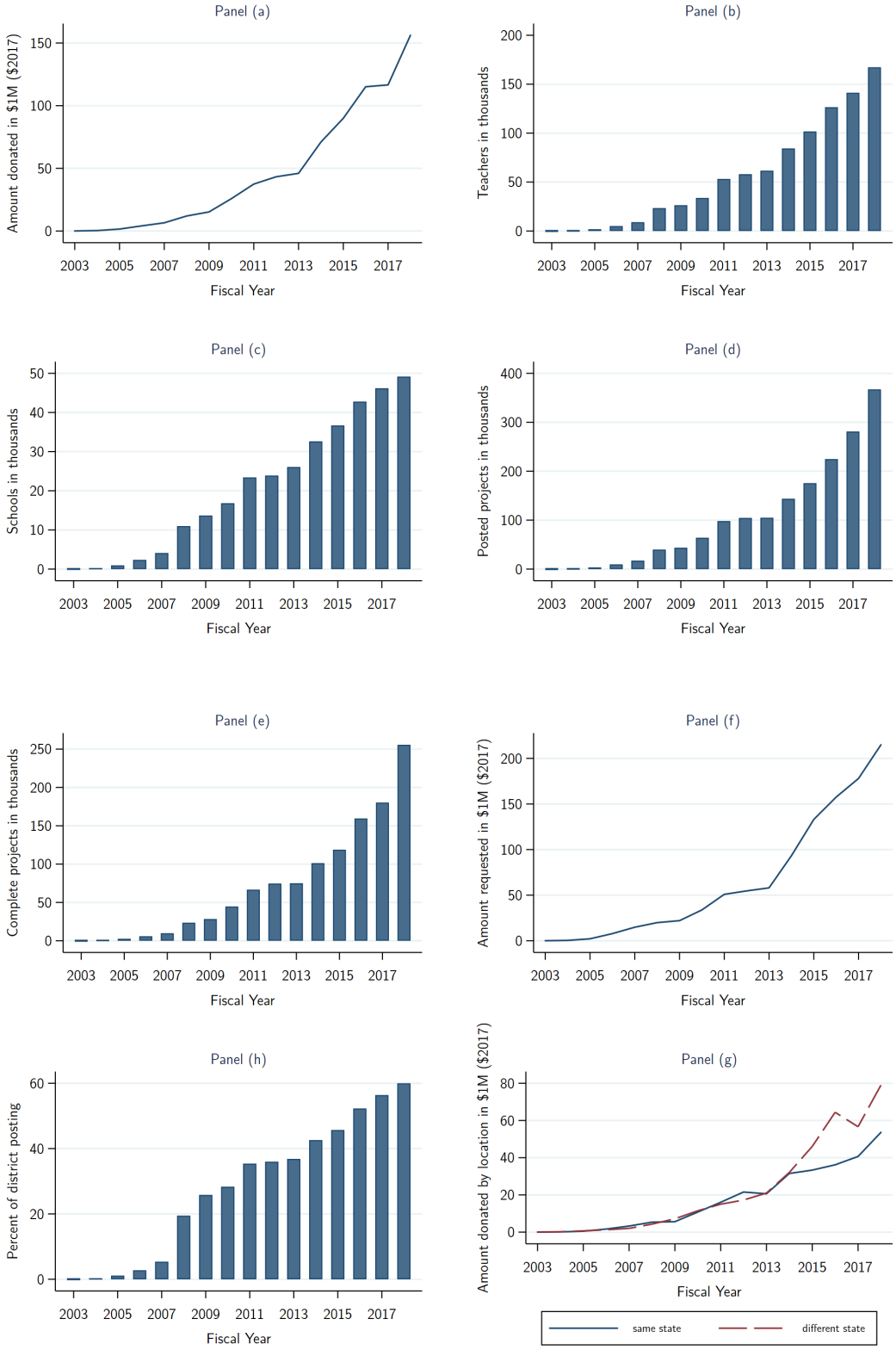

Figure A2: Some characteristics of the DonorsChoose.org data (2003-2018).

