Fundraising on the Internet

Martin Bøg, Heike Harmgart, Steffen Huck, and Abra Marie Jeffers*

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Abstract

We take a first step towards analysing fundraising on the internet. Internet fundraising allows for the possibility of instantaneous feedback on campaign progress. Analysing data from a large number of small scale internet fundraising campaigns we show that the rich feed-back information provided to donors alters subsequent donor behaviour. In particular, early donors set a precedent for later donors.

1 Introduction

In most respects fundraising campaigns on the internet are just like traditional fundraising campaigns. Adressees have to be selected, the aim of the campaign has to be explained, a target might be set, perhaps rewards or forms of recognition are offered. However, there is one notable exception: The internet technology allow the fundraiser the possibility of giving continual and basically costless feedback for donors and potential donors about the progress of the campaign. In this paper we analyse data from a large number of small-scale personal internet fundraising campaigns that do provide such constant feedback on what the campaigns have achieved so far. Our analysis shows, providing feedback fundamentally alters the behavior of donors.

Feedback information in the campaigns studied here is very rich. In fact, next to some summary statistics, all individual donations so far are shown in chronological order. The potential donor who reacts to an invititation to contribute to the campaign has very little choice: The information about past donors is immediately displayed on the campaign's homepage and very difficult to ignore.

We show that the presence of this feedback information induces a particular pattern in the data that cannot be explained by the canonical model of

*The first three authors are all at University College London. The fourth author is at Michigan State. Correspondence to Steffen Huck, Department of Economics & ELSE, University College London, Gower Street, London WC1E 6BT, United Kingdom, Email *s.huck@ucl.ac.uk*.

giving. Perhaps most importantly we provide evidence that, with feedback about individual donations, early donors indeed establish a benchmark for later donors. In particular, we find that later donors tend not to donate more but often less than early donors. The modal donation early on in a campaign provides an upper bound for the modal donation in the entire campaign. We also find that the strength of the early mode (that is how often it has been chosen) is an important determinant for a campaign's success. We also find that the strength of the early mode (that is how often it has been chosen) is an important determinant of a campaign's success.

We observe strong clustering in the data (many donors tend to give identical amounts and modes are often chosen half of the time). Since donors to a campaign on justgiving.com predominantly know the fundraiser personally, as a first pass this clustering can be explained by the fact that the potential donors incomes are correlated with the fundraiser's income. Our main observation however is that the distribution of modal donations from early and late donors are not identical, thus the clustering cannot be explained solely through a model where donor donations are clustered around the income of the fundraiser and arrive randomly to the site. Instead the size of donations are determined by precedent. This suggests that what we observe is driven by social interactions—a phenomenon not yet modelled in the economics literature on philantropy (see, for example, Andreoni's survey (2006)).[1]

In the experimental economics literature there is persuasive evidence on the importance of feedback information, in particular, there are studies that show that with sufficient information about the choices of others in the past many subjects start to *imitate* (see, for example, Apesteguia et al. 2006)—a different, but related phenomenon since in both cases the provision of feedback encourages comparisons between own (planned) choices and the choices of others—an effect not predicted by orthodox economic theory. Another related phenomenon is that of conditional cooperation frequently observed in sequential dilemma games or repeated public good games. In the latter, for example, first-round contributions also induce an upper bound for later rounds (see, for example, Fischbacher et al. 2001).

There is also a small empirical literature emerging on the economics of fundraising, so far an under-researched sector of the economy. Notably, List and others have broken the mould for very powerful field experiments on the matter (see, for example, List and Lucking-Reiley (2002), Landry *et al.* (2006), or Falk (2005)). Closest related to our note here is Frey and Meier

[1]There are various models that if applied to giving behavior would generate such effects: social preferences (see, for example, Fehr and Schmidt 1999), preferences for conformity (Bernheim 1994), peer pressure (as modelled, for example, by Kandel and Lazear 1992) or social norms (as in Lindberg, Nyberg, and Weibull 1999 or Kubler 2001). Huck and Kubler (2000) study a model of charitable giving where donors are prone to social pressure.

