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Keywords: charitable giving; peer effects; donations
JEL Classification: D64, H41

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Abstract

There is a widespread belief that peer effects are important in charitable giving, but surprisingly little evidence on how donors respond to their peers in practice. Analysing a unique dataset of donations to online fundraising pages, we show that peer effects are positive and sizeable: a £10 increase in the mean of past donations increases giving by £2.50, on average. We show that donations respond to large and small donations and to changes in the mode. We find little evidence that donations signal charity quality – our preferred explanation is that donors use information on (the distribution of) earlier donations to decide what is appropriate for them to give.

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"The size of your gift can persuade your peer to make a contribution as significant as yours."

"How to succeed in fundraising by really trying" by Lewis B. Cullman

1. Introduction

This paper is concerned with peer effects in charitable giving – specifically the way in which the amount that donors give responds to donations made by others in their peer group. There is a widespread belief that such peer effects are important, but there is surprisingly little direct evidence. Early studies used cross-section data to define generic reference groups in terms of income (Feldstein and Clotfelter, 1976) and other socio-demographic characteristics such as age and education (Andreoni and Scholz, 1988). More recent experimental studies have looked at the effect of "social cues" – i.e. single pieces of information about how much has been given by other people, unknown to the donor, such as a previous cohort or a typical donor (Frey and Meier, 2004, Alpizar et al, 2008, and Shang and Croson, 2009). There are two studies that have looked directly at peer effects in giving. Meer (2009) focused on peer effects in solicitation, looking at whether people give more if the ask comes from someone that they know. Carman (2004) studied peer effects among workplace teams but, in this case, the peer group included the team captain who played a role in encouraging and motivating giving among team members. Ours is the first paper we are aware of to look at purely horizontal (donor-to-donor) peer effects in giving.

We empirically investigate how donors are influenced by the donations of their peers in the context of individual online fundraising. In the UK, this is a major source of income for many charities. Since 1991, more than two million individual fundraisers have raised more than £1 billion for a wide range of different charities through the biggest individual online fundraising website, and this has been growing over time.[1] The way that individual online fundraising typically works is as follows: Individual fundraisers decide on a fundraising activity to raise money for their chosen charity (these activities often involve a sporting event such as running a marathon or swimming the English Channel, but novelty activities such as head shaving are also popular). The fundraisers then set up personalized webpages on a fundraising website and invite people to make donations to their chosen charities. Most of the donations come from the fundraiser's friends, family and colleagues.[2] Almost all are made online via the fundraising page and are passed directly by the fundraising website to the charity. The online donations are listed on the fundraising page, with the most recent first.[3] Information on how much has been given, and by whom[4], is then visible to each donor that arrives at the fundraising page. When donors go to the page to make a donation they can see all the previous online donations that have been made; we exploit this set up to look at whether donors are influenced by how much other people have given.

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[1] For comparison, total donations from individuals in the UK were estimated to be £13 billion in 2010-11.

[2] We do not have direct information on the identity of the donors or their relationship to the fundraiser. However, we have supporting evidence that they are mainly friends, family and colleagues from a separate survey of approx 19,000 Justgiving donors (see Payne et al, 2011). Of those who had been asked to give to a fundraising page, 84% had been asked by a family member (of whom 87% said that they always gave when asked); 96% had been asked by a friend (67% always gave); 89% had been asked by a colleague (48 % always gave); 70% had been asked by a charity representative (only 9% always gave).

[3] Donors can see up to 30 or 50 past donations by scrolling down without having to click through. Since the median number of donations is 33, this means that most donors can see all previous donations in one go.

[4] Donors can choose to donate anonymously. Unfortunately, whether or not a donation was given anonymously was miscoded for more than half our sample, which means that we cannot do a full analysis on the effects of anonymity. Where we do have information, we find that 11 per cent of donations are made anonymously. Large and small donations are more likely to be made anonymously as might be expected. We find that the effect of large and small donations is not affected by whether or not the donation was made anonymously. We also find that the probability of giving anonymously does not change after a large or small donation.

Of course, donations made to the same page will be correlated because of the common characteristics of the peer group – the fundraiser's friends, family and work colleagues. Our identification strategy relies on the within-page variation in the observed history of donations that arises as a result of donors arriving at the website at different times.[5] In essence, we argue that there is plausibly exogenous variation in the set of donations observed by each donor because exactly when donors make their donation is subject to random factors, such as when they turn on their computer and find time to log on to the fundraising website in order to make a donation. We further discuss our identification strategy in sections 3 and 4.

We provide direct evidence on the direction and magnitude of peer effects in giving. In principle, it is possible that other people's donations could "crowd out" giving (Warr, 1982, Roberts, 1984) but we show that higher (average) donations cause people to increase the amount that they give – a £10 increase in the mean of past donations causes people to give £2.50 more on average. One potential criticism of a simple "linear-in-means" specification is that it can mask the potentially diverse ways in which peer effects can work (Sacerdote, 2011). We are able to shed light on the nature of peer effects in giving and show that the amount given is affected both by "shining knights" (very large donations) and by "widows' mites" (very small donations), as well as there being "herd behaviour" (donations following the mode).

We also exploit the richness of our data to explore some of the underlying mechanisms that might explain why donors respond positively to how much their peers have given. We find no evidence that peer donations provide a signal about the quality of a charity (Vesterlund, 2003),

[5] Mas and Moretti (2009) provide perhaps the closest study to our paper in terms of identification. They look at the effect of peers' productivity in the context of supermarket checkouts, exploiting randomness arising from the scheduling of checkout operatives. They estimate individual-specific fixed effects; we do not have sufficient observations to allow us to do this.

nor that peer effects are only related to fundraising targets (Andreoni, 1998). The explanation that is most consistent with observed behaviour is that donors use information on (the distribution of) past donations as a benchmark in deciding how much it is appropriate for them to give.

The plan of the remainder of the paper is as follows. The next section provides information on our data – a subset of fundraising pages set up by runners in the 2010 London marathon. Section 3 discusses our empirical strategy. Section 4 explores the effect of other donations and the nature of the peer effects by looking at the effect of large and small donations and changes in the mode, while section 5 contains our main econometric analysis. Section 6 explores alternative explanations for why donors might respond to their peers and section 7 concludes.

