

# Web Appendix

## Self-Donations and Charitable Contributions in Online Crowdfunding: An Empirical Analysis

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*Disclosure:* These materials have been supplied by the authors to aid in the understanding of their paper. The AMA is sharing these materials at the request of the authors.

# Web Appendix A: An Example of DonorsChoose Projects


## Spark Interest in Science

My students need 2 PH sensors and 4 temperature sensors for our SPARK unit so that we can use it more effectively.

\$421 GOAL HOORAY! THIS PROJECT IS FULLY FUNDED

---

**Keep the momentum going!** Make a donation to Mrs. Weaver for her next project!  Give



Mrs. Weaver

Grades 6-8  
Valley View Junior High School  
Farmersville, OH

This project will reach **160** students.  
[3](#) donors have given to this project.

SHARE PROJECT

Hello, and thanks for showing interest in our learning community. I teach Science in a rural district to all (160) 7th grade students. This is my first year in this district and these students are excited to be moving forward with some technology which has been very limited up to this point. Just today a student said to me that they would be happy to ask their parents to purchase something for their birthday that we could use in our classroom. These kids are that invested and excited about learning in a more modern science classroom.

We are outdated and need to step up our game. These kids need to be able to have opportunities to advance their exposure to more modern science technology. These students need to be wowed by science and be shown the opportunities that await them if they pursue science as a career choice. With the probes we have requested we will be able to go out into our local stream and take "real" data back to our class that we can watch and analyze over time.

I have the knowledge and the enthusiasm to update and re-invent science for my students, I just lack some of the resources to keep them "SPARKED" for science. They have shown me that they are ready to step up but feel very backward with modern advancements in technology because they have never been exposed to them before. They are ready, able and excited. Help me help them. All I need are a couple of PH probes and some temperature sensors for us to be able to make our dream of inquiry possible. We have one pasco SPARK system that we can use if only we had the probes to attach.

I am not asking for a huge investment, just some seed money to get us started on our way. I know once we start on this journey the momentum from student excitement will keep us going strong. With these few items you will ensure today's and tomorrow's students the availability to learn about science like real scientists with modern equipment. These probes will allow us to connect Science to Math and Technology which is sometimes a stumbling block for students. Thanks in advance for your generous help!

Farmersville, OH
Grades 6-8
Environmental Science
Environmental Science

Technology

### Where Your Donation Goes

MATERIALS	COST	QUANTITY	TOTAL
PASPORT PH SENSOR • CAROLINA BIOLOGICAL SUPPLY COMPANY	\$78.26	2	\$156.52
PASPORT TEMPERATURE SENSOR • CAROLINA BIOLOGICAL SUPPLY COMPANY	\$33.75	4	\$135.00
Materials cost			\$291.52
Vendor shipping charges			\$29.15
State sales tax			\$0.00
3rd party payment processing fee			\$7.29
Fulfillment labor & materials			\$17.00
Total project cost			\$345.00
Suggested donation to help DonorsChoose reach more classrooms			\$75.73
<b>Total project goal </b>			<b>\$420.73</b>
<b>Still needed  <a href="#">View calculation</a></b>			<b>\$0.00</b>

Our team works hard to negotiate the best pricing and selections available.

Top rated for efficiency and transparency.

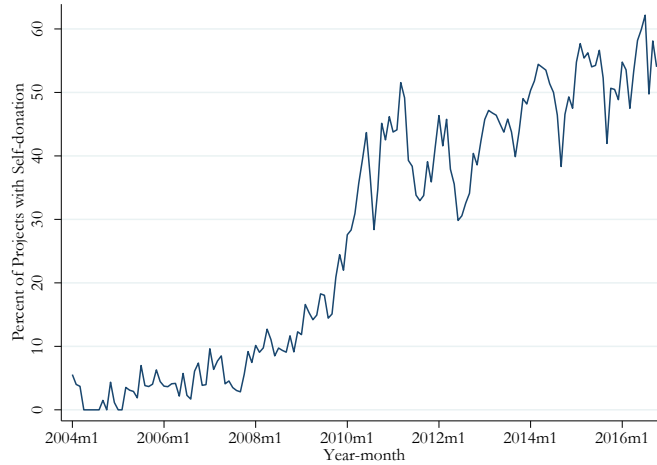
You donate directly to the teacher or project you care about and see where every dollar you give goes.

[See our finances](#)

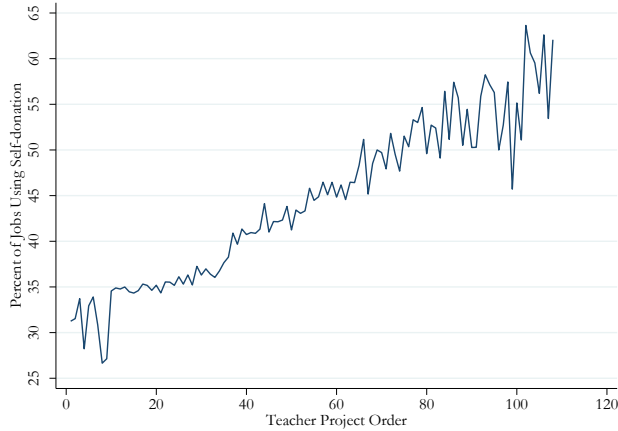
**Web Appendix B: Project, Donations, Self-donation, and Donors' Arrival Characteristics**

***B-1: Projects, Donations, and Self-donation Characteristics***

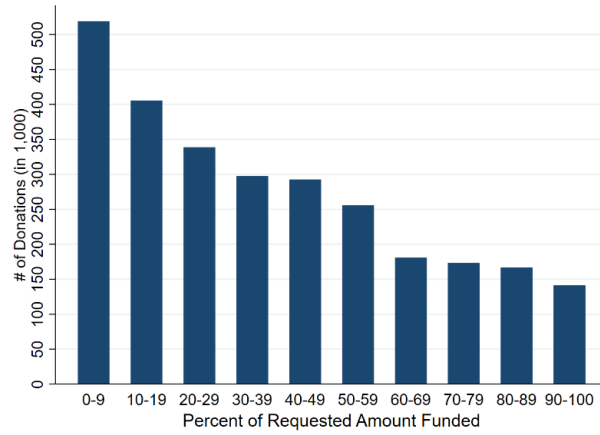
**Figure WB1.** Percentage of Projects with Self-Donations Over Time



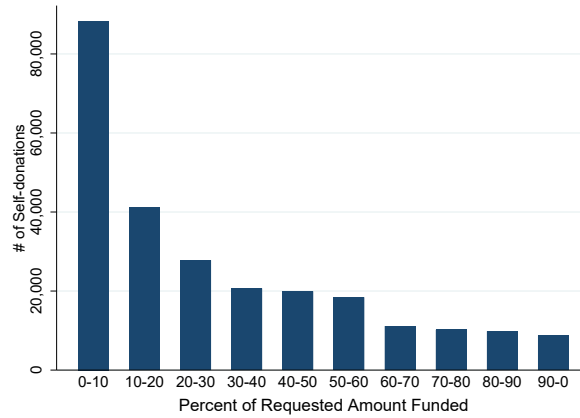
**Figure WB2.** Percent of Projects Having Self-donation by Teacher Project Order



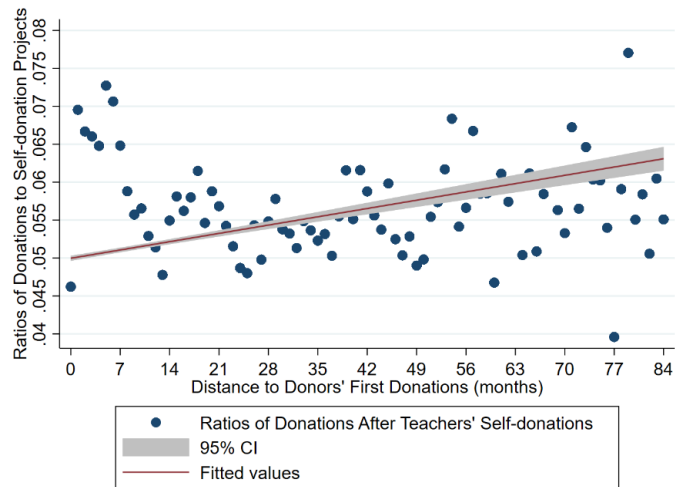
**Figure WB3.** Number of Donations at Different Stages of Funding Cycle



**Figure WB4.** Number of Self-Donations at Different Stages of Funding Cycle



**Figure WB5.** Ratios of Donors' Donations to Projects with Self-donations Over Time



**Table WB1.** Characteristics of Projects with Self-donations

Item	Projects Having Self-donation		
		Yes	No
Projects Funded	Yes	182,626	221,194
	No	22,406	39,304
Receiving Impact Letters	Yes	111,800	76,205
	No	70,826	144,989
Regions (Highest Poverty)	Yes	114,438	161,049
	No	90,594	99,449
Corporate Matching	Yes	67,340	74,633
	No	137,692	185,865
Resource (academic materials such as books, supplies, and technologies)	Yes	179,677	229,074
	No	25,355	31,424

## ***B-2: Donors' Arrival Characteristics***

We use donor random arrivals at the studied platform as our identifying assumption of self-donation effects. Under this assumption, we approach this as a quasi-experiment, dividing previous donations into two groups: the treatment group comprising self-donations and the control group comprising non-self-donations. Upon a donor's arrival, they are randomly assigned to one of these groups, which alleviates endogeneity concerns related to self-donations. We employed two methods to assess the randomness of donor arrivals to our platform. To support this assumption, we used two approaches to assess the randomness of donor arrivals to our studied platform.

In the first approach, we used daily Google Trend (GT) data and SimilarWeb daily traffic data. GT does not provide actual website visit numbers but instead offers a daily search volume index that tracks consumer interest. Previous studies have shown that these search volume indices from GT are leading indicators of consumer demand in many industries (Du and Hsieh 2023). For example, Hu et al. (2014) demonstrate how search trends can be used to understand advertising's overall impact on sales. Du et al. (2015) found that trends identified using GT data could explain a large portion of dynamics in vehicle sales, beyond what can be accounted for by lagged sales, marketing efforts, and brand search trends. These indicate a strong relationship between search volume and website traffic.

We first verify the relationship between GT search interests and actual web visits. We obtain daily visit data to DonorsChoose.org for 15 months (October 1<sup>st</sup>, 2022 to Dec 31<sup>st</sup>, 2023) from SimilarWeb, a company specializing in tracking web traffic<sup>2</sup>, and daily GT search volume index for our studied platform in the same period. We test the correlation between the daily GT search volume index and SimilarWeb daily traffic value during the 15-month period. The results show a strong correlation between the two pieces of data ( $r=0.81$ ,  $p<0.001$ ), which confirms that the GT search volume index is indeed a good proxy of daily traffic to the website DonorsChoose.org.