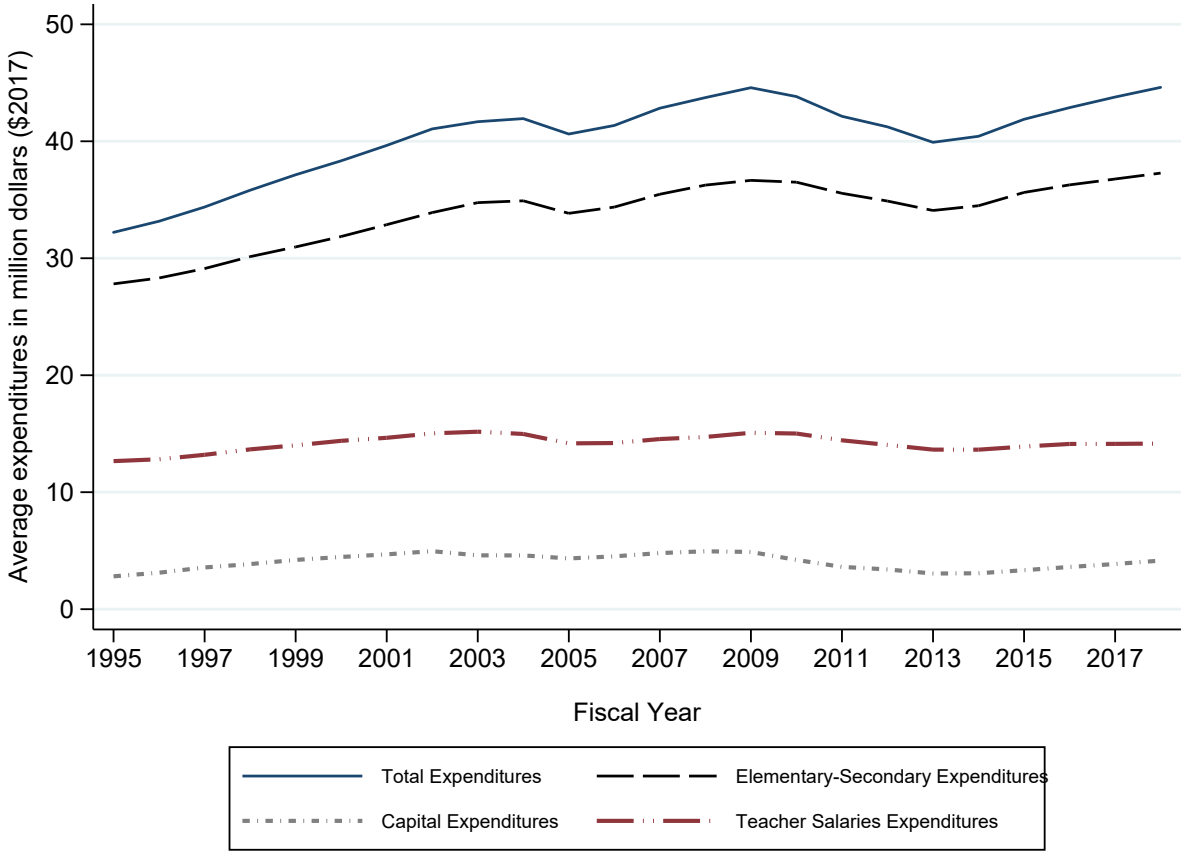

Figure A3: Average expenditures in 2017 dollars in school districts (1995-2018).