2. The setting – online fundraising

In this paper, we focus on the set of fundraising pages set up by people who raised money for charity by running in the 2010 London marathon and who set up fundraising pages on the two largest fundraising websites in the UK – *Justgiving* (www.justgiving.co.uk) and *Virgin Money Giving* (http://uk.virginmoneygiving.com/giving/) The London marathon claims to be the biggest single fundraising event in the world and of the approx 35,000 runners who line up each year, an estimated 20,000 are raising money for charity.

Our initial sample contained information from more than 12,000 fundraising pages. The data were captured on 30th April 2010, five days after the marathon took place. For each page we have all the information that is publicly available (examples of fundraising pages are shown in online Appendix A1). This includes the fundraiser's name, the charity they were fundraising for, their target amount (if they had one), the total amount raised offline at the time the data were captured, the full history of donations to the website, the donors' names (where available) and the amount given.

Table 1 provides a basic summary of the information from the websites. Each fundraiser gets an average of 34.5 donations and raises an average of £1,093 in online donations and £335 in reported offline donations.[6] Donations are spread over time. The typical page is set up just over two months before the marathon. Some fundraisers create pages up to six months before the event. Over this period, fundraisers may sequentially target different sets of people within their wider peer group. In this case, any observed change in donation amounts (eg following a large or small donation or a change in the mode) may simply reflect the arrival of a new donor group. When we test for changes in amounts donated in section 4, we look at arrival rates before and after; we also carry out an additional robustness check focusing only on donations made within the same day.

<< Table 1 near here>>

The mean online donation is £30.31. The distribution of donations is heavily concentrated with spikes at £10 and £20 (and to a lesser extent other rounded amounts) with just over half of all donations at exactly £10 or £20 (see Figure A3.1). There is a small spike at £26 reflecting the marathon distance.

[6] These totals exclude the value of UK Gift Aid tax relief, which is additionally passed to the charity by the tax authorities.

The distributions of donation amounts and the number of donations per page are skewed by the presence of a few very successful fundraisers[7] and generous donors. In our analysis, we exclude pages which have single donations of more than £1,000. We also exclude pages with fewer than ten donations (1,783 pages) or more than 100 donations (212 pages). With these exclusions, our sample is 10,597 pages.

3. Empirical strategy

A commonly estimated model in the peer effects literature is a linear-in-means model. In our case, this can be written:

$$d_{in} = \alpha + \gamma \bar{d}_{i,n-1} + u_{in}$$

where the donation amount, *d*, given by donor *n* to page *i* is estimated as a function of the mean of all past donations to the same page up to that point $\bar{d}_{i,n-1}$.

There are well-known problems in identifying peer effects (see Manski, 1993 and Brock and Durlauf, 2001 for a discussion). In our case we can rule out the reflection problem since the amount given by the n^{th} donor will not affect the donations made by previous donors. Correlated effects are a clear concern. Donors to a page will share socio-economic and demographic characteristics because they are likely to be drawn from a fundraiser's network of friends, family and work colleagues. They will also be subject to the common influence of the same fundraiser who may be more or less effective at encouraging people to give.

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[7] The biggest individual fundraisers include Richard Branson who raised more than £35,000 for Virgin Unite, including a single donation of £6,550, and popstar Natalie Imbruglia, also running for Virgin Unite who raised more than £32,000, including a single donation of £10,000.

Our identification strategy therefore relies on within-page variation in observed past donations arising as a result of donors arriving at a page at different times to make their donation. Of course there is likely to be some endogenous sorting within a page: close family and friends will be among the first to give, as well as people with a strong connection to the cause – and both these groups are likely to give more. This is clear from the observed decline in mean donation size over the first few donations to a page (see Figure 1, panel a). In our analysis, we run regressions excluding the first three donations to a page – this is both to allow for some donation history for subsequent donors to respond to and also because the first three donations are systematically higher than the rest and may possibly behave differently to those that follow. Our main findings are not sensitive to this sample selection.[8] It also clear from a randomly selected sub-sample of pages (Figure 1, panel b) that there is non-systematic variation in the size of donations within a page that causes the within-page mean to vary. We exploit this variation to identify peer effects.

<< Figure 1 near here>>

As a number of papers have pointed out (see discussion in Sacerdote, 2011), a limitation of the linear-in-means model is that it may over-simplify – and potentially obscure – the many different ways in which peer effects work in practice. Following Sacerdote (2011), who presents a typology of potential peer effects in relation to education, we can distinguish a number of different ways in which peer effects might affect giving (see Table 2).

<< Table 2 near here>>

[8] We have repeated all the analyses in the paper excluding the first five donations to each page and also keeping all donations to a page. All the main findings are qualitatively similar although we typically find larger effects when we exclude more of the early donations.

First, donations may be affected by “shining knights”, i.e. by large donations to a page. A large donation is likely to place upward pressure on amounts given among donors who want to signal either their wealth (Glazer and Konrad, 1996) or generosity (Harbaugh, 1998) or the closeness of their relationship to the fundraiser by being amongst the biggest donors. This would be likely only to affect the upper end of the distribution as some donors compete to give the most. Large donations may, however, have a wider effect on all donors to the extent that they crowd out other giving, assuming standard public good giving (Warr, 1982, Roberts, 1984) or crowd it in if there is a threshold for the provision of the public good (Andreoni, 1989). Large donations may also provide a signal about the quality of the charity (Vesterlund, 2003) or affect individuals’ beliefs about how much it is appropriate to give, assuming such beliefs are based on the observed distribution of amounts given.

Second, donations may be affected by “widows’ mites”, i.e. by small donations to a page. Becker (1974) emphasized that donations might be motivated by the desire to avoid social stigma as well as to gain social prestige. Some donors will want to get away with giving as little as possible and a small donation will allow them to reduce how much they give. This is likely to affect donations at the lower end of the distribution. More generally, a small donation may also affect all others in ways similar to a large donation – i.e. through crowd out/ crowd in, signalling effects or benchmarking.