(2004) who show that students from Zurich are more likely to contribute to funds for poor peers if told that previous cohorts have contributed more. However the feedback provided there is historical and static. Our paper is the first that examines feedback in ongoing fundraising campaigns.

2 The Data

Our data is drawn from the British arm of Justgiving.com, an internet platform that provides members of the public with an easy tool to create their own fundraising page. With a few mouse clicks and some very limited typing, everybody can create a fundraising webpage. Each webpage has its own title; may contain a personal message; always specifies a charity that is to benefit from the campaign;[2] may specify a fundraising target; and may inform about offline fundraising activities. Each campaign homepage informs in a table about all donations so far. For each donation there is information about the name of the donor (which may be anonymous)[3], the date of the donation, the amount, and the tax bonus (if the donor is a UK tax payer).[4]

The fundraising campaigns on Justgiving are typically of a personal nature: People collect money for charities in memory of deceased family members, or because they have families or friends who suffer from certain diseases, etc. Fundraisers on Justgiving typically solicit family, friends, work colleagues, etc. for donations.[5] Justgiving itself does not provide the fundraiser with a list of potential donors. In other words the fundraiser knows almost all of her donors personally.

We searched the British Justgiving website in June 2005 for all campaigns that mentioned "cancer" in their campaign's title. We selected "cancer" as a search term as it generated the biggest number of hits and made sure that the objectives of the observed campaigns were fairly similar. In all, we found 365 campaigns where at least one donation had been made on or before the collection date.[6] For each of the 365 campaigns we collected the following information: name of the fundraiser, chosen charity of the fundraiser, target for the fundraising campaign (TARGET), duration of the campaign (DUR), sum raised online (ONL), sum of gift aid (GIFT), sum raised offline (OFF), total sum donated (TSUM), total number of donations

[2]Donations made via Justgiving go indeed directly to the charities (and not to the fundraiser), with Justgiving taking a 5% cut.

[3]Approximately 15% of donations are anonymous. The fundraiser knows the identity of anonymous donors.

[4]Under British tax laws, charitable donations are tax free with some of the tax relief not being paid back to the donor but rather transferred the charity that received the donation.

[5]This can easily be observed from the nature of the comments that are given by donors to the fundraiser.

[6]In all our search for the keyword "cancer" had 462 hits, i.e. 97 campaigns had no contributions at all at the date when we collected the data.

(NDON), modal donation for the entire campaign (MOD), number of modal donations for the entire campaign(NMOD). Since we are interested in seeing how early donor behavior affects the behavior of later donors we also collected the following information: number of donations during the first two days of the campaign (NDON2), total raised during first two days (TDON2), modal donation during first two days (MOD2), number of modal donations during first two days (NMOD2).

Identifying the modal donation over the entire (recorded) campaign (MOD) and for the first two days of the campaign (MOD2) presents two problems. First, if no donation appears more than once we code the mode as missing (except when there was a single donation). This accounts for the 62 missing values for the variable MOD2. Second, for 51 campaigns the mode is not unique. We address this by creating two datasets. The first dataset is referred to as the *minmaxed* data. In this dataset observations that do not have unique modes for either the early mode or the late mode, or both are recoded in the following way. Among the possible modal values for MOD2 we pick the *minimal* value, and among the possible modal values for the entire campaign, MOD, we pick the *maximal* value. The second dataset is constructed at the other extreme and is referred to as the *maxmined* dataset. There we pick the *maximal* value for MOD2 and the minimal value for MOD where appropriate. We consider the *minmaxed* dataset to be the most conservative construction. To further underscore the conservativeness, note that as mentioned above there are 51 observations with multiple modes for MOD2 and/or MOD. For this subsample the mean of MOD2 is 17.5 (compared to 25.2 for the unadjusted part of the sample) and 27.3 for MOD (18.6 for the unadjusted sample).

The *minmaxed* dataset forms the basis for our analysis. However looking at the *maxmined* dataset allow us to bound the effects we identify.

3 Data Analysis

In this section we take a closer look at the data. The data we have collected provide a snapshot taken on a particular date.[7] Table 1 offers some summary statistics for our data.