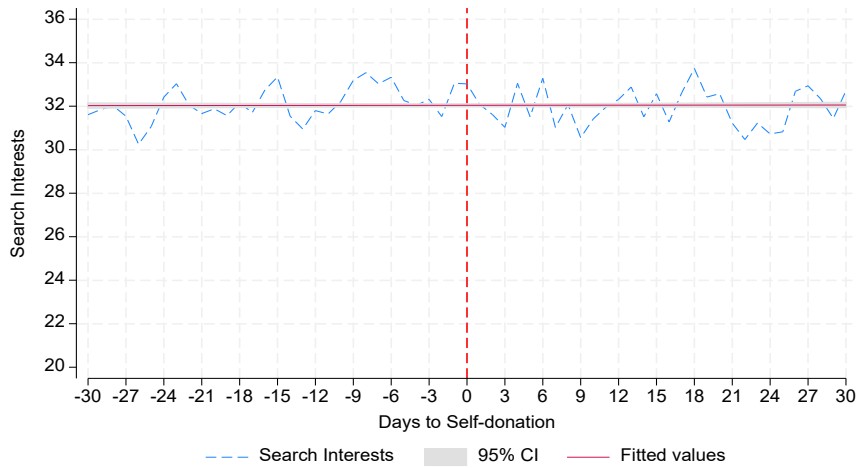
We next collected similar GT search volume index data between January 2012 and October 2016 (Google Trend data were very sparse and irregular before 2012, likely due to the beginning period of this service) after confirming that Google search interests can be a proxy for

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<sup>2</sup> Note that SimilarWeb does not have daily visit data for our study period.

web visits. Using this data, we extracted daily search volume indices 30 days before and after each self-donation using date information in our data and plotted the average GT index data in Figure WB6. Figure WB6 allows us to eyeball the difference in search interest (and thus the visits) to DonorsChoose.org before and after a self-donation. We do not find any significant differences in the visits before and after a self-donation from the figure. Therefore, we can tentatively conclude that potential donors arrive at the website randomly.

**Figure WB6.** Google Search Interests Before and After Self-donations



In the second approach, we used data from Semrush.com, a leading vendor providing a competitive research service on online marketing and advertising (Pagiavlas et al. 2022). This platform provides monthly traffic data that partially overlaps with our observation period (between January 2012 and October 2016). We used data from the same period as the previous test and conduct t-tests to find whether there is a significant difference in traffic to DonorsChoose.org before, during, and after each self-donation. Specifically, we perform two t-tests between two groups sequentially (i.e., one month before vs. during self-donation and one month during vs. after self-donation). The results from these two t-tests are reported in Table WB2 below, which shows no significant differences in traffic to the website in the months around each self-donation.



**Table WB2.** Results of T-test for Traffics Before, During, and After Each Self-donation

<i>Data Periods</i>	<i>Samples (# of self-donations)</i>	<i>Means (log(worldwide visits))</i>	<i>Difference</i>	<i>T-stat</i>
<i>One Month Before vs. During Self-Donation</i>				
One month before self-donation	104,299	10.845	-.002 (0.218)	- 1.232
Self-donation month	104,299	10.847		
<i>One Month During vs. One Month After Self-Donation</i>				
Self-donation month	104,299	10.847	-.003 (0.198)	- 1.289
One month after self-donation	104,299	10.850		

## **Web Appendix C: Addressing Selection and Endogenous Concerns (Matching, Instrument, and Anonymity of Self-donations)**

### ***C-1: Matching to Address Selection Concern***

One concern with the analysis presented within the paper is that teacher and other differences could potentially drive self-donation- or project-related factors, which will lead to selection-related endogeneity confounds in the empirical analysis. To address these potential selection biases, we implemented the propensity score matching (PSM) approach (De Haan et al. 2018) by matching donations on all variables listed in project, teacher, and school level information (*Panel D* in Table 1) and project text information (*Panel E* in Table 1). Specifically, we first estimate a logistic regression and regress whether a project received a self-donation on these matching variables, which provides us with the obtained propensity scores. Next, we implemented a one-to-one nearest neighbor matching algorithm to match projects on this propensity score without replacement (Li and Xie 2020). The matched samples include 74,501 pairs of projects. Table WC1 provides matched variables balance sheet. Projects with and without self-donations in a pair have similar project characteristics and come from teachers with similar backgrounds in project experience and gender.

We then used the matched samples to examine the effect of self-donation on the time interval to the following donation (*hours till the next donation*). We included the same independent variables as in Table 2 column M1 and estimated an OLS model with the project, donation year and month, and matched pair fixed-effects. The coefficient of *Self-donation* in M2 in Table 2 is negative and statistically significant, consistent with our main finding.

To ensure that the matching procedure does not influence our results, we created a different matched sample using a one-on-one *Coarsened Exact Matching* (CEM) (Blackwell et al. 2009; Iacus, King, and Porro 2012) employing nearest-neighbor algorithms. In our CEM matching, we perform an exact match on the coarsened data by matching donations on all variables listed in project, teacher, and school-level information, and project text information. The ensuing matched sample includes 67,003 projects with self-donations and 71,374 projects without self-donations. We observe a significant improvement in sample balance using this CEM procedure. The multivariate L1 statistic drops from 0.722 before matching to 0 after matching in Table WC2. We repeated our analysis on these newly matched samples and found our results in Table WC3 robust to this approach.

**Table WC1.** Balance Sheet after PSM (Outcome variable: Hours to Next Donation)

Variable	Mean			t-test		V(T) /V(c)
	Treated	Control	%bias	t	p>t	
<i>Teacher Gender(female)</i>	0.8773	0.88067	-1	-2.1	0.036	.
<i># of Completed Projects So Far</i>	1.5338	1.1765	4.3	19.77	0	1.08*
<i>Poverty(highest)</i>	0.59099	0.57742	2.8	5.6	0	.
<i>Poverty(high)</i>	0.25129	0.25781	-1.5	-3.04	0.002	.
<i>Poverty(moderate)</i>	0.13114	0.13783	-1.9	-3.99	0	.
<i>Subject(Applied Sciences)</i>	0.05448	0.05467	-0.1	-0.18	0.861	.
<i>Subject(Character Education)</i>	0.01252	0.01362	-1	-1.98	0.047	.
<i>Subject(Civics &amp; Government)</i>	0.00307	0.00288	0.3	0.69	0.49	.
<i>Subject(College &amp; Career Prep)</i>	0.00852	0.00869	-0.2	-0.38	0.704	.
<i>Subject(Community Service)</i>	0.00149	0.00155	-0.2	-0.36	0.716	.
<i>Subject(ESL)</i>	0.01239	0.01301	-0.6	-1.14	0.256	.
<i>Subject(Early Development)</i>	0.02065	0.0216	-0.7	-1.33	0.182	.
<i>Subject(Economics)</i>	0.0031	0.00279	0.5	1.16	0.245	.
<i>Subject(Environmental Science)</i>	0.04268	0.04189	0.4	0.8	0.423	.
<i>Subject(Extracurricular)</i>	0.00372	0.00369	0	0.1	0.921	.
<i>Subject(Financial Literacy)</i>	0.0036	0.00331	0.5	1.02	0.308	.
<i>Subject(Foreign Languages)</i>	0.00501	0.0053	-0.4	-0.82	0.411	.
<i>Subject(Gym &amp; Fitness)</i>	0.00975	0.00932	0.4	0.91	0.361	.
<i>Subject(Health &amp; Life Science)</i>	0.03066	0.02921	0.8	1.72	0.085	.
<i>Subject(Health &amp; Wellness)</i>	0.02393	0.02396	0	-0.04	0.966	.
<i>Subject(History &amp; Geography)</i>	0.0197	0.01944	0.2	0.38	0.703	.
<i>Subject(Literacy)</i>	0.2897	0.2902	-0.1	-0.22	0.825	.
<i>Subject(Literature &amp; Writing)</i>	0.11703	0.11671	0.1	0.2	0.841	.
<i>Subject(Mathematics)</i>	0.13886	0.14385	-1.4	-2.91	0.004	.
<i>Subject(Music)</i>	0.0336	0.03295	0.4	0.74	0.462	.
<i>Subject(Nutrition)</i>	0.00211	0.00166	0.9	2.08	0.037	.
<i>Subject(Parent Involvement)</i>	0.01338	0.01306	0.3	0.56	0.575	.
<i>Subject(Performing Arts)</i>	0.00102	0.0009	0.3	0.73	0.463	.
<i>Subject(Social Sciences)</i>	0.01473	0.0148	-0.1	-0.12	0.904	.
<i>Subject(Special Needs)</i>	0.01056	0.00956	1	2.04	0.041	.
<i>Subject(Team Sports)</i>	0.06654	0.06576	0.3	0.64	0.525	.
<i>Subject(Visual Arts)</i>	0.04884	0.04725	0.7	1.52	0.129	.
<i>Reached Students</i>	3.8302	3.8279	0.2	0.46	0.647	1.03*
<i>Corporate Matching</i>	0.26663	0.26367	0.7	1.36	0.174	.
<i>Home Double</i>	0.05458	0.05655	-0.9	-1.75	0.08	.
<i>Resources(Books)</i>	0.19199	0.18553	1.6	3.35	0.001	.
<i>Resources(Others)</i>	0.11203	0.11391	-0.6	-1.21	0.227	.

<i>Resources(Supplies)</i>	0.38391	0.37874	1.1	2.16	0.031	.
<i>Resources(Technology)</i>	0.29785	0.30806	-2.2	-4.52	0	.
<i>Resources(Trips)</i>	0.01186	0.01177	0.1	0.16	0.871	.
<i>Resources(Visitors)</i>	0.00234	0.00195	0.8	1.68	0.093	.
<i>Requested Amount (log)</i>	6.0037	6.0198	-2.5	-5.15	0	1
<i>Project Description Length</i>	5.7236	5.7305	-2.4	-4.92	0	0.97*
<i>Average Characters per Word</i>	1.873	1.8735	-0.9	-1.87	0.061	1
<i>Text Familiarity</i>	0.04796	0.04229	0.6	1.17	0.244	1.01*
<i>Text Concreteness</i>	0.04413	0.02931	1.5	3.06	0.002	1.01
<i>Text Flesch-Kincaid Readability</i>	-0.10722	-0.08263	-2.4	-5.04	0	0.98*
<i>Text Valence</i>	-0.04579	-0.02512	-2	-4.15	0	1.02*
<i>Text Extremity</i>	-0.01789	-0.00757	-1	-2.11	0.035	1
<i>Text Emotionality</i>	-0.02347	-0.01223	-1.1	-2.3	0.021	0.99
<i>Equity Focus</i>	0.13022	0.12785	0.7	1.44	0.15	.
<i>Project Description(social)</i>	3.3338	3.3402	-1.6	-3.26	0.001	0.99
<i>Project Description(achieve and reward)</i>	2.4812	2.4969	-2.6	-5.4	0	1.04*
<i>Project Description(punctuation)</i>	2.0461	2.0597	-2.6	-5.38	0	1
<i>Project Description(informal)</i>	0.30999	0.31667	-1.5	-3.03	0.002	0.99
<i>Project Description(risk)</i>	0.28754	0.28707	0.1	0.22	0.826	1
<i>Project Description(spelling)</i>	0.53115	0.53546	-0.9	-1.91	0.056	0.98*
<i>#PlatformProjects</i>	7.3442	7.4096	-6.4	-16.62	0	0.70*
<i>#PlatformProjects(same zip code)</i>	0.96266	0.96425	-0.2	-0.35	0.726	0.87*
<i>Grades PreK-2</i>	0.40659	0.40733	-0.2	-0.3	0.762	.
<i>Grades 3-5</i>	0.15673	0.15648	0.1	0.14	0.887	.
<i>Grades 6-8</i>	0.12138	0.12046	0.3	0.57	0.568	.
<i>Grades 9-12</i>	0.40365	0.40287	0.2	0.32	0.746	.
<i>School Type(charter)</i>	0.0937	0.09357	0	0.09	0.931	.
<i>School Type(kipp)</i>	2.2e-05	6.6e-05	-0.7	-1.4	0.162	.
<i>School Type(magnet)</i>	0.08716	0.08491	0.8	1.63	0.104	.
<i>School Type(public)</i>	0.81911	0.82145	-0.6	-1.24	0.216	.