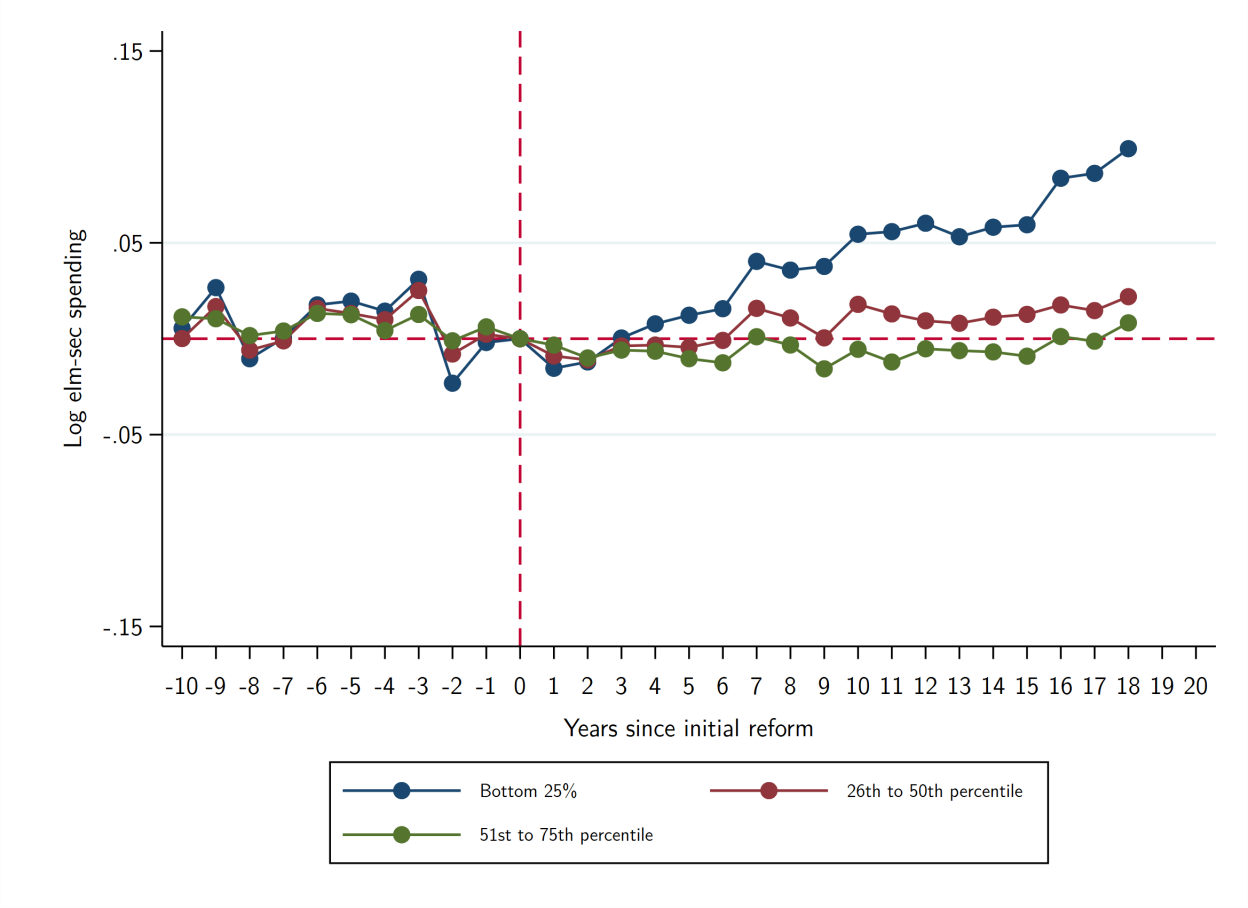

Figure A4: This figure shows an event study graph of the change in elementary-secondary school spending before and after court-mandated school finance reforms that occurred between 1995 and 2010. The event time indicators are interacted with the base year spending quartiles. Each series represents the difference in the log of elementary-secondary school spending in the associate quartile compared to the omitted category (the highest-spending quartile) before and after the reforms. This specification includes log enrollment, year-fixed effects, and district-fixed effects. Data source for school finance reforms: Bayer et al. (2020).

Table A1: Two-stage least squares estimates of the effects fundraising effort on donations

	First stage	Second stage	First stage	Second stage
	Log amount requested	Log amount donated	Log amount requested	Log amount donated
	(1)	(2)	(3)	(4)
Log amount requested		1.00		1.20
	(0.059)		(0.17)	
Log amount of neighbors'	-0.044		-0.0078	
requests in t-1	(0.005)		(0.007)	
Log number of neighbors'	0.16		-0.051	
posted projects in t-1	(0.012)		(0.017)	
F-statistic	90.18		14.64	
N	58343	58343	44418	44418
Year and District FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	No	No
County-Year FE	No	No	Yes	Yes

Standard errors in parentheses.

This table shows the impact of amount requested on amount donated for years 1995-2018. It shows the 2SLS estimates using the amount requested and number of posted project by neighboring districts at t-1 as instruments. Columns 1 and 2 include state-by-year fixed effects, while the other columns include county-by-year fixed effects. Donation and request amounts are in constant 2017 dollars. All the columns include the log number of students, a share of children in poverty, enrollment shares by race, and log number of teachers.

Table A2: Two-stage least squares estimates of the effects of elementary-secondary spending on private contributions

	First stage	Second stage	First stage	Second stage
Panel A: Extensive Margin	Log spending	Any giving	Log spending	Any giving
	(1)	(2)	(3)	(4)
Budget shock instrument	0.06		0.08	
	(0.003)		(0.002)	
Log spending		0.43		0.11
		(0.04)		(0.04)
F-statistic	13.84		78.44	
N	193319	193319	162114	162114
Panel B: Intensive Margin	Log spending	Log amount received	Log spending	Log amount received
Budget shock instrument	0.07		0.07	
	(0.003)		(0.002)	
Log spending		1.18		-0.07
		(0.21)		(0.29)
F-statistic	13.75		81.46	
N	90324	90324	78922	78922
Panel C: Combined Effects		Panel A and B		Panel A and B
Log spending		5.58		1.12
		(0.59)		(0.53)
N		193319		162114
Year and District FE	Yes	Yes	Yes	Yes
Controls	No	No	Yes	Yes

Standard errors in parentheses.