Third, there may be “herd behaviour.” Donors with a desire to conform may try to target how much they give on the modal amount (Bernheim, 1994). In this case, the amount given may be affected by (changes in) the mode of donations to a page. As with small and large donations, a change in the mode may affect only some donors or all other donors to a page.

The online fundraising data allow us to explore these different types of peer effects. In particular, we can look directly at the effect of "shining knights" and "widows' mites" and of changes in the mode on amounts given. We also look at whether large and small donations affect only some donors (in the upper/lower end of the distribution) and/or whether the effects appear to be more general.

4. Estimates of peer effects – a natural experiment approach

To look at the effects of "large" and "small" donations and changes in the modal amount we estimate the following specification:

$$d_{in} = \alpha + \beta T_{in} + z_{in}'\delta + u_{in}$$

where d_{in} refers to the n^{th} donation to fundraising page i (in pounds) and T_{in} is a "treatment" indicator equal to one if the donation follows a large/small donation or a change in the mode and equal to zero otherwise. We define a "large" donation as being at least twice the page mean (and more than £50). The mean "large" donation is £102. A "small" donation is defined as half the page mean. The mean "small" donation is £8.61. We look separately at increases and decreases in the mode.[9] z_{in} is a vector of controls for the systematic component of the timing of donations – the order on the page and the date of donation respectively. The error term is decomposed into a constant page-specific effect that will pick up common differences in donations across pages and a pure random error term: $u_{in} = \eta_i + v_{in}$. We estimate this model using a fixed effects regression

[9] Where there is more than one mode, we look at increases in the maximum of the modes and decreases in the minimum of the modes.

that removes the effect on donations of the page-specific unobservable factors. We exclude the first three donations on a page from our regression sample, although they are used to define the change in mode and large/small donations. We drop pages where a large or small donation occurs within the first three donations; we also restrict the first change in the mode to occur after the first three donations.[10]

Our identifying assumption is that there is random variation in the timing of donations, after controlling for systematic within-page variation, such that the random error term, v_{in}, is uncorrelated with the "treatment" variable, T_{in}. We would argue that this assumption is plausible, at least within a narrow window, given that the exact timing of when people make an online donation will be subject to a number of exogenous factors. Exactly when donors arrive at the page – and hence whether they arrive just before or just after a large/small donation – will be influenced by a number of random factors such as when they turn on their computer and when they find a moment to log on to the fundraising website to make an online donation. Under our identifying assumption, the coefficient β will identify the average causal effect of a large/small donation on the amount subsequently given.

There are two possible violations of this identifying assumption. One is if large/small donations affect the extensive margin – i.e. the probability that donors make a donation. In this case, the observed donations before and after would be subject to a differential selection process. A second is if fundraisers sequentially target different groups of donors – in which case the first large/small donation would herald the arrival of a new group of donors. We have no information

[10] We obtain qualitatively similar results when we exclude the first five donations.

on visits to the websites, nor on donor characteristics that allow us to test for these effects directly. However, we can look at the arrival rate of donations (i.e. the number of donations made to a page per day) to give some indication of whether either of these is likely to be material. Both a change in the extensive margin and the arrival of a new group of donors would be associated with a change in the arrival rate.

Figure 2 plots the distributions of the arrival rates (i.e. the number of donations per day) on the days before and after each of the four treatments we look at. There is little obvious change in the distributions and this is confirmed by Kolgomorov-Smirnov tests. The p-values for the equality of distributions before/after large and small donations are 0.219 and 0.352 respectively while the p-values for the equality of distributions before/after increases and decreases in the mode are, respectively, 0.094 and 0.668. In all four cases we fail to reject that the distributions of arrival rates are the same.

<< Figure 2 near here>>

<< Figure 3 near here>>

By contrast, Figure 3 provides clear evidence of effects on amounts given after each of the four “treatments”. Donations increase after both a large donation and an increase in the mode, while donations fall after both a small donation and a decrease in the mode. These findings are confirmed by regression results, summarized in Table 3. We vary the size of the window before and after – looking at a narrow window of one donation before/after and also five donations before/after and five before and ten after. We do a further robustness check where we restrict the before and after donations to lie within the same day, making it less likely that they have been made by different groups of (sequentially-targeted) donors.

The results in panels (a) – (d) confirm that there is a change in how much subsequent donors give following each of the four treatments. The coefficients indicate fairly sizeable effects. Within a narrow window of one donation either side, large donations are associated with a £12.49 increase in donation size, compared to a previous donation level around £20, while a small donation reduces donation size by a similar magnitude. The effects also appear to be fairly persistent affecting at least ten donations that follow; this is likely to work not just through the first large/small donation or change in mode, but also through changes in subsequent donations.

<<Table 3 near here>>

As discussed in the previous section, large and small donations may affect amounts given either by triggering competition among some donors (other large/small donations) or, more generally, by influencing all other donors through crowd out/ in, signalling or benchmarking. We shed light on this by looking at the effect on subsequent amounts given, excluding other large and small donations. This will tell us whether the effect is (just) to trigger other large/small donations or whether it goes wider than this. The results, shown in panels (e) and (f), indicate that large and small donations do indeed trigger other similar-sized donations (the coefficients are smaller than in panels (a) and (b)) but that there are effects even on "regular-sized" donations.

The coefficients in panels (a) – (d) indicate that the peer effects are increasing in amount size – a large donation is associated with a bigger effect than an increase in the mode. We explore this further by looking at the effects of different-sized large donations (twice previous mean, three times previous mean, five times previous mean and more than ten times previous mean). As in previous studies (Shang and Croson, 2009) we find that larger donations produce a greater response from subsequent donors, at least up to very large donations of ten or more times the page mean. Combined with our results on the effects of large/small donations and changes in the mode, this supports our use of the linear-in-means model in the next section.