**Table WC2. Balance Sheet Before and after CEM**

Variables	L1 Statistics	
	Unmatched Samples	Matched Samples
<i>Teacher Gender(female)</i>	0.00059	0
<i># of Completed Projects</i>	0.18046	0
<i>Poverty(highest)</i>	0.06009	0
<i>Poverty(high)</i>	0.02496	0
<i>Poverty(moderate)</i>	0.03311	0
<i>Resources (academic)</i>	0.00409	0
<i>Reached Students</i>	0.00947	0
<i>Corporate Matching</i>	0.02873	0
<i>Home Double</i>	0.00654	0
<i>Teaching Materials</i>	0.00303	0
<i>Requested Amount (log)</i>	0.03898	0
<i>Project Description Length</i>	0.03425	0
<i>Average Characters per Word</i>	0.02215	0
<i>Text Familiarity</i>	0.02481	0
<i>Text Concreteness</i>	0.03277	0
<i>Text Flesch-Kincaid Readability</i>	0.03484	0
<i>Text Valence</i>	0.02501	0
<i>Text Extremity</i>	0.01043	0
<i>Text Emotionality</i>	0.00835	0
<i>Equity Focus</i>	0.01809	0
<i>Project Description(social)</i>	0.01486	0
<i>Project Description (punctuation)</i>	0.05114	0
<i>Project Description (informal)</i>	0.04046	0
<i>Project Description (achieve and reward)</i>	0.00000	0
<i>Project Description(risk)</i>	0.00442	0
<i>Project Description(spelling)</i>	0.00301	0
<i>Grades PreK-2</i>	0.01093	0
<i>Grades 3-5</i>	0.00844	0
<i>Grades 6-8</i>	0.00074	0
<i>Grades 9-12</i>	0.00175	0
<i>School Type (public)</i>	0.00478	0

**Note:** To make matching more efficient, we define the means of continuous values as the cut points. We also change the categorical variables to binary. Specifically, we represent project subjects in Applied Sciences, Economics, Environmental Science, ESL, Financial Literacy, Foreign Languages, Gym & Fitness, History & Geography, Health & Life Science, Literature & Writing, Literacy, Mathematics, Music, Performing Arts, Social Sciences, and Visual Arts as academic projects. In addition, we define resource types in books, supplies, and technology as educational materials. Finally, we categorize schools into either public or not public.

Multivariate imbalance measure for the unmatched sample: L1=0.72239

Multivariate imbalance measure for the matched sample: L1=0

**Table WC3.** Effects of Self-donation on Hours to Next Donation Using Matched Data from CEM Matching

Variables	Coefficient	SE
<i>Self-donation</i>	-11.403***	0.642
<i>Donation Information</i>	YES	
<i>Social Network Information</i>	YES	
<i>Platform-level Information</i>	YES	
Observations	1,014,901	
R-squared	0.470	
Log-likelihood	-6441203.9	
Project fixed effects	YES	
Year-month fixed effects	YES	

*Note:* This table reports coefficients and standard errors from an OLS regression of *Hours to Next Donation* on *Self-donation*, donation information, social network, and platform level information using matched projects (67,003 projects having self-donation and 71,374 projects having no self-donation) obtained from coarsened exact matching (CEM). Table 1 provides variable definitions. \*\*\* indicates statistical significance at the 1% level from two-tailed tests.

## ***C-2: An Instrumental Variable Approach to Address Endogeneity Concerns***

Another concern is the potential endogeneity of the *Self-donation* variable. Our estimation in the main analysis may pick up the effects of unobservables that happen to be correlated with both hours to next donation and teacher's self-donation. Since we have controlled most information that donors have access to during their decision process, this concern is perhaps not very serious within our context. However, since this is a study using archival data, out of an abundance of caution, we also use an Instrumental Variable (IV) approach to mitigate endogeneity concerns further.

An ideal instrument in this context should affect a *teacher's* likelihood of using self-donation but should not directly affect donors' likelihood of donating to the teacher's focal project (the exogeneity constraint). An ideal IV is a variable that donors cannot easily observe or consider while the teacher can. As researchers, we can also observe this variable.

We follow the spirit of Dranove et al. (2014), who used the number of same-alliance hospitals adopting electronic medical records as an instrument for a focal hospital's electronic medical record adoption. We similarly used the number of successful projects from other teachers in the same school with self-donations in the past three months before a current donation as the instrumental variable (*# of Successful Self-donated Projects from Same School Last Three Months*)<sup>3</sup>. We posit that this instrument is valid for the following reasons. First, teachers want their projects to succeed, and they are likely to follow the strategy of other successful projects from teachers with whom they may interact. Therefore, if teachers observe greater success in projects with self-donation within the same school, they become more likely to self-donate. Also, it seems unlikely that the behaviors of other teachers in their past projects will affect the current donors' donation propensity to donate to the current project. This intuitive reasoning points towards the validity of our proposed instrument.

We have also empirically verified the validity of this IV in several ways. First, we regressed *Self-donation* on *# of Successful Self-donated Projects from Same School Last Three Months* and the results in Table WC4 indeed show a significantly positive relationship. Second, we show that

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<sup>3</sup> We chose three months because half a semester is about 12 weeks and teachers who requested donations have likely received the requested materials. Therefore, teachers who are starting focal projects are almost certain to know the funding successes of previous projects from the same school. For robustness, we also used 4, 5, and 6-month time windows and obtained same findings.

the proposed IV is strong in a statistical sense via calculation of the first stage Partial F-statistics, which is 72.133 and higher than 10 – a threshold suggested by Stock and Yogo (2002). Third, we examine the distribution of this variable to show its variability. Table WC5 shows its descriptive statistics. We also provide separate descriptive statistics when focal donation is either self-donation or non-self-donation in this table, respectively. Fig WC1 shows the histograms of all samples and samples with non-zero instrument values. About 50% of instrumental variable values are more than zero. These results confirm that the IV shows significant variation. Therefore, the intuition, as well as formal tests, show that we have a valid instrument.

**Table WC4.** Effects of Number of Successful Projects with Self-donations from Same School Last 3 Months on Self-donation

Variables	Coefficient	SE
<i># of Successful Self-donated Projects Last Three Months</i>	0.010***	0.0004
<i>Donation Information</i>	YES	
<i>Social Network Information</i>	YES	
<i>Platform-level Information</i>	YES	
<i>Teacher, Project, School Information</i>	YES	
Observations	2,682,455	
Log-likelihood	-475708.37	
Resource Type Fixed Effects	YES	
Year-month Fixed Effects	YES	
State Fixed Effects	YES	
Grade Level Fixed Effects	YES	
School Type Fixed Effects	YES	

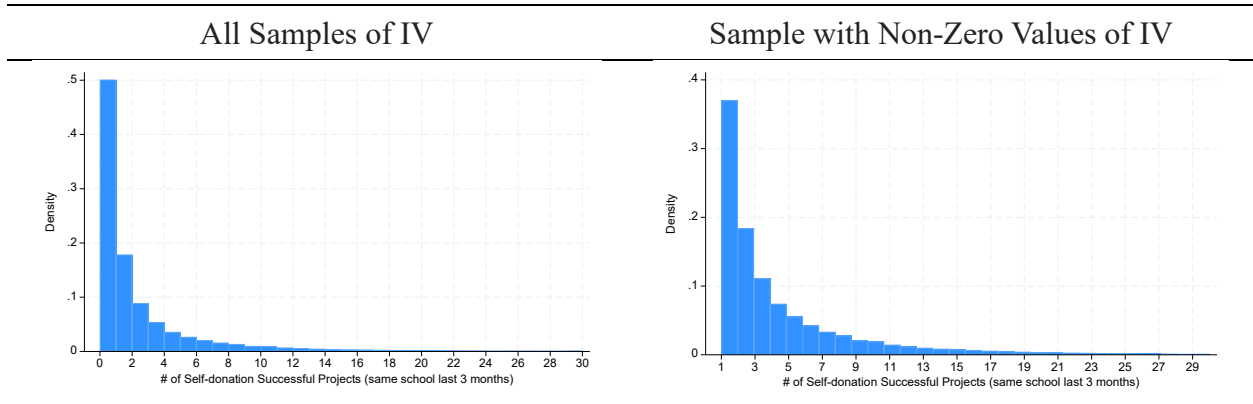
*Note:* This table reports coefficients and standard errors from a probit model of regressing *Self-donation* on *# of Successful Self-donated Projects Last Three Months*, donation, social network, platform-level, and teacher, project, and school information. Table 1 in the paper provides variable definitions. \*\*\* indicates statistical significance at the 1% level from two-tailed tests. The sample includes 2,682,455 donations from 465,530 projects.

**Table WC5.** Descriptive Statistics of Instrument Variable ( $N = 2,682,455$ )

Focal Donations	Mean	Std.	25% Quartile	50% Quartile	75%quartile
<i>All donations</i>	2.24	4.62	0	1	2
<i>Self-donations</i>	2.60	4.86	0	1	3
<i>Non Self-donations</i>	2.20	4.59	0	0	2



Fig. WC1. Histogram of Instrument Variable (IV)



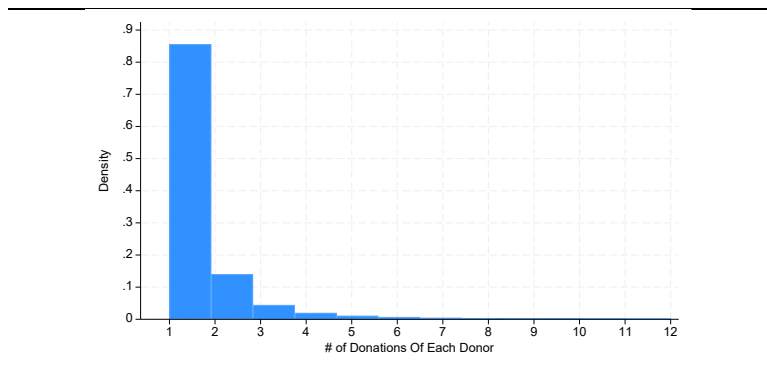
We use the same dataset for analysis. Although the 2SLS approach is the most common and standard IV estimation method, it requires the endogenous variable to be continuous (Imbens and Wooldridge 2007). Since our measure of *Self-donation*, the endogenous variable, is binary, the 2SLS approach will be biased. Following the recommendation of Wooldridge (2010), we implement a two-step control function (CF) approach for our nonlinear model. We first run a probit model to regress *Self-donation* on the proposed IV and other donation, project, teacher, school, social network (donation level), and platform level variable (Panels C, D, E, F, and G in Table 1). Then, we calculate the generalized residuals<sup>4</sup>. Finally, we insert these generalized residuals into the second stage estimation. Results in M3 in (Table 2 in the paper) show the robustness of our findings.