The median target is £1,000. Not all fund raisers set targets, however a large majority does: 312 out of 365. The median duration of a campaign in our sample is 33 days, but note that our sample includes campaigns which have not finished. The median amount raised online is £210, which suggests that most campaigns are relatively small scale. Again, the median for a completed project is likely to be above £210. Some projects have a considerable amount of offline contributions. Although the median is 0,

[7]Consequently, we are picking up campaigns that are finished, campaigns which are ongoing and campaigns which have just begun.

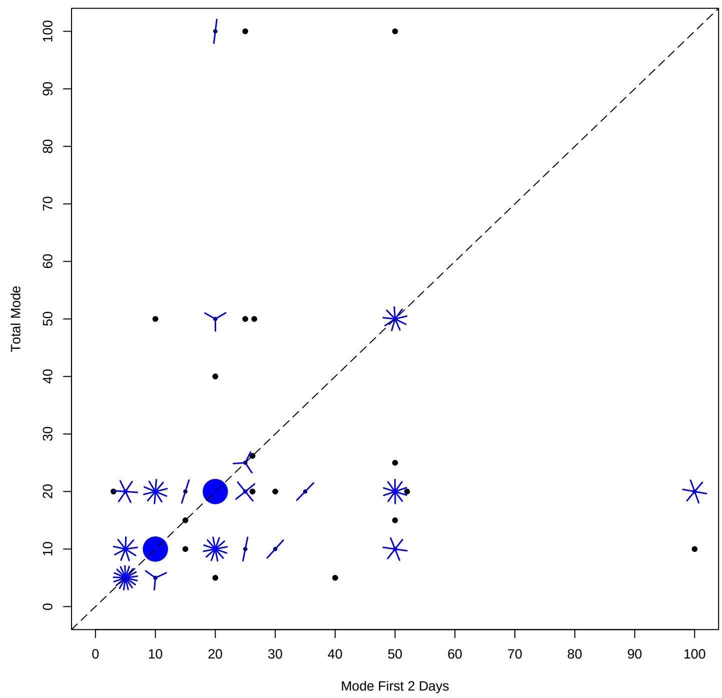
the mean amount raised offline is £681. The median project raised £410 (including gift aid). The median number of donations was 12, and the median number of donations during the first two days of a campaign was 2, raising a median amount of £45.

Table 1: Summary Statistics

Variable	TARGET	DUR	ONL	OFF	TSUM	NDON	NDON2	TDON2	MOD2	NMOD2	MOD	NMOD
Mean	2,697.5	51.5	867.1	680.5	1,718.7	20.1	3.79	126.2	24.0	2.40	19.9	8.41
Median	1,000	33	210	0	410	12	2	45	20	2	20	5
Std.	12,696.4	61.5	5,786.3	4,463.4	11,038	41.9	4.9	636.5	44.6	2.25	38.4	11.9
Max	200,000	550	105,334	78,480	205,229	703	44	11,815	675	18	675	157
Min	50	0	5	0	6.41	1	1	4	3	1	5	1
Obs.	312	365	365	365	365	365	365	365	303	303	341	341

Note: *Minmaxed* dataset.

Figure 1: Sunflower Plot



3.1 Transition Matrix

In order to find out whether there is any impact of the rich feedback information that Justgiving provides by default we examine the impact of what happens during the first two days of the campaign on the campaign's overall success. A first look at the joint distribution of the early and late modal donation is presented in figure 1. The *sunflowerplot* shows the joint distribution of the mode during the first two days (MOD2) and the mode during the entire (recorded) campaign (MOD). The more petals in a flower the higher the density.[8] The total number of observations is 253, which includes all observations with non-missing values for MOD2 and MOD and where there are recorded donations after the first two days.

What happens to the modal donation over time? In table 2 we have noted the probability that the mode observed during the first two days is mapped into other modal outcomes. In total the matrix comprises 253 observations for which we are able to observe the mode during the first two

[8]Two observations are excluded from the plot, which had a mode for the first two days above 100, in order to facilitate the display of the bulk of the data.

days and the total mode, and there is at least one donation after the second day of the campaign start.

