THE SUBSTITUTION EFFECT OF MATCHES

An Undergraduate Research Scholars Thesis

by

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ABSTRACT

The Substitution Effect of Matches. (May 2014)

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My research will try to determine if there is a substitution effect among charities specifically, when a charity introduces a match to bring in more money does the match actually bring in more money from donors who would not have made a donation to charity or does it shift money that would have been donated to a different charity that would have been funded to itself. The purpose of a matching scheme is to bring in new dollars that would not have been donated to the charity. However, if the substitution effect occurs and is statistically significant then the efficiency of matching schemes would be questioned because rather than bring in new money from donors by shifting the amount of money that would have been donated, the overall amount of donations in the charity ecosystem remains unchanged.

CHAPTER I

INTRODUCTION

This paper will be a continuation of my previous undergraduate research from last year. I had 3 main questions.

1. Does the presence of a match increase the likelihood of a project getting funded?
2. Conditional on getting funded, do matches bring in more money
3. Is there a substitution effect among matches i.e. does a match truly brings in more money or just shifts money from projects that would have been funded.

Most of the previous literature on the subject focused on the effect that matches had on the amount of money received by the charitable organization. Karlan, List (2008) examined the effect that different matching ratios had on the amount of money received. They examined 3 different ratios 1:1, 2:1, 3:1 where one, two and three dollars are given respectively for each dollar contributed by the solicited donors. They found that contrary to current fundraising practices, the larger ratios had no additional impact over the smaller ratios in terms of money raised. They also found out that the presence of a lead gift was more impactful than matching systems in terms of overall money raised. Huck and Rasul (2010) who thoroughly review the existing literature on both linear matching schemes and the presence of lead donors uses data from a field experiment, suggest that the presence of a lead donor signals the quality of the project and is one of the main reasons it is more efficient than a linear matching scheme. Their results also show that although the number of donations received rises when linear matching schemes are implemented, the amount given falls by a larger percentage resulting in reduced overall donations. They find that non-linear matching schemes that require a minimum donation to be given before they are matched–can be profitable in that they cause donations received to be crowded in with little or no change in the overall proportion of recipients that donate in the first place. Fourth, leveraged matching schemes–which match donations by a fixed amount irrespective of the donation given–are ineffective as they lead to an almost full crowding out of donations given so that the project overall receives the same net contribution.

One recent empirical paper (Reinstein 2011) evaluates competition between charitable sectors using survey data and concludes that donors may substitute between charitable sectors following a temporary shock (i.e., a natural disaster or other event that increases the funding need in particular sector).

The field experiments above have examined only one charitable cause each. The effect that a certain match has on similar causes across different time periods has not been examined due to the nature of the experiments performed in previous studies.

We obtained data from DonorsChoose, an online fundraising platform for public school teachers that acts as an intermediary between teachers across the United States who need funding and the donors. The data consists of aggregate data of the projects (each project corresponds to a certain teacher that needs funding), matches and donations from 2007 to 2012.

I managed to answer the first two questions and the results were similar to the previous literature on the topic. I was unable to answer the third and most interesting question due to time and data constraints.

The data from DonorsChoose comes in 3 main files the donations data, the project data and the match data. DonorsChoose works as follows if a teacher in a (usually poor) school needs books, supplies or even money for a field trip they can post a request detailing why they need the money as well as information on the students. This requests are the projects. Anyone using DonorsChoose can donate to any project and all the donations made are contained in the donations file.

This information is contained in the matches file. Each project has a descriptor of whether it was matched as well as the type of match. In order to answer the third question I had to merge all three files in order to determine which projects met the matching criteria but were not matched. These "similar projects" will be the control group. We will then compare the money flow into these projects to the ones that got matched. This comparison will form the basis of our insight into substitution.

If a certain type of projects has a certain type of criteria we can see how much any project that met the criteria is expected to receive on average. The substitution effect comes into play if a project meeting certain criteria is matched and one that meets the same criteria is not matched. Since we know on average how much a project meeting those criteria receives if the amount of money flowing into the matched project increases while the one flowing into the unmatched project decrease when the overall amount of donations in the whole system remains constant then it is fair to conclude that the match drew funds away from a project that would have been donated to and in fact matches just shift money overall and do not create new money.