Finally, we look at whether there is evidence of spillover effects from donors giving more in response to a large donation on one fundraising page to how much they give on other fundraising pages. We do this by exploiting the fact that, within the *Justgiving* sample, we can identify donors who give to more than one fundraising page. We construct a donor-level panel of amounts given sequentially across different pages.[11]

We estimate an equation of the following form:

$$d_{sn} = \alpha + \beta_1 T_{sn} + \beta_2 T_{s(n-1)} + \eta_s + \omega_{sn}$$

where d_{sn} refers to the nth donation of donor s. T_{sn} is an indicator equal to one if there has been a large donation (within ten donations) to that page, while $T_{s(n-1)}$ is an indicator equal to one if the previous page visited had a large donation. β_1 captures the own-page effect and β_2 any spillover effect of a large donation on a previously-visited page. We estimate this equation on the full sample of (Justgiving) donors but the own-page and spillover effects are identified from donors who give to multiple pages. We include a trend to allow for the fact that donors may reduce their donations as they are asked to sponsor more people.

Our results confirm the own-page crowd-in effect. Our estimate is 5.91 (SE 3.11) which is significant at the 10 per cent level. The estimated spillover effect is also positive (5.60), but

[11] We drop 4 per cent of donations which were made on the same day since we cannot identify donation order.

insignificant (SE 1.80), suggesting that there is no crowd out of a large donation to one page on donations to other fundraising pages.

5. Econometric analysis

In this section we present estimates from a linear-in-means model. The attraction of the mean is that it provides a simple summary statistic of the distribution of donations that donors appear to be responding to. We have shown in the previous section that donors respond to large and small donations and to the mode. The linear-in-means model provides an attractively parsimonious specification to capture these behaviours, particularly when, in the following section, we want to test for heterogeneity of effects.

We estimate the following specification:

$$d_{in} = \alpha + \gamma \bar{d}_{i,n-1} + z'_{in}\delta + u_{in}$$

where d_{in} refers to the n^{th} donation to fundraising page i and $\bar{d}_{i,n-1}$ is the mean of all donations made online to the fundraising page up to the point at which the n^{th} donor arrives at the page.[12] As before, z_{in} is a set of indicators for the order in which the donation occurs on the page and date controls, including indicators for the days since the page was set up (capped at 100) and also for the days in the immediate run up to the day of the marathon.

We are interested in the coefficient γ which measures the extent to which a higher level of past donations across the page is associated with people giving more or less. The OLS estimate of γ is

[12] The donor will also see the amount raised offline up to the point at which they arrive at the website, while we only know the total amount raised offline at the time the data were captured. As a robustness check, we run the regressions only on pages with no offline donations.

likely to be biased upwards by unobservable factors that affect all donations to a page that can be captured in a page-specific error term, i.e. $u_{in} = \eta_i + v_{in}$ These factors will include both shared (unobserved) characteristics of the donors to a page, such as their income, as well as (unobserved) characteristics of the fundraiser, such as their persuasive power or their personal connection to a particular cause.[13] For this reason, we cannot identify the effect of past donations from variation across pages, but only from variation within pages over time.

Estimating a fixed effects model using a within-groups specification, however, will lead to a downwards-biased estimate of γ because the mean-differenced error term, $u_{in} - \frac{1}{N-1}\sum_{j=2}^{N} u_{ij}$, will be negatively correlated with the mean-differenced lagged dependent variable, $\bar{d}_{i,n-1} - \frac{1}{N-1}\sum_{j=1}^{N-1} \bar{d}_{ij}$. In the case of estimating the effect of the past mean of all donations, this bias will not be negligible even though we have a long panel (the average number of donations per page in our analysis is 37 and we observe many pages with 50 or more donations), unlike the standard case of "Nickell bias" (Nickell, 1981). We show this formally in Appendix A2.

Our preferred approach, therefore, is to estimate γ using the Arellano and Bond (1991) GMM estimator, [14] i.e. the page-specific effect η_i is eliminated by first-differencing:

$$\Delta d_{in} = \gamma \Delta \bar{d}_{i,n-1} + \Delta z'_{in} \delta + \Delta v_{in}$$

In this first-differenced model there is now an endogeneity problem due to the correlation between $\bar{d}_{i,n-1}$ and $v_{i,n-1}$. Again, the bias of the OLS estimator in this first-differenced model does

[13] The fact that fundraiser characteristics may influence all donations to a page means that exploiting information on multiple donations by the same donor to different pages is unlikely to lead to an unbiased estimate.
[14] We estimate the GMM model using xtabond2, see David Roodman (2006)

not decrease with N, as shown in Appendix A2. In our main specification we use the two-period lag and the three-period lag of the page-mean as instruments for the (change in) mean of past donations, with different reduced form coefficients per donation order. The Arellano-Bond test for serial correlation does not reject the null of no second-order serial correlation, implying that the two-period lag is valid as an instrument. The Hansen test further does not indicate that the instrument set is not valid. Our main findings are robust to a number of alternative specifications, presented in the Appendix.

Our main results are presented in Table 4. For comparison, we show both the upward biased OLS and the downward biased fixed effects results for all specifications. Our preferred GMM results lie between these two for all specifications. We also present results for the effect of the last donation and the effect of the mean of the past five and ten donations. As demonstrated in online Appendix A2 the extent of downward bias to the fixed effects estimator is greater when looking at the past mean of all donations to a page than for the simple lagged dependent variable.

<< Table 4 near here >>

Across all specifications, the GMM estimate of γ is positive and significant, implying positive peer effects; a £10 increase in the mean of past donations leads to people giving £2.50 more on average. To illustrate what this means in practice, the effect of a £150 donation following three donations of £20 would be to increase giving by £8.13, while the effect of a £150 donation following six donations of £20 would be to increase giving by £4.64 (in both cases, the effect on giving in the case of the lagged dependent variable would be to increase giving by £2.86). This highlights an important feature of estimating the effect of the past mean – that the effect of a single donation diminishes, the later it occurs on a page. This is intuitively plausible since a donor may give less weight to a single large donation if there are more other donations on the page. We also find further empirical support for this finding by repeating the analysis from the previous section and looking at the effect of a single "large" donation made after ten donations and after fifteen donations to a page (compared to a large donation that occurs between five and ten donations). The estimated effect of a large donation is reduced by £1.19 when it occurs after ten or more donations and by £2.50 when it occurs after fifteen or more donations. This lends further support to including the past mean of all donations as the preferred empirical specification and we focus on this specification in the next section.