However, there may still be concerns of homophily among donors. If teachers can learn from each other, can donors also show similar homophily, which may cast doubt on the validity of the instrument? To address this concern, we first examine how frequently donors donate at the focal platform to address this concern. We find that over 80% of donors only had one donation (Fig. WC2). Among donors who donated more than once, on average, the time interval between two consecutive donations was more than 69 days ( $mean = 69.31, std. = 208.58$ ). In addition, we examine how frequently a donor donated to the same school. Tabel WC6 provides the descriptive statistics of number of donations from the same donor to the same school over our observation period, which shows that almost 90% of donors donated to the same school only once (Fig. WC3). These findings provide evidence for no significant serial correlation among donations from the same donors over time. However, homophily can still occur among different donors over time,

<sup>4</sup> Imbens and Wooldridge (2007) and Wooldridge (2010) provide a more detailed explanation for the calculation.

even when the majority of donors donate only once to the same school. Specifically, homophily can weaken the validity of our instrument if # of Successful Self-donated Projects Last Three Months from the same school attracted more donors who may subsequently positively influence donations of donors for the current project in the same school through homophily. For example, it is possible that a donor who saw more donations to a school in the previous three months can become more likely to donate to current projects from the same school.

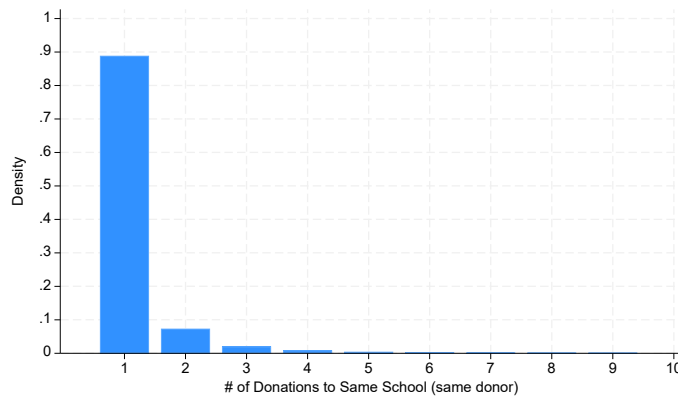
**Fig. WC2.** Distribution of # of Donations of Each Donor



**Table WC6.** Descriptive Statistics of # of Donations (from Same Donor to Same School)

Mean	Std.	25% Quartile	50% Quartile	75% quartile
1.239	1.310	1	1	1

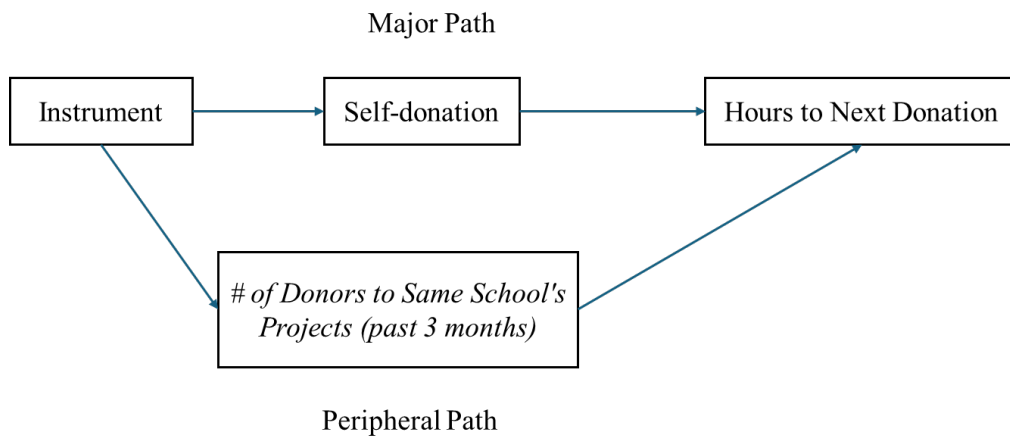
**Fig. WC3.** Distribution of # of Donations of Same Donor to Same School



To address such a homophily concern, we counted the total number of unique donors who donated to other projects in the same school in the past three months and included it in our analysis

(*# of Donors to Same School's Projects (past 3 months)*).<sup>5</sup> If the homophily of these donors affects the validity of our proposed instrument, their effect path likely starts from instrument via *# of Donors to Same School's Projects (past 3 months)* to *Hours to Next Donation* (Fig. WC4). We did two tests to show that the impact of homophily among donors on our results with the proposed instrument is less a concern. In the first test, we included *# of Donors to Same School's Projects (past 3 months)* as a control variable in the second stage of our instrumental variable analysis, which can help isolate the effect of the instrument on *Hours to Next Donation* through self-donation (pp. 102-104, Cunningham 2021). In the second approach, we directly regress *Hours to Next Donation* on this variable and other controls. Columns 2 and 3 in Table WC7 report the results of these two tests. We find that the coefficients of (*# of Donors to Same School's Projects (past 3 months)*) are positive and significant. This implies that the speed of donations for the current project will be *slower* (instead of faster) if more donors donated to other projects from the same school in the past three months, which shows that our estimates of the self-donation effects are conservative (i.e., the effect size of self-donation in Column 2 is slightly larger than Column 1). Therefore, we feel that homophily among donors is not a significant concern in this study.

**Fig. WC4.** Main and Peripheral Path from Instrument to Hours to Next Donation



<sup>5</sup> This variable has a mean of 34.69 and a standard deviation of 80.00.

**Table WC7. Controlling Potential Homophily**

Variables	Using Instrument (M3 in Table 2 of Main Paper)		Using Instrument + Controlling # of Donors to Same School's Project (past 3 months)		# of Donors to Same School's Project (past 3 months) as Main Independent Variable	
	Coefficients	SE	Coefficients	SE	Coefficients	SE
<i>Self-donation</i>	-19.695***	1.193	-19.843***	1.193		
<i># of Donors to Same School's Projects (past 3 months)</i>			0.099***	0.008	0.098***	0.008
<i>Donation Information</i>	YES		YES		YES	
<i>Social Network Information</i>	YES		YES		YES	
<i>Platform-level Information</i>	YES		YES		YES	
<i>Teacher, Project, School Information</i>	YES		YES		YES	
Observations	2,682,455		2,682,455		2,682,455	
R-squared	0.463		0.463		0.463	
Project fixed effects	YES		YES		YES	
Donation year-month fixed effects	YES		YES		YES	

**Note:** The first column (M1) reports coefficients and standard errors from an OLS regression of *Hours to Next Donation* on *Self-donation*, donation information, social network information, and platform-level information with project-fixed effects using instrument variable approach (M3 in Table 2 of main paper). The second column (M2) estimates the same model as M1 but added *# of Donors to Same School's Projects (past 3 months)* as a control. The last column (M3) estimates an OLS regression of *Hours to Next Donation* on *# of Donors to Same School's Projects (past 3 months)*, donation information, social network information, and platform-level information with project-fixed effects. Table 1 provides variable definitions. \*\*\* indicates statistical significance at the 1% level from two-tailed tests, respectively. The sample includes 2,682,455 donations from 465,530 projects. Because the dependent variables are *Hours to Next Donation*, the first donations (465,530 donations) are excluded.

**C-3: Evidence for the Mechanism: Anonymity of Donations**

**Table WC8.** Effects of Anonymity on the Relationship Between Self-donation and Hours to Next Donation

Variables	Coefficients	SE
<i>Self-donation</i>	-9.626***	0.415
<i>Anonymity</i>	7.696***	0.302
<i>Self-donation</i> × <i>Anonymity</i>	10.924***	1.110
<i>Donation Information</i>	YES	
<i>Social Network Information</i>	YES	
<i>Platform-level Information</i>	YES	
Observations	2,682,455	
R-squared	0.463	
Log-likelihood	-17019926	
Project fixed effects	YES	
Year-month fixed effects	YES	

*Note:* This table reports coefficients and standard errors from an OLS regression of *Hours to Next Donation* on *Self-donation*, *Anonymity*, and its interaction term with *Self-donation*, donation information, social network, and platform-level information. Table 1 in the paper provides variable definitions. \*\*\* indicates statistical significance at the 1% level from two-tailed tests. The sample includes 2,682,455 donations from 465,530 projects. Because the dependent variables are *Hours to Next Donation*, the first donations (465,530 donations) are excluded from estimation.

**Table WC9.** Effects of Self-donation Interaction with Anonymity on Hours to Next Donation

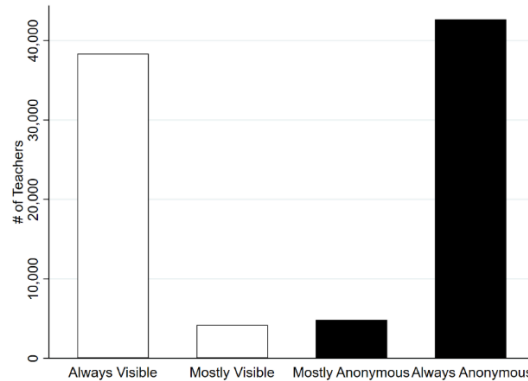
Self-donation	Anonymity	
	<i>Yes</i>	<i>No</i>
<i>Yes</i>	77.164***	58.544***
<i>No</i>	75.866***	68.170***
Differences	1.298 ( $p=0.214$ )	-9.626***

*Note:* \*\*\*  $p < 0.01$

One potential downside of this analysis is that the stewards might be strategically deciding regarding anonymity based on some unobservables, casting doubt on the validity of the results. We have two reasons to believe that endogeneity concerns do not significantly affect our results. First, Figure WC5 below clearly shows the bi-modal nature of teacher decisions, indicating that

most teachers' self-donations are either always visible or anonymous.<sup>6</sup> This suggests that the choice to remain visible vs. anonymous is likely driven by personal characteristics rather than any strategic motive.

**Fig. WC5.** Histogram of Teacher Choice to Remain Visible vs. Anonymous for Self-donations



**Note:** "Mostly Visible (Anonymous)" means that a teacher was visible (anonymous) in the majority of self-donations

Second, we handle the issue of anonymity in a more rigorous manner by implementing a Heckman Selection Correction approach. To be specific, we first regressed whether donors choose anonymity (*Anonymity*) on information that might affect donors' decisions. The information includes donation, project, project description, teacher, and platform level information described in Table 1. As an exclusion restriction, we included the ratio of the number of anonymous donations to all donations a donor made in the previous three months before this donor's current donation (*AnonymityRatio*) as a regressor. This covariate would affect the anonymity decision since the donors who previously donated anonymously are likely to remain so (refer to Figure WC5). However, it is unlikely to affect other donors' donations for focal projects (donors for the same project do not know whether and how frequently a steward self-donated anonymously in their previous projects). The correlation between *AnonymityRatio* and *Anonymity* is 0.3940 ( $p < 0.01$ ). The results of this first stage regression are in Table WC10. Then, we calculated Inverse Mills ratios (IMR) using the residuals and included it in our main model. The results are in Table WC11. Table WC12 shows the marginal effects of interaction

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<sup>6</sup> At the same time, there is some variation at the teacher-level that allows us to use this in our model despite the project fixed effects.

term between *Anonymity* and *Self-donation*. Our qualitative and quantitative results are fairly similar to those that do not use first-stage correct (Table WC4). We find that anonymity wipes out all the signaling gains from self-donation, as expected.