This table reports two-stage least squares estimates of the impact of the elementary-secondary expenditures on private contributions received by districts for years 2006-2018. Beginning in 2006, the Common Core of Data asks districts to report "gifts of cash or securities from private individuals or organizations." In the first stage, we regress each district's log elementary-secondary spending on the budget shock (shift-share instrument) and school finance reforms after 1995, following (Bayer et al., 2020). The second stage regresses donations on predicted spending from the first stage. Expenditures and amount donated are in constant 2017 dollars. Panel A shows the results for the extensive margin, while Panel B shows the intensive margin. Panel C presents the marginal effect of unconditional mean for the associated specifications. Columns 1 and 2 show the results including no controls, while columns 3 and 4 include the log number of students, share of children in poverty, enrollment shares by race, and log number of teachers. All columns include year fixed effects and district fixed effects.

Table A3: Two-stage least squares estimates of the effects of elementary-secondary spending on project postings and donations by subject type

	(1)	(2)	(3)	(4)
Combined Effects	Log amount donated to		Log amount requested for	
	Academic		Academic	
Log spending	-1.82	-4.21	-2.10	-4.79
	(0.47)	(0.36)	(0.52)	(0.38)
N	348801	265503	348801	265503
	Enrichment		Enrichment	
Log spending	0.88	-1.20	0.96	-1.41
	(0.31)	(0.28)	(0.34)	(0.30)
N	348801	265503	348801	265503
	Support		Support	
Log spending	-0.04	-1.48	0.03	-1.65
	(0.26)	(0.25)	(0.29)	(0.27)
N	348801	265503	348801	265503
	Other		Other	
Log spending	0.67	-0.31	0.82	-0.35
	(0.13)	(0.13)	(0.15)	(0.15)
N	348801	265503	348801	265503
Year and District FE	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes

Standard errors in parentheses.

This table reports two-stage least squares estimates of the impact of elementary-secondary expenditures on project postings and donations by subject type for years 1995-2018. In the first stage, we regress each district's log elementary-secondary spending on the budget shock (shift-share instrument) and school finance reforms after 1995, following (Bayer et al., 2020). The second stage regresses amount donated (columns 1-2) and amount requested (columns 3-4) on predicted spending from the first stage. Expenditures and amount requested (donated) are in constant 2017 dollars. It presents the marginal effect of unconditional mean. Columns 1 and 3 show the results including no controls, while columns 2 and 4 include the log number of students, share of children in poverty, enrollment shares by race, and log number of teachers. All Columns include year fixed effects and district fixed effects.

Table A4: Two-stage least squares estimates of the effects of elementary-secondary spending on project postings and donations by resource type

	(1)	(2)	(3)	(4)
Combined Effects	Log amount donated to		Log amount requested for	
	Supplies		Supplies	
Log spending	-1.26	-3.59	-1.48	-3.98
	(0.45)	(0.35)	(0.48)	(0.36)
N	348801	265503	348801	265503
	Enrichment		Enrichment	
Log spending	0.49	-0.28	0.59	-0.32
	(0.17)	(0.18)	(0.18)	(0.19)
N	348801	265503	348801	265503
	Technology		Technology	
Log spending	-0.87	-3.33	-1.03	-3.91
	(0.40)	(0.32)	(0.46)	(0.35)
N	348801	265503	348801	265503
	Needs/Others		Needs/Others	
Log spending	0.26	-1.61	0.26	-1.79
	(0.24)	(0.22)	(0.27)	(0.24)
N	348801	265503	348801	265503
Year and District FE	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes

Standard errors in parentheses.

This table reports two-stage least squares estimates of the impact of the elementary-secondary expenditures on project postings and donations by resource type for years 1995-2018. In the first stage, we regress each district's log elementary-secondary spending on the budget shock (shift-share instrument) and school finance reforms after 1995, following (Bayer et al., 2020). The second stage regresses amount donated (columns 1-2) and amount requested (columns 3-4) on predicted spending from the first stage. Expenditures and amount requested (donated) are in constant 2017 dollars. It presents the marginal effect of unconditional mean. Columns 1 and 3 show the results without controls, while columns 2 and 4 include the log number of students share of children in poverty, enrollment shares by race, and log number of teachers. All columns include year fixed effects and district fixed effects.