CHAPTER II

METHODS

We obtained 3 data sets from DonorsChoose: a projects data set, a donations data set and a matching data set. The data sets contained data covering a 10 year period from 2003 to 2012. The projects data set consisted of an observation for each project in the 10 year period, the project's characteristics (such as location, subject and grade level), whether the project was matched and the start and end dates for when the project was live (when donors could donate to that project). Originally we started with 438,234 observations. We dropped 36,452 from 2002 to 2006 because the data from those years contained incomplete information regarding the project characteristics. We dropped a further 14 observations because they contained negative project costs and we dropped 1 more observation because it took -1 days to fund. We ended up with 401,677 observations.

The donations data set consisted of an observation for each donation made in the 10 year period, its characteristics (amount, cash/credit card and donor location) and the day on which the donation was made. We dropped 32,459 observations from the data set because we had dropped the projects which the donations were made to in the projects data set. We ended up with 1,770,254 donations.

The matching data set consisted of an observation for each match from 2008 to 2012, its characteristics and a start and end period for which the match was live. We had 1,303 matches, each of which could potentially have had numerous projects which met its characteristics. For example, if corporation A matches high school math classes in Texas for March 2012, any high school math class in Texas, in March 2012 was eligible. However, meeting all the eligibility requirements does not guarantee that a certain project will be matched. DonorsChoose decides which eligible matches will actually get matched. DonorsChoose implements two types of matches:

1. Double Your Impact: A 1:1 linear matching scheme in which the corporate or foundation partner donates one dollar for every dollar donated by the public.
2. Almost Home: A matching scheme in which the corporate or foundation partner donates the last $100 of an almost funded project.

Our key variable was the flow of money into the projects i.e. how much each project receives each day it is live. We needed to know the exact dates that projects were matched so we could accurately compare the effect of matches. The match dates that DonorsChoose availed to us were not accurate but were more of an indicator. In order to get the proper matching dates I had to use the donation data. There were numerous donation types in the donation data ranging from cash, check, credit card to matches. In order to isolate the match dates we only used donations that were double your impact donations or almost home donations. Typically most foundation partners have 1-4 matches. Isolating match dates for foundation partners with only one match was simple, I used the first donation as the start date of the match and the last donation made by the foundation partner as the end date. In the cases where foundation partners contributed to more than one match, I treated a gap of more than a month between donations as donations made for different matches with the date before a gap as the end of a match and the date after the gap as the beginning of the subsequent match. I then compared my extracted dates to the rough dates given by DonorsChoose and after removing the outliers the extracted matched occurred within a couple of days to weeks of the rough dates but were likely to be more accurate.

We also needed to know which matches a project was eligible for in order to compare the effect that the match had on 2 similar projects that were eligible to be matched only one of which was matched. The projects data file had all the characteristics of each project and I merged it to the matches data file which had all the characteristic of each match. I then compared all the match data to the project data in order to find projects that had met a certain match criteria but were not matched.

We were then able to create a project day panel which contained 32,283,616 observations. Each observation in the panel represented a single day fore each project in our data set for the duration of the project length. It also contained the money that was received on each day, whether the project was matched or not and the amount of competing projects.

When a teacher posts a project on DonorsChoose, they have to take a picture of the students that will be affected and tell their story by discussing the great need of the students and how a successful project would impact the students. These factors obviously have an effect on the donations received but it would be impractical if not impossible to try and discern the difference between pictures or how one teacher's story is more moving or impactful than another's. To that end we used a fixed effects model for our regression. We assume that the unobserved heterogeneity in terms of pictures and teachers message is constant over time and is correlated with our observed variables in the data set. Using a fix effects model allows us to control for those variables.

However, we realized that using a fixed effects model resulted in not having variation between projects because we had controlled for that but in order to get an accurate measurement of the effects of the matches we needed to use an ordinary least squares method.

Our regressions were the same as those above however we added teacher and project effects.