**Table WC10.** First stage: Effects of Donors' Previous Anonymous Donation Ratios on Anonymity

DV: Anonymity	Coefficient	SE
<i>AnonymityRatio (3 mons)</i>	1.270***	0.003
<i>Donation Information</i>	YES	
<i>Social Network Information</i>	YES	
<i>Platform-level Information</i>	YES	
<i>Teacher and School Information</i>	YES	
<i>Project and Project Description Information</i>	YES	
Observations	2,682,455	
Log Likelihood	-1048114.5	
Resource Type Fixed Effects	YES	
Year-quarter Fixed Effects	YES	
State-city Fixed Effects	YES	
Grade Level Fixed Effects	YES	
School Type Fixed Effects	YES	

*Note:* This table reports coefficients and standard errors from a probit regression of *Anonymity* on *AnonymityRatio*, donation, teacher, school, project, project description, social network, and platform level information. Table 1 in the paper provides variable definitions. \*\*\*indicate statistical significance at the level from two-tailed tests. The sample includes 2,682,455 donations from 465,530 projects.

**Table WC11.** Effects of Self-donation Interaction with Anonymity on Hours To Next Donation

Variables	Coefficients	SE
<i>Anonymity</i>	7.924***	0.313
<i>Self-donation</i>	-9.658***	0.416
<i>Anonymity</i> × <i>Self-donation</i>	11.034***	1.111
<i>IMR</i>	1.212***	0.434
<i>Donation Information</i>	YES	
<i>Social Network Information</i>	YES	
<i>Platform-level Information</i>	YES	
Observations	2,682,455	
Log Likelihood	-17019922	
R-squared	0.463	
Project Fixed Effects	YES	
Teacher fixed Effects	YES	
Year-month Fixed Effects	YES	

*Note:* This table reports coefficients and standard errors from an OLS regression of *Hours to Next Donation* on *Self-donation*, *Anonymity*, and its interaction term with *Self-donation*, donation information, social network, platform-level information, and IMR. Table 1 in the paper provides variable definitions. \*\*\* indicates statistical significance at the 1% level from two-tailed tests, respectively. The sample includes 2,682,455 donations from 465,530 projects. Because the dependent variables are *Hours to Next Donation*, the first donations (465,530 donations) are excluded from estimation.

**Table WC12.** Effects of Self-donation Interaction with Anonymity on Hours to Next Donation

Self-donation	Anonymity	
	<i>Yes</i>	<i>No</i>
<i>Yes</i>	77.435***	58.477***
<i>No</i>	76.059***	68.135***
Differences	1.376 ( $p=0.189$ )	-9.658***

*Note:* \*\*\*  $p < 0.01$



## **Web Appendix D: Effects of Self-donation on Hours of Next Donation (Robustness Checks)**

### ***D-1: Alternative Explanations (Ruling Out Effects from Local Donors)***

Several potential alternative explanations may affect our findings. The first one is that a self-donation might appeal to donors who know the teacher personally. Thus, social pressure might explain the donation behavior of others based on a teacher's donation. Since we have access to donors' locations (i.e., zip code, state, and city), we address this concern by examining how the percentage of local donors out of all donors for a project affects our findings. Local donors are donors who share the same zip code as the schools. Specifically, we created five subsamples. The first subsample only includes donations from projects without contributions from local donors. Over 47% of projects did not receive a single donation from local donors. About 2.1 million donations from nearly 240,000 projects were excluded. The analysis using this subsample will address our concern. For the remaining projects that received donations from local donors, we assign each of these projects into one of four subsamples created based on four quartiles of percent of donors from local community distribution. We estimate the same model as M3 in Table 2 using each of these subsamples.

Results in Table WD1 column 1 show that self-donation accelerates fundraising (-8.462,  $p < 0.01$ ) for projects without local donors, confirming our finding. Results in columns 2 to 5 of the same table confirm our finding and show that self-donation is more effective when the percentage of local donors is moderate rather than too high or too low.

We want to emphasize that these analyses do not rule out the role of social pressure on giving but show that self-donation has an effect over and beyond the well-studied impact of social pressure (DellaVigna, List, and Malmendier 2012).

**Table WD1.** Effects of Self-donation on Hours to Next Donation (Percent of # of Donations from Locals)

Variables	No Local Donors		Percent of # Donors are Locals (>0%)							
			First Quartile		Second Quartile		Third Quartile		Fourth Quartile	
	Coeffs	SE	Coeffs	SE	Coeffs	SE	Coeffs	SE	Coeffs	SE
<i>Self-donation</i>	-8.462***	0.817	-5.363***	0.632	-11.421***	0.896	-11.167***	0.937	-4.220**	1.75
<i>Donation Order</i>	2.292***	0.066	0.619***	0.041	1.403***	0.083	2.475***	0.093	0.508***	0.189
<i>Donation Amount</i>	-1.905***	0.249	2.265***	0.187	-1.391***	0.292	-3.527***	0.322	-1.548**	0.624
<i>Percent of Requested Amount Funded So Far</i>	-1.873***	0.015	-0.913***	0.012	-1.350***	0.02	-1.565***	0.02	-1.583***	0.038
<i>Avg Donation (Local) So Far</i>			-4.648***	0.265	-6.241***	0.424	-8.047***	0.506	-13.673***	1.23
<i># Of Accumulated Self-donation</i>	-35.523***	2.916	-29.879***	1.829	-47.054***	2.829	-58.966***	3.154	-38.169***	4.799
<i>Accumulated Self-donation Amount</i>	19.543***	1.752	18.120***	1.118	28.427***	1.672	30.982***	1.829	17.359***	3.043
<i>Days to Expiration</i>	75.638***	1.12	75.078***	0.779	85.031***	1.182	96.618***	1.265	94.228***	2.046
<i>Social Network Information</i>	YES		YES		YES		YES		YES	
<i>Platform-level Information</i>	YES		YES		YES		YES		YES	
Observations	744,714		808,776		465,697		483,776		179,492	
R-squared	0.542		0.308		0.393		0.516		0.498	
Log-likelihood	-4721996.7		-5039566.7		-2970784.1		-3092260.7		-1169393.5	
Project fixed effects	YES		YES		YES		YES		YES	
Year-month fixed effects	YES		YES		YES		YES		YES	

*Note:* This table reports coefficients and standard errors from OLS regressions of *Hours to Next Donation* on *Self-donation*, donation information, social network, and platform-level information using donations to projects with different percentages of donations from local donors. The first column reports results using projects that had no local donors. Columns 2,3, 4, and 5 report results using donations from projects that received donations from local donors and had percentages of local donors in the first, second, third, and fourth quartile of percent of local donors' distribution. Table 1 provides variable definitions. \*\*\* and \*\* indicates statistical significance at the 1% and 5% level from two-tailed tests, respectively

### ***D-2: Alternative Explanations (Controlling for Donor Herding)***

The "herding" behavior of crowdfunding funders is well documented in the crowdfunding context and may be an alternative explanation/confound for our findings. Several studies provide convincing evidence of "herding" among lenders in debt-based crowdfunding (Zhang and Liu 2012) and contributors in reward-based crowdfunding (Dai and Zhang 2019); Lenders (or contributors) tend to lend (or contribute) to funding requests that have already attracted a larger number of lenders (or contributors). Thus, herding is time-related and more likely to occur after the initial stage of a donation-based crowdfunding project. It captures the accumulative effects of the previous donations. Although a time dummy variable is included in all previous model specifications, we did not specifically address the herding concern by controlling this accumulative impact on donors' donating decisions in the main analyses. This missing control may lead to biased estimation.

To address this concern, we follow the spirit of the study from Zhang and Liu (2012) and construct a new dataset that only includes the donation data of the first two donations of all projects. At this stage, projects have not received a large number of donations, and thus donors are more independent at this stage. It is unlikely that accumulative effects that lead to herding exist. Consequently, "herding" is less likely to occur. The unit of analysis is a donation. The dependent variable and main independent variables remain the same as the main analysis. We estimate an OLS model and control information in *Panels C, D, E, F, and G* in Table 2. We report the results in Table WD2, column 1. The coefficient of *Self-donation* is negative and significant at a .01 level, confirming our main findings.

### ***D-3: Alternative Explanations (Controlling for Teacher Learning)***

Fundraisers can learn from previous experience in crowdfunding (Freeman and Jin, 2011; Xu and Ni, 2022). We have all the donations information for all teachers' projects during our study period. Over 69.46% of teachers have multiple projects. Hence, teacher learning may be an alternative explanation/confound for our findings. To address this concern, we only include all donations of teachers' first projects since teachers had no prior experience at DonorsChoose when posting their first project. We estimate the same model specification as our primary analysis. The results in Table WD2, column 2 confirm our finding.

**Table WD2.** Effects of Self-donation on Hours to Next Donation (Excluding Herding and Teacher Learning)

Variables	Herding Effects		Teacher Learning (First Project)	
	Coefficient	SE	Coefficient	SE
<i>Self-donation</i>	-69.365***	4.757	-12.070***	0.669
<i>Donation Information</i>	YES		YES	
<i>Social Network Information</i>	YES		YES	
<i>Platform-level Information</i>	YES		YES	
<i>Teacher and School Information</i>	YES		NO	
<i>Project Information</i>	YES		NO	
<i>Project Description Information</i>	YES		NO	
Observations	362,450		795,012	
R-squared	0.201		0.387	
Log-likelihood	-2502633.7		-4961551.5	
Resource type fixed effects	YES		NO	
Project subject fixed effects	YES		NO	
School state fixed effects	YES		NO	
Grade-level fixed effects	YES		NO	
School-type fixed effects	YES		NO	
Project fixed effects	NO		YES	
Year-month fixed effects	YES		YES	

*Note:* The first column reports coefficients and standard errors from OLS regressions of *Hours to Next Donation* on *Self-donation*, donation, social network, platform, project, teacher, and school levels of information using the first two donations of each project. This model includes donation year-month, school state, school type, grade level, and resource type fixed effects. The last column reports coefficients and standard errors from OLS regressions of *Hours to Next Donation* on *Self-donation*, donation information, social network, and platform-level information using donations from teachers' first projects. The estimation includes project and donation year-month fixed effects. Table 1 provides variable definitions. \*\*\* indicates statistical significance at the 1% level from two-tailed tests.