6. Inside the black box – exploring why peers matter

We would like to understand why peers matter. As discussed in section 3, there are a number of potential explanations. On the basis of our findings so far, we can rule out that donors are (just) aiming to be the most generous donor to a page since both small donations and changes in the mode matter; large donations also have a wider effect than simply triggering similar-sized donations. For similar reasons, we can also rule out that donors are (just) trying to avoid being the least generous donor to a page. The observed effects of large and small donations also imply that donors do not just try to follow the herd and match the mode.

Table 2 summarized a number of potential explanations for why large/ small donations and changes in the mode may affect all donations that follow. Our estimates of peer effects are positive, ruling out classic crowd out. Andreoni (1998) discusses the case in which threshold contribution levels, such as a minimum level of funding required before the public good can be produced, can result in crowd in – essentially large donations make it more likely that the threshold will be reached, which can encourage other donations. The potential effects of thresholds are relevant to the London marathon fundraising pages, the majority of which have fundraising targets. We find that peer effects are stronger for pages with a target, but we also find a positive and significant effect for pages without a target (Table 5, column (I)). This indicates that targets do not provide the full explanation for the observed peer effects.

<< Table 5 near here>>

There are further interesting differences in behaviour around the target. Regression analysis, summarised in Table 6, cols (I) and (II) shows, first, that the size of the first donation to take the total over the target donation is significantly higher and second that donations are lower on average after the target than before. Assuming as before that there is some random variation in exactly when donors arrive at a page (and that they are equally likely to arrive before or after the target, within a narrow window), this could be interpreted as a negative effect of hitting the target on donations. One important caveat to this is that it is possible for fundraisers to change their target (eg to increase the target amount once it has been reached). We have no evidence on the extent to which this happens in practice.

Finally, col (III) of Table 6 provides the results from a further GMM regression in which the past mean of donations is interacted with an indicator for the donor arriving after the target has been reached. This tests whether the crowd in effect of past donations is the same on either side of the target. We find that the coefficient on the interaction term is negative and similar in magnitude to the coefficient on the past mean implying that there is no crowd in effect of past donations once the target has been reached.

<<Table 6 near here>>

Another possibility is that donations may be important as a signal of the quality of the charity, with higher (lower) donations indicating that the particular cause is more (less) worthy of support (Vesterlund, 2003). To explore this empirically we adopt an idea, proposed by Heutel (2009), that the information content of past donations should be more important for smaller charities and for younger charities, for charities operating overseas whose activities are less easy to observe directly and for younger donors. To implement this we match data from the Charity Commission Register, comprising all registered charities in England and Wales. We are able to find a match in the case of 78 per cent of fundraising pages (some of those we cannot match are Scottish and Irish charities), although information is not always available for all charities even where a match is made.

Table 5 summarizes the results from a set of regressions that include interaction terms, allowing the effect of the past mean to vary by, respectively – the size of the charity, the age of the charity, the location of charitable activity (UK or overseas), the age of the fundraiser (which proxies for the age of donors, defined by a cut off of 40). The results provide little support for this particular signalling story. The effect of past donations is actually stronger for larger charities and for older charities although the differences are not statistically significant. We find no difference in peer effects between overseas and UK-based charities. We find no evidence of statistically significant differences by age.[15]

Instead of signalling charity quality, past donations may alternatively signal to donors how much it is socially appropriate for them to give. This is our preferred explanation for why past donations affect the amount given. When they arrive at a page, donors observe the distribution of

[15] We get information on the age of the fundraiser by matching to the marathon results. 18-40 is the youngest category given in this database. We obtain similar results if we use older cut-offs.

past donations and use this to form – or update – their beliefs about how much they should give. These beliefs are likely to be donor- (and possibly fundraiser-)specific; donors will have some idea of where they should locate within the distribution depending on their characteristics relative to those of other donors, including the proximity of their relationship to the fundraiser, their support for a particular charity and their income (and possibly what their peers know about their income). Large/ small donations and the mode will all affect amounts donated subsequently because they will be used to inform donors' beliefs. We cannot test this benchmarking story explicitly but it is consistent with the observed pattern of behaviour, including both donor responses to past donations and the fact that, individually, past donations have less effect if they occur later on in the page.

7. Discussion

This paper adds to the empirical literature on what Andreoni has referred to as "the inherent sociality of giving" by providing new evidence on the importance of peer effects in charitable giving in the context of online individual fundraising.

Online fundraising is important to look at in its own right as a sizeable – and growing – channel for raising money for charities in the UK and elsewhere. It also provides an excellent setting to look at peer effects since it offers an environment in which donors observe donations from people within their naturally occuring peer groups (i.e. their friends, family and colleagues).

There is an inevitable issue about the extent to which our findings can be generalised beyond this particular setting. The online fundraising context in which donors can see all other donations – and know that their donations will be seen – is arguably quite distinctive. However, it is one that is potentially relevant to practitioners and policy-makers interested in whether they can exploit the power of peer effects by providing similar levels of publicity to donations in other settings. Furthermore, by looking at data that span more than 1,000 different charities, we have been able to demonstrate that peer effects are not limited to particular charities or groups of donors, suggesting that the effects are likely to be more broadly generalisable.

The richness of the data also allows us to explore potential explanations for why peers matter. We can reject that donors systematically compete to be the top, or strive to avoid being the bottom or align themselves with the mode or median. Our preferred explanation, which is consistent with the empirical findings, is that donors give what they think that they personally are expected to give where the distribution of the donations of their peers (along with other factors, such as income and specific cause) feed into the formation of that expectation.

In this paper we have analysed only a small sub-sample of the population of online fundraising pages that are potentially available. Going forward, information from online fundraising pages, particularly matched with social network data, has the potential to yield even further insights into how donors behave in social settings.

Appendices for online publication

Appendix A1 – Online fundraising

Justgiving (JG) www.justgiving.com was set up in 2001. It is used by individuals to give directly to charities but also, primarily, by individual fundraisers who are raising money for charities – either by seeking sponsorship for taking part in events such as the London marathon or setting up pages to collect memorial donations or donations in lieu of a wedding gift or birthday present. JG is a profit-making company, charging charities a monthly fee of £15 to use the service, and also taking 5 per cent of the gross value (i.e. including the value of tax relief) of donations given.