Amount received per day= $\beta 1$ Log project length + $\beta 2$ was donation matched + $\beta 3$ date effects + $\beta 4$ number of projects live + $\beta 5$ number of matches live+ $\beta 6$ teacher effects + $\beta 7$ project effects+ εi

Probability donation was made= $\beta 1$ Log project length + $\beta 2$ was donation matched + $\beta 3$ date effects +$\beta 4$ number of projects live + $\beta 5$ number of matches live+ $\beta 6$ teacher effects + $\beta 7$ project effects+ εi

Teacher effects consisted of information on different organizations the teacher was in i.e. Teach for America and Kipp. It also included whether it was a teachers first project. Project effects consisted of state and subject information. We run both models with variations for state and subject effects which accounted for what we originally tried to do with the fixed effects. The results are shown in Tables 1 & 2.

For the OLS regressions we also created a variable that counted the number of matches a project would have been eligible in the past 30 days. This was done in order to see the effect a match expiring had on a project that would have been eligible for it. By our hypothesis the effect would be negative because once the match for a given subset of project expires, donors tend to donate to another matched project.

We created a variable called other match ratio which we defined as the ratio of matched projects to the total number of projects this is our competition variable, the higher it is the more competition a project faces.

CHAPTER III

RESULTS

In Table 1 we examined the effect of our variables of interest on the probability of getting funded. The length of a project was shown to have a negative and significant effect on getting funded. Projects that last longer tend to do so because they are not funded. A project lasts until it is funded or expires without getting funded. It seems to reason that the longer a project lasts the less likely it will be funded due to new projects and matched that are created every day competing for a limited amount of dollars. A donation getting matched was shown to have a small positive but significant effect confirming previous literature. The other match ratio was found to be negative which confirms our hypothesis that completion from matches draws money from other projects. However when state and subject effects were included the ratio was found to be positive.

In Table 2, the results were similar for project length. However in both regression getting matched resulted in receiving less money which confirms previous literature, matches bring in more donors but a lower amount per donor. Without state and subject effects if matches occurred within a 30 day period before the period was posted, the project was likely to receive less money which confirms our hypothesis. When a match ends all the donors who contributed to that match crowd to another match. Any project that meets the previous criteria is unmatched and unlikely to receive as much as when it was matched. However this effect is negative and significant when state and subject effects are accounted for. The other match ratio variable was negative and significant which implies that a higher amount of competition reduces the amount given to a project.

CHAPTER IV

CONCLUSION

This paper use data from DonorsChoose to estimate the effect of matches on donations. The results suggest that there intertemporal substitution occurs and that matches tend to draw away funds from projects rather than create new funds.

Our R^2 value was low which suggests there are other factors we have yet to account for in order to explain the amount of money received by a project. Including state and subject effects affected some of our variables of interest in unlikely ways flipping the sign on some of them.

The research is not complete areas we could look in further include using a probit model for estimating the likelihood of receiving a donation and separating the almost home and double your impact matches.

TABLES

Table 1

Probability of Receiving donation

	No state and subject effects	With state and subject effects
Project length	-0.013***	-0.013***
	(0.00)	(0.00)
Donation was matched	0.008***	0.006***
	(0.00)	(0.00)
othermatch ratio	-0.003**	
	(0.00)	
ratio of eligible matches past 30 days	0.062***	
	(0.00)	
Teachers First Project	0.001***	0.001***
other match ratio with state and subject effects		0.003***
		(0.00)
eligible ratio past 30 with state and subject	0.015***	
	(0.00)	
constant	0.085***	0.086***
	(0.00)	(0.00)
R^2	0.022	0.022
Degrees of Freedom	369947	369945
BIC	-2.2e+07	-2.2e+07

* p<0.05, ** p<0.01, *** p<0.001

Table 2

Amount Received per day

	No state and subject effects	With state and subject effect:
Project Length	-0.035***	-0.035***
	(0.00)	(0.00)
Donation was matched	-0.060***	-0.083***
	(0.01)	(0.01)
othermatch ratio	-0.223***	
	(0.03)	
ratio of eligible matches past 30 days	-0.323*** (0.05)	
Teachers First Project	0.059***	0.058***
	(0.00)	(0.00)
other match ratio with state and subject effects		-0.003 (0.02)
eligible ratio past 30 with state and subject		0.125*** (0.02)
constant	4.478***	4.488***
	(0.04)	(0.04)
R^2	0.062	0.062
Degrees of Freedom	269370	269366
BIC	2669848.0	2669869.3

* p<0.05, ** p<0.01, *** p<0.001

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