#### ***D-4: Heterogeneity of Self-Donation Order, Amount, Percentage of the Requested Amount Raised***

To understand how self-donations accelerate the inflow of donations, we investigate by interacting this variable with donation order, donation amount, and the percentage of requested contributions and present the results in Table WD3. We discover many new insights across the four different model specifications (from M1 to M4). *First*, we find a significant positive interaction effect between the self-donation and the donation order, indicating that the purported self-donation effect is weaker at the later stages of the donation cycle. Consistent with the signaling theory, a commitment signaled by donating to an own project earlier is more effective than after receiving many other donations. This is because signaling is more effective in an uncertain environment, and this uncertainty is likely to be heightened in the earlier fundraising cycle. *Second*, the negative interaction between self-donation and the donation amount on time to the following donation reveals that a higher (self-donation) amount reduces the time to the next donation. Again, consistent with signal theory, this implies that contributing a higher donation amount to an own project carries a stronger signal of commitment to potential donors. *Third*, the interaction between self-donation and the percentage of the requested amount raised is positive. This means that when a higher percentage of the requested amount has been raised, a self-donation has a weaker effect on the time to the next donation (relative to when a lower percentage is raised). This finding re-confirms that self-donation in the early stage of the project signals a stronger commitment than at a later stage. Overall, this analysis shows that self-donations made early with a higher amount signal a teacher's stronger commitment to the project and, therefore, are more effective in attracting potential donors.

**Table WD3.** Effects of Interactions between Self-Donations and Donation Order, Donation Amount, and Percentage of Requested Donations Funded So Far on Hours to Next Donation

Variables	M1		M2		M3		M4	
	Coeffs	SE	Coeffs	SE	Coeffs	SE	Coeffs	SE
<i>Self-donation</i>	-11.982***	0.502	-8.397***	0.391	-15.612***	0.567	-17.573***	0.584
<i>Donation Order</i>	1.448***	0.031	1.477***	0.031	1.484***	0.031	1.546***	0.031
<i>Self-donation</i> × <i>Donation Order</i>	0.629***	0.060					0.377***	0.075
<i>Donation Amount</i>	-1.106***	0.132	-0.561***	0.137	-1.216***	0.132	-0.427***	0.137
<i>Self-donation</i> × <i>Donation Amount</i>			-5.480***	0.375			-8.897***	0.415
<i>Percent of Requested Amount Funded So Far</i>	-1.420***	0.008	-1.424***	0.008	-1.432***	0.008	-1.451***	0.008
<i>Self-donation</i> × <i>Percent of Requested Amount Funded So Far</i>					0.229***	0.014	0.375***	0.018
<i>Donation Information</i>	YES		YES		YES		YES	
<i>Social Network Information</i>	YES		YES		YES		YES	
<i>Platform-level Information</i>	YES		YES		YES		YES	
Observations	2,682,455		2,682,455		2,682,455		2,682,455	
R-square	0.463		0.463		0.463		0.463	
Log-likelihood	-17020397		-17020336		-17020294		-17020024	
Likelihood ratio $\chi^2$	M1 v.s. Baseline 127.53 (p<0.001)		M2 v.s. Baseline 249.81 (p<0.001)		M3 v.s. Baseline 332.40 (p<0.001)		M4 v.s. Baseline 873.21 (p<0.001)	
Project fixed effects	YES		YES		YES		YES	
Year-month fixed effects	YES		YES		YES		YES	

*Note:* The first column reports coefficients and standard errors from OLS regressions of *Hours to Next Donation* on *Self-donation* and its interaction with donation order, donation information, social network, and platform level information. The second column reports results from the same model as M1 but replaces the interaction term with the interaction term between *Self-donation* and *Donation Amount*. The third column reports results from the same model as M1 but replaces the interaction term with the interaction term between *Self-donation* and the *Percent of Requested Amount Funded So Far*. The last column reports model results that include all interactions from models 1 to 3. \*\*\* indicates statistical significance at the 1% level from two-tailed tests.

**D-5: Alternative Dependent Variable (Next Donation Amount)**

In the main analysis, we used Hours to Next Donation as the dependent variable. To test the robustness of our finding, we used an alternative dependent variable, Next Donation Amount, to rerun our analysis. We repeated all analyses in Table 2 but replaced the dependent variables with the new one. Results in Table WD4 show Self-donation is positively and significantly related to next donation amount. We find that that self-donations not only expedite the next donation but also increase its amount, further confirming our hypothesis 1(a).

**Table WD4.** Effects of Self-donation on Next Donation Amount

Variables	M1		M2		M3	
	Coeff	SE	Coeff	SE	Coeff	SE
<i>Self-donation</i>	3.470***	0.086	3.617***	0.132	2.388***	0.261
<i>Residual</i>					0.678***	0.155
<i>Donation Information</i>	YES		YES		YES	
<i>Social Network Information</i>	YES		YES		YES	
<i>Platform-level Information</i>	YES		YES		YES	
Observations	2,682,455		1,057,227		2,682,455	
R-squared	0.736		0.734		0.736	
Log Likelihood	-12946475		-5106752.5		-12946464	
Year-month fixed effects	YES		YES		YES	
Teacher fixed effects	YES		YES		YES	
Project fixed effects	NO		YES		YES	

**Note:** The first column (M1) reports coefficients and standard errors from an OLS regression of *Next Donation Amount* on *Self-donation*, donation information, social network information, and platform-level information with project-fixed effects. The second column (M2) estimates the same model as M2 using samples matched on teacher, project, project description, social network, and platform-level information. The last column (M3) estimates the same model as M1 using an instrumental variable approach. Table 1 provides variable definitions. \*\*\* indicates statistical significance at the 1% level from two-tailed tests. The sample includes 2,682,455 donations from 465,530 projects. Because the dependent variables are *Hours to Next Donation*, the first donations (465,530 donations) are excluded

## Web Appendix E: Effects of Self-Donations on Funding Success

### *E-1: Project Description Processing*

We first quantify linguistic styles from project descriptions regarding *familiarity*, *concreteness*, *readability*, *valence*, *extremity*, and *emotionality*. Specifically, we used *Evaluative Lexicon* (E.L.) 2.0 (Rocklage, Rucker, and Nordgren 2018) to measure the positivity (valence) of emotion, how positive or negative it is (extremity), and the extent to which it is based on an emotional appeal contained in the description. E.L. is a computational linguistic tool that uses an extensive list of evaluative words such as "loved," "outstanding," and "distressing" that have been rated by a large set of external judges for their implied valence (0 =highly negative, 9=highly positive), valence extremity (the absolute distance from the midpoint (4.50) of the valence scale), and emotionality (0 = not at all emotional, 9 = very emotional). These measures have been used in the past in academic research in marketing (e.g., Herhausen et al., 2019; Melumad, Meyer, and Kim, 2021; Moradi et al. 2023; Song, Li, and Sahoo 2022; Xiang et al. 2019).

We used *MRC psycholinguistic database* to measure words' familiarity and concreteness. Concreteness refers to how much a word refers to an actual, tangible, or "real" entity. More concrete language can make readers believe that the speaker is attending to and understanding their personal needs (e.g., Allison et al. 2018; Packard and Berger 2021; Parhankangas & Renko 2017). Familiarity refers to how often a word is typically seen or heard. Word familiarity affects readers' comprehension of the texts (Packard and Berger 2021). Next, we measure the readability of texts (i.e., *Text Flesch-Kincaid Readability*) (e.g., Gao et al. 2023; Netzer et al. 2019), the project description length, and the average characters per word to control for the text characteristics. Finally, we implemented Pyspellchecker (Barrus 2020) to obtain spelling errors in project descriptions (e.g., Gao et al. 2023; Netzer et al. 2019).

Next, we extract perceived teacher preparedness and project social impact from project descriptions. Contributors are more likely to contribute in crowdfunding when fundraisers are perceived to be more prepared, and projects are perceived to have a social impact (Dorfleitner, Oswald, and Zhang 2021; Tajvarpour, Hossein, and Pujari 2022). A well-prepared project description shows that fundraisers devoted time and effort to ensure that the project is in line with the standards of a successful project (Mollick 2014). Following the study of Tajvarpour, Hossein, and Pujari (2022), we used informal language (e.g., "thnx," "pls," and "gonna"), punctuation, and risk rhetoric (e.g., lose, lack, avoid) to measure preparedness. Formal language



and punctuation use reflect professionalism (Yazdani, Gopinath, and Carson, 2018). A text with good punctuation and formal language reflects that the fundraiser has invested time and effort in preparing the project. In previous marketing studies, informal language is a reverse measure of preparedness (Yazdani, Gopinath, and Carson 2018; Ransbotham, Lurie, and Liu 2019). Also, project descriptions, like other narratives, have risk-related and reward-focused words. Risk-related words make the project appear challenging to achieve and are likely perceived to be indicative of a lack of competency and illy prepared, making it less likely to receive external support from contributors (Chan and Parhankangas 2017).

Thus, in our studied context, projects with teachers' narratives that reveal such rewards and achievement (e.g., accomplish, overcome, and solve) and being empowered social relationships (e.g., parents, friends, and children) will create a positive external perception in the minds of donors and positively affect crowdfunding success.

We use the LIWC dictionary (Pennebaker et al. 2015) to capture words that focus on informal language, punctuation, risks, social, awards, and achievement. LIWC is well-accepted and widely used in marketing (e.g., Yazdani, Gopinath, and Carson 2018; Ransbotham, Lurie, and Liu 2019) to measure psychological states.

***E-2: Results Using Matching Methods (PSM and CEM)***

We conducted a series of analyses to check the robustness of our findings, similar to the tests presented in Table 3. First, we address the selection concerns by implementing PSM and CEM approaches and find that the average funding success rate of the matched projects with self-donations is significantly higher.

**Table WE1.** Effects of Self-donation on Funding Success Using PSM

Matching Methods	Groups	# of Matched Projects	Funding Rates (ATT)	Difference in Funding Rate (Treatment-Control)	S.E.	T-stat
PSM	Treatment	113,057	0.891	0.048***	0.001	36.84
	Control	113,048	0.843			

**Note:** This table reports ATT effects of *Having Self-donation* on project *Funding* using a one-to-one nearest neighbor PSM technique to match projects receiving self-donation with projects without self-donation on platform, project, teacher, and school levels of information. \*\*\* indicates statistical significance at the 1% level from two-tailed tests.

**Table WE2.** Effects of Self-donation on Funding Success Using CEM

Variables	Coeffs	SE
<i>Having Self-donation</i>	0.2719***	0.0179
Pseudo R2	0.033	
LR $\chi^2$	234.12	
Log-likelihood	-43092.963	

*Note:* This table reports coefficients and standard errors from a logit regression of *Funding* on *Having Self-donation* using matched projects (80,291 projects having self-donation and 97,132 projects having no self-donation) obtained from coarsened exact matching (CEM). \*\*\* indicates statistical significance at the 1% level from two-tailed tests.

### ***E-3: Alternative Explanations (Role of Local Donors and Teachers Learning)***

Second, we rule out the role of social pressure by using only the projects that received no donations from local donors. Results in Table WE3 column 1 show that self-donation increases funding success probability (0.042,  $p < 0.01$ ) for this subset of observations as well. Third, we address the concern that teacher learning might somehow be confounding the self-donation effects by estimating our model using only teachers' first projects. Results in Web Appendix Table WE3 column 3 confirm that teacher's donations positively affect project success.

### ***E-4: Alternative Dependent Variables***

Finally, we test the robustness of our findings using three alternative dependent variables: the ratio of donations raised to the amount requested (*i.e.*, donations raised  $\times$  100/amount requested), the difference between the amount requested and donations raised (*i.e.*, amount requested minus donations raised), and the average time interval between consecutive donations for a project. Results in Table WE4 again support our findings.