Table 2: Modal Transition Matrix

	Modal Donation Entire Campaign (MOD)									Obs.
MOD2	5	10	15	20	25	26.2	40	50	100	
3				1.00						1
5	.53	.28		.19						32
10	.04	.82		.13				.01		76
15		.25	.25	.50						4
20	.01	.15		.77			.01	.04	.02	82
25		.18		.36	.27			.09	.09	11
26.2				.50		.50				2
26.5								1.00		1
30		.67		.33						3
35				1.00						2
40	1.00									1
50		.21	.04	.36	.04			.32	.04	28
52				1.00						1
100		.14		.86						7
150				1.00						1
200								1.00		1
Obs.	22	95	2	108	4	1	1	16	4	253

Note: *Minmaxed* dataset.

The table is very suggestive: 15.4% of the observations are placed above the diagonal; 61.7% of the observations are placed on the diagonal, and the remaining 22.9% are placed below the diagonal. We are interested in the question whether the modal donation during and after the first two days are drawn from the same distribution. In total there are 97 off diagonal observations, 58 of which are below the diagonal. A one-sided binomial test rejects the hypothesis at the 5% level ($p < .0335$) that the off diagonal elements are evenly distributed above and below the diagonal. This is suggestive evidence that what happens early on provides an upper bound for what will happen overall. Notice also that increases in the mode are typically only observed for very low initial modes (£5) or "strange" modes (£26.50).[9]

Recall that the above analysis is performed on the *minmaxed* dataset, as such the reported p-value can be interpreted as an upper bound. We construct the lower bound on the p-value by recoding the observations with multiple modes such that MOD2 is set to it's *maximal* value, and MOD is set to its minimal value. This yields the following transition matrix:

[9]If the reader wonders why £26.20 occur as a mode (actually, more than once)— this is precisely the length of a marathon in miles.

Table 3: Modal Transition Matrix

MOD2	Modal Donation Entire Campaign (MOD) 3	5	10	15	20	25	26.2	40	50	100	Obs.
3	1.00										1
5		.70	.19		.11						27
10		.07	.88		.04				.01		72
15			.25	.25	.50						4
20		.05	.21		.71			.01	.01	.01	87
25			.33		.33	.33					9
26.2			.50				.50				2
26.5									1.00		1
30			.67		.33						3
35					1.00						2
40		1.00									1
50		.03	.22	.06	.41	.03			.22	.03	32
52					1.00						1
100			.22		.88						9
150					1.00						1
200									1.00		1
Obs.	1	30	102	3	98	4	1	1	11	2	253

Note: *Maxmined* dataset.

In the *maxmined* transition matrix 19 observations lie above the diagonal, whereas 77 observations lie below. The hypothesis that the off-diagonal elements are evenly distributed above and below is now strongly rejected ($p < 0.0001$).

The two main findings revealed by this simple analysis are summarized in the following

Observation 1 Late modal donations tend to match the early modal donation.

Observation 2 If the modal donation shifts in time it almost always shifts to a smaller amount.

3.2 Regression Analysis

The transition matrices strongly indicate that early donor behaviour affects behaviour later on in the campaign. In this section we take a closer look at what determines the dynamics of a campaign. We run regressions with controls to better understand what determines whether the modal donation goes up, down or remains the same over the entire campaign relative to the beginning of the campaign. The regressions confirm what we found above: the strong precedent set by early donors, even when we control for observed heterogeneity. In addition, the regressions reveals forces which strengthen or weaken this precedent.

We focus the analysis on the *minmaxed* dataset.[10]

Probit Regressions As a first step and building on the insights of the transitions matrices we fit a probit regression to our data. We are particularly interested in identifying the determinants of whether the mode for the campaign goes down or remains equal to the mode during the first two days. Consider the binary random variable, Y, which takes the value 1 if the mode goes down, and 0 otherwise. We fit the following regression:

$$\Pr(Y = 1|X) = \Phi(\beta' X)$$

where Φ is the normal CDF, X is a vector of controls and β the vector of coefficients.

We are particularly interested in whether the degree to which an early mode is focal that is the frequency with which the early mode appears in the donation history, the *strength* of the mode, has an effect on the probability that mode goes down. We therefore include MOD2 and its square,

[10] We have also estimated the same models using the *maxmined* dataset. Not much new insight is gained from this however. There are no sign changes and the change in coefficients are always as expected from the way the data set is constructed. Also, to avoid outlier problems we drop 4 observations. These are observations with a target greater than £15,000 and with a mode greater than £100.