Virgin Money Giving (VMG) http://uk.virginmoneygiving.com/giving/ was set up in 2009, in conjunction with Virgin Money taking over as the official sponsor of the London marathon. Although Virgin Money is a profit-making company, VMG is non-profit making. It charges charities a one-off, set-up fee of £100 and takes 2 per cent of nominal donations.

JustGiving

Home | About us | Your account | Help

James Nicholson's Fundraising Page

Virgin London Marathon 2010 on 25/04/2010

My not-so-heroic sprint finish!!!

Photos (1)

Raising money for

Phab Limited

Charity Registration No. 283931

Phab is a national charity dedicated to promoting and encouraging the coming together, on equal terms, of disabled and non-disabled people to achieve an integrated and inclusive society.

Get a page like this

30 Remind me to donate later

Page owner

Target: **£1,500.00**

Raised so far: **£1,564.00**

104%

Donate now

My story

Tough Guy...........Conquered. Grim Challenge...........Destroyed. London Duathlon............All over it. Now for the big one!!

I've finally decided to stop being a big jessie and making excuses like "my knees can't take it," "I'm not built for long distance running," "my brother's girlfriend keeps beating me," and just suck it up. I'm running, and I use that term loosely, the 2010 London Marathon. I'm raising money for Phabkids, a charity promotes and encourages disabled and non-disabled children and adults to take part in sports and social activities with the aim of achieving social inclusion. I'm sure you agree that this is a worthwhile cause.

I would be grateful if you could spare a small amount to help me get to my £1500 target for Phabkids, and feel free to come and laugh at me going through hell next April. Thanks very much for looking.

James

finally remembered!!! Good luck tomorrow it'll be a fantastic achievement!

Donation by **Rebecca Waterman** 24/04/10

£25.00
+ £7.05 Gift Aid

Good Luck mate, however being sat in that suit !!! for so long and pub lunches swinging that lamp , with all those lids cheering you. The pressure.!!

Donation by **Dan Hatton** 21/04/10

£10.00
+ £2.82 Gift Aid

Go for it Jimbo...just remember 'pain don't hurt'! But when in doubt...'fast arms' is the answer - Good Luck!

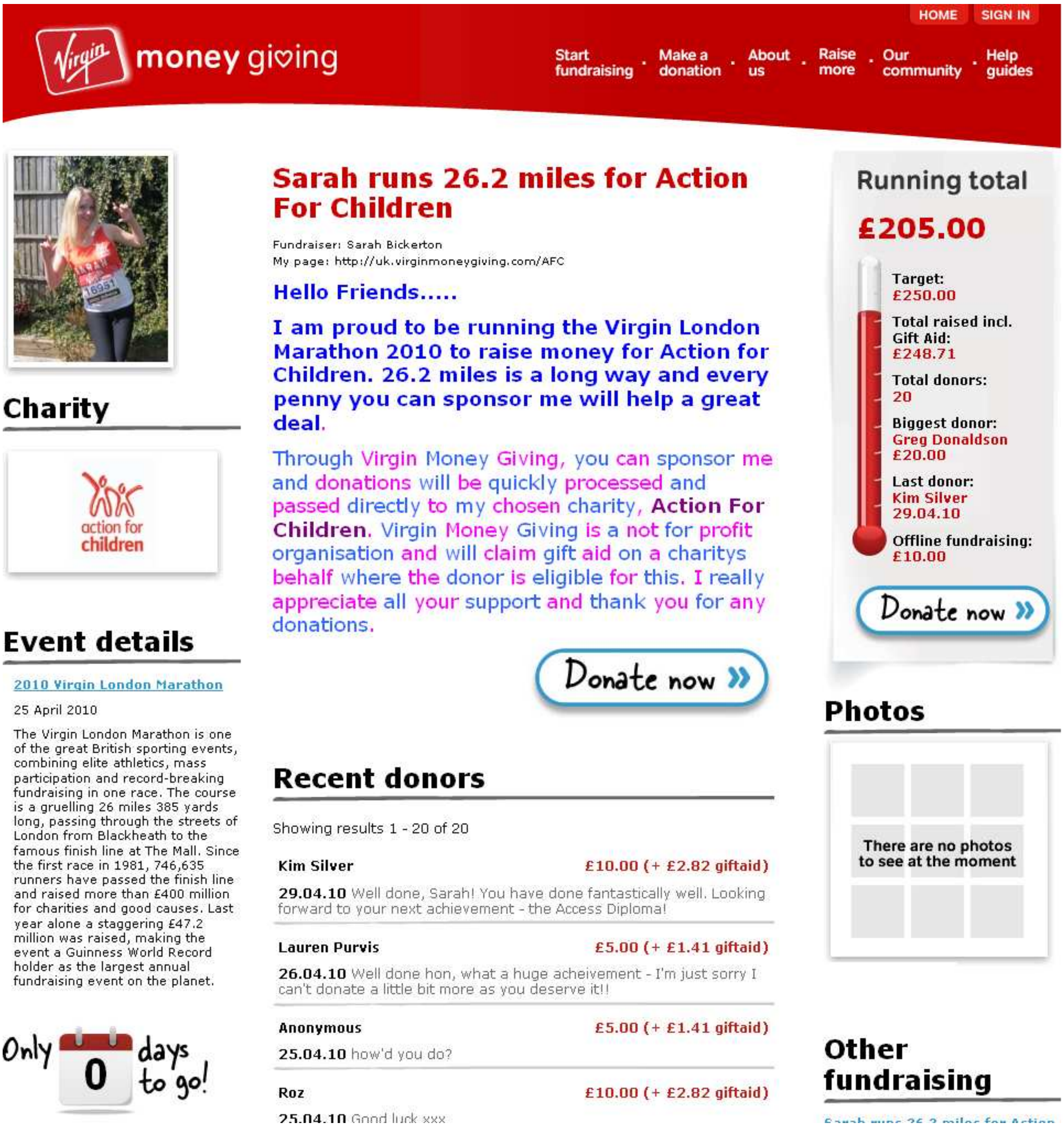
Donation by **Harry and Em x** 14/04/10

£10.00
+ £2.82 Gift Aid

Praying my card refuses this transaction so I get everyone seeing I've donated money to charity, without actually having to pay anything. Good Jim-Nic!