### ***E-5: Role of Self-Donation Frequency, Recency, and Amount***

In our context, a teacher could self-donate to the project multiple times during a funding cycle. How do self-donation patterns, including *frequency* (the number of self-donations in a project), *recency* (hours elapsed from the project starting time to the first self-donation), and *amount* (the log-transformed total amount self-donated in a project), influence funding success? To answer this question, we regress the funding success indicator on these variables: teacher characteristics, school characteristics, project description information, and platform level information, and report the results as M1 in Table WE5. Consistent with predictions 2(a) and 2(b), we find that less-frequent, higher-amount donations made in the early stage of the project fundraising have more pronounced positive effects on funding success. This result indicates that project stewards, given

a fixed donation budget, can send the strongest signal and maximize the self-donation impact on the funding success of their projects by making a single large self-donation right after posting the project. These findings are robust to the different versions of the dependent variable, as shown in Table WE5.

**Table WE3:** Effects of Self-Donations on Funding Success (Percent of # of Donations from Locals and Addressing Teaching Learning)

Variables	Local Donors						Addressing Teacher Learning (First Job)	
	No Local Donors		Percent of Donors are Local Donors				Coeffs	SE
	Coeffs	SE	Coeffs	SE	Coeffs	SE		
<i>Having Self-donation</i>	0.042***	0.015	0.057***	0.016	0.085***	0.015	0.606***	0.023
<i>Local Donors Percent (Q1)</i>					0.983***	0.030		
<i>Local Donors Percent (Q2)</i>					0.612***	0.027		
<i>Local Donors Percent (Q3)</i>					0.171***	0.018		
<i>Local Donors Percent (Q4)</i>					-0.709***	0.017		
<i>Having Self-donation × Local Donors Percent (Q1)</i>					0.281***	0.041		
<i>Having Self-donation × Local Donors Percent (Q2)</i>					0.395***	0.038		
<i>Having Self-donation × Local Donors Percent (Q3)</i>					0.310***	0.027		
<i>Having Self-donation × Local Donors Percent (Q4)</i>					0.627***	0.028		
<i># of Completed Projects</i>	0.030***	0.002	0.040***	0.003	0.023***	0.001		
<i>Having Self-donation × # of Completed Projects</i>			-0.015***	0.004				
Teacher and School Information	YES		YES		YES		YES	
Project Information	YES		YES		YES		YES	
Project Description Information	YES		YES		YES		YES	
Social Network Information	YES		YES		YES		YES	
Platform-level Information	YES		YES		YES		YES	
Observations	219,510		219,510		465,530		98,583	
Log-likelihood	-78037.346		-78029.566		-148930.16		-30225.103	
Resource type fixed effects	YES		YES		YES		YES	
Project subject fixed effects	YES		YES		YES		YES	

Year-quarter fixed effects	YES	YES	YES	YES
School state fixed effects	YES	YES	YES	YES
Grade-level fixed effects	YES	YES	YES	YES
School-type fixed effects	YES	YES	YES	YES

**Note:** The first column reports coefficients and standard errors from a logistic regression of *Funding* on *Having Self-donation*, social network, platform, project, teacher, and school levels of information using projects that did not receive donations from local donors. The second column is built on the first model by adding an interaction term between *Having Self-donation* and *# of Completed Projects*. The third column reports coefficients and standard errors from a logistic regression of *Funding* on *Having Self-donation*, *Local Donors Percent*, and its interaction terms with *Having Self-donation*, social network, platform, project, teacher, and school levels of information. Local Donor Percent has five different values (1-no local donor, 2- percent in the first quartile of percent of local donors (>0%), 3- percent in the second quartile, 4- percent in the third quartile, and 5- percent in the fourth quartile). The last column reports coefficients and standard errors from a logistic regression of *Funding* on *Having Self-donation*, social network, platform, project, teacher, and school levels of information using teachers' first projects. Table 1 provides variable definitions. \*\*\*, \*\*, and \* indicate statistical significance at the 1%, 5%, and 10% levels from two-tailed tests, respectively.

**Table WE4.** Effects of Self-Donations on Funding Success (Alternative D.V.s)

Variables	DV: Total Donation/Requested Amount %		DV: Distance to Requested Amount (\$)		DV: Average Donation Time							
	Coeffs	SE	Coeffs	SE	Coeffs	SE	Coeffs	SE	Coeffs	SE	Coeffs	SE
<i>Having Self-donation</i>	3.868***	0.085	3.999***	0.088	-	0.766	-	0.786	-	0.558	-	0.573
<i># of Completed Projects</i>	0.091***	0.005	0.139***	0.009	34.96***	0.049	35.76***	0.081	7.053***	0.035	5.577***	0.059
<i>Having Self-donation</i> × <i># of Completed Projects</i>			-0.072***	0.011	0.427***		0.724***		0.442***	0.097	-	0.071
Teacher and School Information	YES		YES		YES		YES		YES		YES	
Project Information	YES		YES		YES		YES		YES		YES	
Project Description Information	YES		YES		YES		YES		YES		YES	
Social Network Information	YES		YES		YES		YES		YES		YES	
Platform-level Information	YES		YES		YES		YES		YES		YES	
Observations	465,530		465,530		465,530		465,530		465,530		465,530	
R-squared	0.125		0.125		0.190		0.190		0.070		0.070	
Log-likelihood	-2190909.9		-2190887.9		-3212840		-3212829.6		-3065849.5		-3065783.3	
Resource type fixed effects	YES		YES		YES		YES		YES		YES	
Project subject fixed effects	YES		YES		YES		YES		YES		YES	
Year-quarter fixed effects	YES		YES		YES		YES		YES		YES	
School state fixed effects	YES		YES		YES		YES		YES		YES	
Grade-level fixed effects	YES		YES		YES		YES		YES		YES	
School-type fixed effects	YES		YES		YES		YES		YES		YES	

**Note:** The first column reports coefficients and standard errors from an OLS regression of *Total Donation/Requested Amount %* on *Having Self-donation*, social network, platform, project, teacher, and school levels of information. The second model builds on the first model by adding an interaction term between *Having Self-donation* and *# of Completed Projects*. The third column reports results from replacing the dependent variable in the first model with *Distance to the Requested Amount (\$)*. The fourth column reports results from replacing the dependent variable in the second model with *Distance to Requested Amount (\$)*. The fifth and last columns repeat the analyses in columns 3 and 4 but replace the dependent variable to *Average Donation Time*, respectively. Table 1 provides variable definitions. \*\*\* indicates statistical significance at the 1% level from two-tailed tests.

**Table WE5.** Effects of Self-Donation Frequency, Recency and Amount on Funding Success, Total Donation/Requested Amount %, Distance to Requested Amount (\$), and Average Donation Time

Variables	Funding Success		Total Donation/Requested Amount %		Distance to Requested Amount (\$)		Average Donation Time	
	Coeffs	SE	Coeffs	SE	Coeffs	SE	Coeffs	SE
<i>Frequency</i>	-0.0831***	0.00507	-0.661***	0.0320	5.262***	0.300	0.806***	0.200
<i>Recency</i>	-0.160***	0.00560	-1.043***	0.0369	3.535***	0.345	17.43***	0.230
<i>Money Value</i>	0.731***	0.00737	5.672***	0.0466	-49.90***	0.437	-12.38***	0.291
Teacher and School Information	YES		YES		YES		YES	
Project Information	YES		YES		YES		YES	
Project Description Information	YES		YES		YES		YES	
Social Network Information	YES		YES		YES		YES	
Platform-level Information	YES		YES		YES		YES	
Observations	205,020		205,032		205,032		205,032	
R-squared			0.189		0.213		0.130	
Pseudo R2	0.255							
Log-likelihood	-52671.522		-934284.01		-1393101.9		-1309464.9	
Resource type fixed effects	YES		YES		YES		YES	
Project subject fixed effects	YES		YES		YES		YES	
Year-quarter fixed effects	YES		YES		YES		YES	
School state fixed effects	YES		YES		YES		YES	
Grade-level fixed effects	YES		YES		YES		YES	
School-type fixed effects	YES		YES		YES		YES	

**Note:** The first column reports coefficients and standard errors from a logistic regression of *Funding* on *Frequency*, *Recency*, *Money Value*, social network, platform, project, teacher, and school levels of information. The second column reports results by replacing DV with *Total Donation/Requested Amount %*. The third column reports results by replacing DV with *Distance to Requested amount (\$)*. The last column reports results by replacing DV with *Average Donation Time*. Table 1 provides variable definitions. \*\*\*, \*\*, and \* indicate statistical significance at 1%, 5%, and 10% levels from two-tailed tests, respectively. The sample includes 205,032 projects from 96,044 teachers.

## **Web Appendix F: An Example of Impact Letters**

I want to express my wholehearted gratitude for your generous donation to my classroom library. It fills my heart with joy when I remember the look on my students' faces when the books arrived.

Your donation has helped my students tremendously. First, they are extremely eager to read. Knowing that there are so many books in the classroom, they read a lot, take the books home, and they frequently ask to exchange their books after they have finished reading them. Second, they now have reading books to take home and thus do not have to go out to the streets to look for distractions or walk to the neighborhood library. Third, their fluency scores have improved tremendously. Two months ago, my fifth graders were reading an average of 131.5 words per minute. After they have been reading the new books, their fluency has gone up 13 words to an average of 144.4 words per minute! That's an almost 10% increase! The fourth graders improved from an average of 123 words per minute to an average of 129.6 words per minute for an increase of about 5% or 6.6 words per minute!

As you can see, your donation has had a great impact on the achievement and morale of my students.

**With gratitude,  
Mr. Rivas**



## Web Appendix G: Full Results of Main Paper

**Table WG1. Effects of Self-donation on Hours to Next Donation (Corresponding to Table 2 in Main Paper)**

Variables	M1		M2		M3	
	Coeffs	SE	Coeffs	SE	Coeffs	SE
<i>Self-donation</i>	-8.687***	0.391	-5.962***	0.613	-19.695***	1.193
<i>Donation Order</i>	1.452***	0.031	1.291***	0.052	1.385***	0.031
<i>Donation Amount</i>	-1.091***	0.132	-1.157***	0.214	-1.058***	0.132
<i>Percent of Requested Amount Funded So Far</i>	-1.417***	0.008	-1.378***	0.013	-1.421***	0.008
<i>Avg Donation (Local) So Far</i>	-5.112***	0.203	-4.588***	0.326	-5.254***	0.203
<i># Of Accumulated Self-donation</i>	-39.657***	1.231	-38.574***	1.988	-39.156***	1.232
<i>Accumulated Self-donation Amount</i>	23.173***	0.740	19.220***	1.185	23.871***	0.744
<i>Days to Expiration</i>	82.129***	0.507	85.345***	0.805	82.138***	0.507
<i>Previously Co-donated</i>	23.855***	0.758	24.518***	1.170	23.784***	0.758
<i>Having Donation Relationship</i>	4.240***	0.483	5.472***	0.805	4.191***	0.483
<i>Network Density (donation)</i>	18.956***	0.797	20.594***	1.302	17.866***	0.805
<i>#PlatformProjects</i>	7.537***	0.305	9.869***	0.496	7.553***	0.305
<i>#PlatformProjects(same zip code)</i>	-47.124***	0.171	-47.728***	0.277	-47.177***	0.171
<i>Residual</i>					6.890***	0.705
Constant	3,927.289***	11.482	3,911.460***	17.874	3,926.835***	11.484
Observations	2,682,455		1,057,227		2,682,455	
R-squared	0.463		0.456		0.463	
Log-likelihood	-17020461		-6728018.5		-17020405	
Year-month fixed effects	YES		YES		YES	
Teacher fixed effects	YES		YES		YES	
Project fixed effects	YES		YES		YES	

**Note:** The first column (M1) reports coefficients and standard errors from an OLS regression of *Hours to Next Donation* on *Self-donation*, donation information, social network information, and platform-level information with project-fixed effects. The second column (M2) estimates the same model as M2 using samples matched on teacher, project, project description, network, and platform-level information. The last column (M3) estimates the same model as M1 using an instrumental variable approach. Table 1 provides variable definitions. \*\*\* and \* indicate statistical significance at the 1% and 10% levels from two-tailed tests, respectively. The sample includes 2,682,455 donations from 465,530 projects. Because the dependent variables are *Hours to Next Donation*, the first donations (465,530 donations) are excluded.