Table 4: Probit Regression

Variable	Marginal Effects
MOD2	0.0150815***
	(0.0035331)
DTAR	0.2078309*
	(0.1206802)
TARGET	0.0342588
	(0.0431363)
TDON	0.005558***
	(0.0013425)
NMOD2	-0.044146***
	(0.0137355)
MOD2×NMOD2	-0.0046028***
	(0.00155504)
Pseudo R^2	.452
No. Observations	249

Notes: Minmaxed data set. Robust Standard Errors in parenthesis. ***,**, *: significant at 1%, 5%, 10%. Marginal effects calculated at sample means using delta-method in STATA, where appropriate.

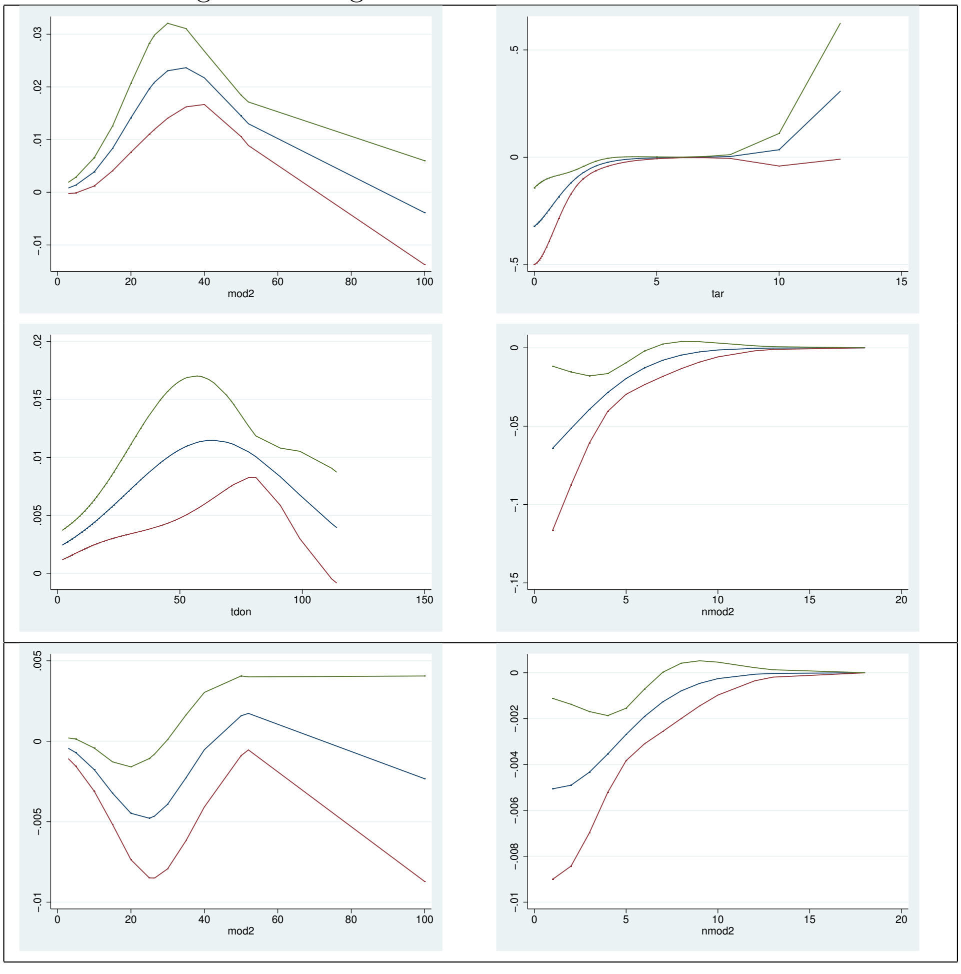
the number of modal donations on the first two days, NMOD2, as well as an interaction term between the modal donation in the first two days and the number of modal donations in the first two days, MOD2×NMOD2. As controls we include the campaign target (in thousands), TARGET, and its square as well as a dummy variable, DTAR, which takes the value 1 if the target is missing and 0 otherwise. We also use the total number of donations TDON.