Donation by **Jamie Bartlett** 13/04/10

£20.00
+ £5.64 Gift Aid



HOME SIGN IN

Virgin money giving

Start fundraising · Make a donation · About us · Raise more · Our community · Help guides

Sarah runs 26.2 miles for Action For Children

Fundraiser: Sarah Bickerton
My page: http://uk.virginmoneygiving.com/AFC

Hello Friends.....

I am proud to be running the Virgin London Marathon 2010 to raise money for Action for Children. 26.2 miles is a long way and every penny you can sponsor me will help a great deal.

Through Virgin Money Giving, you can sponsor me and donations will be quickly processed and passed directly to my chosen charity, **Action For Children.** Virgin Money Giving is a not for profit organisation and will claim gift aid on a charitys behalf where the donor is eligible for this. I really appreciate all your support and thank you for any donations.

Donate now »

Charity

action for children

Event details

2010 Virgin London Marathon

25 April 2010

The Virgin London Marathon is one of the great British sporting events, combining elite athletics, mass participation and record-breaking fundraising in one race. The course is a gruelling 26 miles 385 yards long, passing through the streets of London from Blackheath to the famous finish line at The Mall. Since the first race in 1981, 746,635 runners have passed the finish line and raised more than £400 million for charities and good causes. Last year alone a staggering £47.2 million was raised, making the event a Guinness World Record holder as the largest annual fundraising event on the planet.

Only 0 days to go!

Running total

£205.00

Target: £250.00

Total raised incl. Gift Aid: £248.71

Total donors: 20

Biggest donor: Greg Donaldson £20.00

Last donor: Kim Silver 29.04.10

Offline fundraising: £10.00

Donate now »

Recent donors

Showing results 1 - 20 of 20

Kim Silver £10.00 (+ £2.82 giftaid)
29.04.10 Well done, Sarah! You have done fantastically well. Looking forward to your next achievement - the Access Diploma!

Lauren Purvis £5.00 (+ £1.41 giftaid)
26.04.10 Well done hon, what a huge acheivement - I'm just sorry I can't donate a little bit more as you deserve it!!

Anonymous £5.00 (+ £1.41 giftaid)
25.04.10 how'd you do?

Roz £10.00 (+ £2.82 giftaid)
25.04.10 Good luck xxx

Photos

There are no photos to see at the moment

Other fundraising

Appendix A2 – Bias of fixed effects estimator

Considering a simple AR(1) panel data model

$$\text{Model LDep: } d_{in} = \gamma d_{i,n-1} + \eta_i + v_{in}$$

for $i = 1,...,I$ and $n = 1,...,N$, it is well known the fixed effects estimator for γ is biased downward, but that this bias is a decreasing function of T , Nickell (1981).

In our model, we specify the lagged average donations as a determinant of current donations:

$$\text{Model LAvg: } d_{in} = \alpha \bar{d}_{i,n-1} + \eta_i + v_{in}$$

where $\bar{d}_{i,n-1} = \frac{1}{n-1}\sum_{j=1}^{n-1} d_{ij}$. In this case the fixed effects estimator is also biased downward, but this bias decreases more slowly with N than the bias in the LDep model, especially at lower values of γ.

In order to illustrate this, we performed a Monte Carlo analysis. We set the sample size $n = 10,000$ in order to obtain large sample results, and specified the error distributions as

$$\eta_i \sim N\left(0, \sigma_\eta^2\right);\ v_{in} \sim N\left(0,1\right).$$

As the bias is a function of the ratio $\sigma_\eta^2 / \sigma_v^2$, setting the variance of v_{it} equal to 1 is not restrictive. The initial observation was generated as

$$d_{i1} = \eta_i + v_{i1}.$$

We present the biases of the fixed effects estimators of γ in the two models LDep and LAvg in Table A2.1, for different values of N, γ and σ_{η}^{2}, for 1,000 Monte Carlo replications.

Table A2.1 Bias of the Fixed Effects Estimator

		$N=5$		$N=20$		$N=40$	
γ	σ_η^2	LDep	LAvg	LDep	LAvg	LDep	LAvg
0.25	0.25	-0.3300	-0.6200	-0.0670	-0.4347	-0.0324	-0.3503
	1	-0.3238	-0.6004	-0.0667	-0.4233	-0.0323	-0.3425
	4	-0.3010	-0.5332	-0.0655	-0.3832	-0.0320	-0.3147
0.50	0.25	-0.4176	-0.7524	-0.0831	-0.5458	-0.0395	-0.4306
	1	-0.3688	-0.6366	-0.0800	-0.4531	-0.0388	-0.3619
	4	-0.2513	-0.3941	-0.0695	-0.2697	-0.0361	-0.2209
0.75	0.25	-0.4692	-0.8040	-0.0997	-0.6061	-0.0470	-0.4814
	1	-0.3193	-0.5324	-0.0762	-0.3251	-0.0403	-0.2442
	4	-0.1402	-0.2264	-0.0392	-0.1139	-0.0257	-0.0822

Notes to Table

Sample size $I=10,000$, bias from 1,000 Monte Carlo repetitions

For every design, the bias in the LAvg model is larger (in absolute value) than that in the LDep model, and the bias decreases more rapidly with N in the LDep model than in the LAvg model, especailly for jointly smaller values of α and σ_η^2. For example, the bias at $N=40$, for $\gamma=0.5$ and $\sigma_\eta^2=1$, is equal to -0.0388, or 7.8%, for LDep, but it is still -0.3619, or 72.4%, for LAvg.