**Table WG2.** Effects of Self-Donations and Moderating Effects of Teacher Experience on Funding Success (Corresponding to Table 4 in Main Paper)

Variables	M1		M2		M3		M4	
	Coeffs	SE	Coeffs	SE	Coeffs	SE	Coeffs	SE
<i>Having Self-donation</i>					0.448***	0.010	0.473***	0.011
<i># of Completed Projects</i>	0.030***	0.001	0.029***	0.001	0.027***	0.001	0.047***	0.003
<i>Having Self-donation × # of Completed Projects</i>							-0.027***	0.003
<i>Teacher Gender(female)</i>	-0.210***	0.016	-0.217***	0.016	-0.214***	0.016	-0.211***	0.016
<i>Poverty(highest)</i>	0.080***	0.029	0.075***	0.029	0.096***	0.029	0.094***	0.029
<i>Poverty(high)</i>	-0.071**	0.029	-0.075**	0.029	-0.074**	0.029	-0.076**	0.029
<i>Poverty(moderate)</i>	0.003	0.030	-0.001	0.030	-0.016	0.030	-0.017	0.030
<i>Equity Focus</i>	0.035*	0.018	0.038**	0.018	0.037**	0.019	0.038**	0.019
<i>Reached Students</i>	-0.026***	0.005	-0.031***	0.005	-0.029***	0.005	-0.029***	0.005
<i>Requested Amount (log)</i>	-1.163***	0.008	-1.201***	0.008	-1.210***	0.008	-1.209***	0.008
<i>Corporate Matching</i>	0.312***	0.012	0.309***	0.012	0.316***	0.012	0.314***	0.012
<i>Home Double</i>	1.092***	0.029	1.099***	0.029	1.112***	0.029	1.111***	0.029
<i># of Co-donations</i>	0.411***	0.006	0.410***	0.006	0.399***	0.006	0.393***	0.006
<i># of Donation Relationships</i>	-0.268***	0.006	-0.263***	0.006	-0.306***	0.006	-0.298***	0.006
<i>Network Density (project)</i>	0.130***	0.038	0.126***	0.038	0.129***	0.037	0.125***	0.037
<i>#PlatformProjects</i>	-0.225***	0.008	-0.220***	0.008	-0.201***	0.008	-0.200***	0.008
<i>#PlatformProjects(same zip code)</i>	0.551***	0.006	0.550***	0.006	0.530***	0.006	0.529***	0.006
<i>Project Description Length</i>			-1.709***	0.361	-1.185***	0.366	-1.196***	0.366
<i>Average Characters per Word</i>			0.472***	0.150	0.464***	0.152	0.464***	0.152
<i>Text Familiarity</i>			-0.066***	0.012	-0.070***	0.012	-0.070***	0.012
<i>Text Concreteness</i>			0.033***	0.012	0.032***	0.012	0.032***	0.012
<i>Text Flesch-Kincaid Readability</i>			0.559***	0.102	0.416***	0.103	0.419***	0.103
<i>Text Valence</i>			-0.028***	0.006	-0.026***	0.006	-0.026***	0.006
<i>Text Extremity</i>			-0.006	0.005	-0.006	0.005	-0.006	0.005
<i>Text Emotionality</i>			0.003	0.005	0.003	0.005	0.003	0.005
<i>Project Description(social)</i>			0.012	0.017	0.023	0.017	0.022	0.017
<i>Project Description(achieve and reward)</i>			0.228***	0.012	0.197***	0.012	0.197***	0.012
<i>Project Description(punctuation)</i>			0.001	0.011	-0.002	0.011	-0.002	0.011

<i>Project Description(informal)</i>			0.005	0.011	0.003	0.011	0.003	0.011
<i>Project Description(risk)</i>			-0.043***	0.011	-0.044***	0.011	-0.044***	0.011
<i>Project Description(spelling)</i>			-0.156***	0.012	-0.179***	0.012	-0.179***	0.012
Constant	11.442***	1.564	20.113***	2.757	17.143***	2.787	17.204***	2.788
Observations	465,530		465,530		465,530		465,530	
Pseudo R2	0.1522		0.1556		0.1609		0.1612	
Log-likelihood	-154399.51		-153784.23		-152815.1		-152763.8	
			M2 v.s. M1		M3 v.s. M2		M4 v.s. M3	
LR $\chi^2$			1230.56 (p<0.01)		1938.27 (P<0.01)		102.60 (p<0.01)	
Resource type fixed effects	YES		YES		YES		YES	
Project subject fixed effects	YES		YES		YES		YES	
Year-quarter fixed effects	YES		YES		YES		YES	
School state fixed effects	YES		YES		YES		YES	
Grade-level fixed effects	YES		YES		YES		YES	
School Type Fixed Effects	YES		YES		YES		YES	

**Note:** The first column (M1) reports coefficients and standard errors from a logit regression of *Funding* on the teacher, school, project, social network, and platform level information. The second column (M2) estimates the same model but adds project description information. The third column (M3) estimates the same model as M2 but adds *Having Self-donation*. The fourth column (M4) estimates the same model as M3 but adds an interaction term between *Having Self-donation* and  $\times \#$  of *Completed Projects*. Table 1 provides variable definitions. \*\*\*, \*\*, and \* indicate statistical significance at the 1%, 5%, and 10% levels from two-tailed tests, respectively. The sample includes 465,530 projects.

**Table WG3. Effects of Self-Donations on Having Impact Letter (Corresponding to Table 5 in Main Paper)**

Variables	No Selection Correction		Selection Correction with Heckprobit Model			
			Outcome Equation		Selection Equation	
	Coeffs	SE	Coeffs	SE	Coeffs	SE
<i>Having Self-donation</i>	0.972***	0.008	0.563***	0.005	0.202***	0.006
<i>Teacher Gender(female)</i>	0.105***	0.013	0.044***	0.007	-0.113***	0.009
<i># of Completed Projects So Far</i>	2.204***	0.009	1.100***	0.004	0.0139***	0.001
<i>Poverty(highest)</i>	-0.090***	0.025	-0.042***	0.014	0.031*	0.016
<i>Poverty(high)</i>	-0.044*	0.026	-0.030**	0.015	-0.055***	0.016
<i>Poverty(moderate)</i>	0.034	0.026	0.022	0.015	-0.006	0.017
<i>Reached Students</i>	-0.005	0.005	-0.004	0.003	-0.015***	0.003
<i>Corporate Matching</i>	0.390***	0.009	0.260***	0.005	0.416***	0.006
<i>Home Double</i>	-0.096***	0.018	0.007	0.010	0.589***	0.014
<i>Requested Amount (log)</i>	0.263***	0.007	0.054***	0.005	-0.642***	0.005
<i>Project Description Length</i>	-4.178***	0.334	-2.443***	0.188	-1.137***	0.201
<i>Average Characters per Word</i>	-0.314**	0.135	-0.117	0.076	0.162**	0.082
<i>Text Familiarity</i>	0.058***	0.010	0.030***	0.006	-0.031***	0.006
<i>Text Concreteness</i>	-0.019**	0.010	-0.011**	0.006	0.012**	0.006
<i>Text Flesch-Kincaid Readability</i>	1.291***	0.094	0.758***	0.053	0.368***	0.056
<i>Text Valence</i>	-0.022***	0.005	-0.014***	0.003	-0.016***	0.003
<i>Text Extremity</i>	-0.001	0.004	-0.000	0.002	-0.004	0.003
<i>Text Emotionality</i>	-0.005	0.004	-0.002	0.003	0.002	0.003
<i>Project Description(achieve and reward)</i>	0.010***	0.001	0.007***	0.001	0.010***	0.001
<i>Project Description(social)</i>	0.037***	0.014	0.021***	0.008	0.018*	0.009
<i>Project Description(punctuation)</i>	-0.031***	0.009	-0.019***	0.005	-0.008	0.006
<i>Project Description(informal)</i>	0.006	0.009	0.002	0.005	0.002	0.006
<i>Project Description(risk)</i>	0.027***	0.009	0.013**	0.005	-0.023***	0.006
<i>Text Description(spelling errors)</i>	-0.049***	0.011	-0.043***	0.006	-0.109***	0.007
<i>Equity Focus</i>	-0.031**	0.016	-0.013	0.009	0.027***	0.010
<i># of Co-donations</i>					0.222***	0.003

<i># of Donation Relationships</i>					-0.166***	0.003
<i>Network Density (project)</i>					0.019	0.020
<i>#PlatformProjects</i>					-0.115***	0.004
<i>#PlatformProjects(same zip code)</i>					0.270***	0.003
<i>Rho</i>					0.579***	0.018
Constant	19.653***	2.438	11.890***	1.353	11.776***	1.511
Observations	403,820		403,820		465,530	
Pseudo R2	0.306			n/a		
Log-likelihood	-193634.39			-348345.31		
Resource type fixed effects	YES		YES		YES	
Project subject fixed effects	YES		YES		YES	
Year-quarter fixed effects	YES		YES		YES	
School state fixed effects	YES		YES		YES	
Grade-level fixed effects	YES		YES		YES	
School-type fixed effects	YES		YES		YES	

**Note:** The first column reports coefficients and standard errors from a logistic regression of *Impact Letter on Having Self-donation*, platform, project, teacher, and school levels of information. The sample includes 403,802 projects. The last two columns report coefficients and standard errors from a Heckprobit regression. Outcome equation refers to the analyzed sample of 403,820 successfully funded projects. Selection equation refers to the sample of 465,530 projects which were either successful or failed to raise requested amount. The exclusion restriction used in the selection equation is *# of Co-donations, # of Donation Relationships, Network Density (project), #PlatformProjects* and *#PlatformProjects(same zip code)*. Value of *Rho* is statistically significant ( $p < 0.01$ ) and shows the existence of selection, justifying the use of Heckman selection correction technique. Table 1 provides variable definitions. \*\*\* indicates statistical significance at the 1% level from two-tailed tests. All estimations include resource type, project subject, school state, school grade and type, and project year-quarter fixed effects.

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