In table 4 marginal effects (computed at the sample means) are reported. Notice that we do not handle the squared terms as separate variables, rather these terms are treated as interactions (e.g. Ai and Norton (2003)). In figure 2 we plot estimates for the marginal effects computed across the entire support of respective variables. Since the model is non-linear the marginal effect depends upon where they evaluated. The figure also shows 95% confidence intervals for the estimates.

The marginal effect of MOD2 is, as expected from the transition matrix, significantly positive. The number of modal donations during the first two days, NMOD2, is significantly negative. That is the more modal donations there are in the first two days, the less likely that the mode drops. Finally, the interaction term between MOD2 and NMOD2 is significantly negative. This effect is the cross derivative of MOD2 and NMOD2 on the dependent variable, and tells us that the marginal effect of MOD2 is decreasing in NMOD2, and vice versa. We summarize this in the following observation:

Observation 3 The more frequent (and, hence, stronger) an early mode, the less likely it is to fall.

Figure 2: Marginal Effects and Interaction Effect

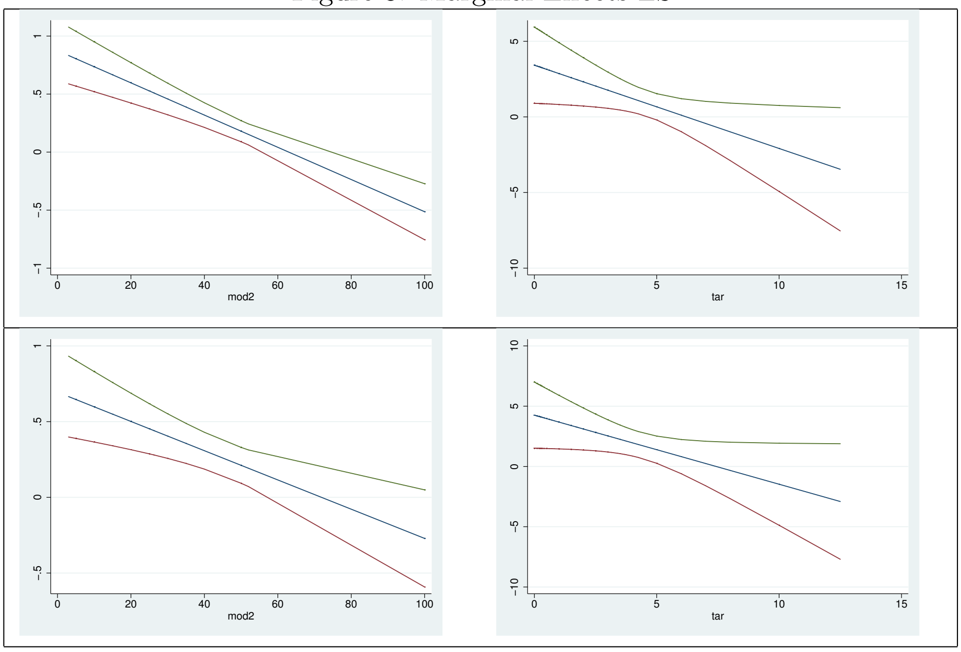


Note: Minmaxed Dataset. First four panels are marginal effects. Last two panels shows interaction effect MOD2×NMOD2 varying one variable while the other one is fixed on the sample mean. Blue line is the point estimate. 95% confidence intervals also drawn.

Least Squares In this section we present results of LS regressions on our data. The modal donation for the entire campaign, MOD, is the dependent variable. The regressors are identical to those used in the probit regression.

Table 5 contains the regression results of two different regressions. The first regression is an unweighted regression in which every campaign receives equal weight. The second regression is a weighted regression, in which each campaign receives weight in proportion to the total number of donations, TDON, the campaign received. We do this for two reasons. First, for larger campaigns the estimate of the modal donation is more likely to be precise, nevertheless smaller campaigns also contain information. There is, of course, also a simple economic justification for our weighting scheme. The weighted regression place more weight on campaigns that are likely to have raised a significant amounts of donations. Figure 3 plots the marginal effects for the variables that enter squared in our regressions across the full support of the variables.

Figure 3: Marginal Effects LS



Note: Minmaxed dataset. Top panel: OLS estimation, Bottom Panel: WLS estimation. Blue line is the point estimate. 95% confidence intervals also drawn.

Table 5: LS Regressions

Variable	Marginal Effects OLS	WLS
MOD2	0.585805***	0.4935825***
	(0.0866104)	(0.0929488)
DTAR	-0.1564003	1.503645
	(3.278778)	(3.78745)
TARGET	2.599886***	3.404887***
	(0.9268116)	(1.007893)
TDON	-0.053044	-0.113118**
	(0.0429901)	(0.0441644)
NMOD2	0.4875054	0.199297
	(0.3711342)	(0.3288233)
MOD2×NMOD2	0.1025879**	0.1306731**
	(0.0448361)	(0.0581374)
R^2	.290	.382
No. Observations	249	249

Notes: Minmaxed dataset. Robust Standard Errors used in estimation. ***,**, *: significant at 1%, 5%, 10%. Marginal effects calculated at sample means using delta-method in STATA, where appropriate.

Note that MOD2 and TARGET enter our estimation in linear-quadratic fashion, and there is an interaction term MOD2×NMOD2, the size and the magnitude of the reported marginal effects for these variables depend on where they are evaluated. From the table we can see that the effect of raising the modal donation during the first two days is again significant. The number of early mode donations is insignificant. However, NMOD2 does matter—namely through the intreaction with the early mode. This is perhaps the most interesting result from the LS regressions. The interaction term has a statistically significant positive sign and is of substantial size.[11] Not only does an increase in the early mode raise the overall mode but the

[11] A minor caveat applies however. A high number of modal donations during the first two days, makes it more likely that the modal donation for the first two days will also be the modal donation for the entire campaign. We are not too concerned about this however, since the effect remains (and is of the same size) in the WLS estimations that place more weight on larger campaigns where the purely numerical impact of what happens during the first two days is small. In other words, since we see this effect also in the WLS regressions the effect must indeed be driven by social interactions.

more frequent the early mode the bigger is the effect.

Observation 4 The overall mode is increasing in the early mode and this effect is increasing in the strength of the early mode.

4 Discussion

We find a strong systematic relation between what happens very early on in an internet fundraising campaign and what happens later. The observed clustering and subsequent drop in the modal donation cannot be explained simply by donors incomes being clustered around the income of the fundraiser and random arrival—on the contrary, donations weakly decrease over time and this process follows a systematic pattern. A few particular effects stand out: The higher the mode early on, the more likely it is to fall. The more frequent the early mode, the less likely it is to fall—and this effect gets stronger for higher early modes.

In our view there are two main lessons to be drawn from these findings. First, the evidence suggests that donations are affected by social interactions. Indeed, it appears as if donors are trying "to get away" with as little as is socially acceptable and what is socially acceptable is defined by previous modal behavior. The canonical model of giving in the economics literature cannot account for any of these effects. The only interaction that arises in the standard model is of strategic nature (see, for example, Andreoni 2006). There are no interactions over and above the purely strategic (free-rider) incentives—except in models with uncertainty about the quality of the fundraising project where high early donations can signal high quality (e.g. Vesterlund 2003) and encourage higher later donations. However, this type of model does not predict the systematic decline in donations that we observe.

It is perfectly adequate to model traditional fundraising with traditional models as the information that triggers the social interactions that we observe is absent there. With internet technology, however, we will surely see the rise of internet campaigning (Howard Dean's spectacular internet fundraising in the 2004 US primaries provided a first glimpse of that potential). If the theoretical literature on philantropy wants to keep pace with these developments models of giving that incorporate elements of social preferences or social norms are called for.

Second, it is, of course, the choice of the fundraiser whether to take advantage of the feedback mechanism that internet campaigning so easily provides. Fundraising on the internet can be designed just like a traditional paper-based campaign without feedback information. But what we show here is that it may be in the best interest of the fundraiser to provide such information.

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