Setting $x_{in}=d_{i,n-1}$ for the LDep model and $x_{in}=\bar{d}_{i,n-1}$ for the LAvg model, we can write the generic model as

$$d_{in}=\gamma x_{in}+\eta_i+v_{in}$$

for $n=2,..,N$ and $i=1,...,I$. The fixed effects estimator is given by

$$\hat{\gamma}_{FE} = \frac{\sum_{i=1}^{I}\sum_{n=2}^{N}\left(x_{in}-\overline{x}_i\right)\left(d_{in}-\overline{d}_i\right)}{\sum_{i=1}^{n}\sum_{n=2}^{N}\left(x_{in}-\overline{x}_i\right)^2}$$
$$= \gamma + \frac{\sum_{i=1}^{I}\sum_{n=2}^{N}\left(x_{in}-\overline{x}_i\right)\left(v_{in}-\overline{v}_i\right)}{\sum_{i=1}^{I}\sum_{n=2}^{N}\left(x_{in}-\overline{x}_i\right)^2}$$

where $\overline{d}_i = \frac{1}{N-1}\sum_{n=2}^{N} d_{in}$, $\overline{x}_i = \frac{1}{N-1}\sum_{n=2}^{N} x_{in}$ and $\overline{v}_i = \frac{1}{N-1}\sum_{n=2}^{N} v_{in}$.

This can be further simplified to

$$\hat{\gamma}_{FE} - \gamma = \frac{\sum_{i=1}^{I}\sum_{n=2}^{N} x_{in}\left(v_{in}-\overline{v}_i\right)}{\sum_{i=1}^{I}\sum_{n=2}^{N}\left(x_{in}-\overline{x}_i\right)^2}$$

and hence

$$\text{plim}\left(\hat{\gamma}_{FE}-\gamma\right) = \frac{\text{plim}\frac{1}{I}\sum_{i=1}^{I}\sum_{n=2}^{N} x_{in}\left(v_{in}-\overline{v}_i\right)}{\text{plim}\frac{1}{I}\sum_{i=1}^{I}\sum_{n=2}^{N}\left(x_{in}-\overline{x}_i\right)^2}$$
$$= -\frac{\text{plim}\frac{1}{I}\sum_{i=1}^{I}\sum_{n=2}^{N} x_{in}\overline{v}_i}{\text{plim}\frac{1}{I}\sum_{i=1}^{I}\sum_{n=2}^{N}\left(x_{in}-\overline{x}_i\right)^2}$$

as $E\left[x_{in}v_{in}\right]=0$.

Table A2.2 provides the Monte Carlo means of the numerator and denominator in the bias expression for the two models, for $\gamma=1$ and $\sigma_\eta^2=1$.

Table A2.2 Bias Components for the Fixed Effects Estimator, $\gamma = 0.5$, $\sigma_\eta^2 = 1$

	$N=5$		$N=20$		$N=40$	
	LDep	LAvg	LDep	LAvg	LDep	LAvg
$\frac{1}{I}\sum_{i=1}^{I}\sum_{n=2}^{N} x_{in}\left(v_{in}-\overline{v}_i\right)$	-1.06	-0.91	-1.79	-1.49	-1.90	-1.64
$\frac{1}{I}\sum_{i=1}^{I}\sum_{n=2}^{N}\left(x_{in}-\overline{x}_i\right)^2$	2.88	1.42	22.36	3.28	48.96	4.53

Notes to Table
Sample size $I = 10,000$, bias components from 1,000 Monte Carlo repetitions
It is clear, that the bias decreases more rapidly in the LDep model because the variance term $\frac{1}{I}\sum_{i=1}^{I}\sum_{n=2}^{N}\left(x_{in}-\overline{x}_i\right)^2$ increases more rapidly with N. This is of course expected, as $\overline{d}_{i,n-1}$ eventually converges to a constant. The covariance terms $\frac{1}{I}\sum_{i=1}^{I}\sum_{n=2}^{N} x_{in}\left(v_{in}-\overline{v}_i\right)$ are of the same order of magnitude.

To conclude, we present in Table A2.3 the biases of the OLS, First-differenced OLS and one-step GMM estimates for the LAvg model with $\gamma = 0.5$ and $\sigma_\eta^2 = 1$, using for the GMM estimator sequential lags $\overline{d}_{i,n-2}$ and $\overline{d}_{i,n-3}$ as in Section 5. As expected, the OLS estimator is substantially upward biased. The OLS estimates for the model in first differences are severely downward biased. In comparison, the GMM estimates are virtually unbiased.

Table A2.3 Biases in LAvg model, $\gamma = 0.5$, $\sigma_\eta^2 = 1$

	OLS	OLS First Differences	GMM First Differences
$N=5$	0.4571	-0.9238	-0.0113
$N=20$	0.4870	-1.5527	-0.0084
$N=40$	0.4962	-1.8540	-0.0115

Notes to Table
Sample size $I = 10,000$, bias from 1,000 Monte Carlo repetitions

Appendix A3 – Further tables

Table A3.1: Additional GMM regression results

	(I)	(II)	(III)	(IV)	(V)	(VI)
Past_mean (£)	0.250**	0.283**	0.188**	0.151**	0.216**	0.256**
	(0.028)	*(0.078)*	(0.031)	(0.049)	*(0.025)*	(0.039)
Instruments	$\bar{d}_{i,n-2}, \bar{d}_{i,n-3}$	$\bar{d}_{i,n-2}, \bar{d}_{i,n-3}$ Collapsed	$\bar{d}_{i,n-3}, \bar{d}_{i,n-4}$	$\bar{d}_{i,n-3}, \bar{d}_{i,n-4}$ Collapsed	$\bar{d}_{i,n-2}, \bar{d}_{i,n-3}$ $\bar{d}_{i,n-4}$	$\bar{d}_{i,n-2}, \bar{d}_{i,n-3}$ One-step
Arellano-Bond test for AR(1), p-value	0.000	0.000	0.000	0.000	0.000	0.000
Arellano-Bond test for AR(2), p-value	0.322	0.325	0.327	0.332	0.325	0.326
Hansen test, p-value (over-id restrictions)	0.864 (217)	0.021 (1)	0.811 (217)	0.209 (1)	0.547 (323)	0.864 (218)

Notes to table

All regressions include additional controls for place within page (linear trend), indicators for days since page was set up (capped at 100) and indicator variables for two days and one day before the marathon, the day of the marathon and (any) days after the marathon. **$p<0.01$

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Table 1: Sample summary statistics

	Mean	St. dev.	Min.	1st pctile	Med.	99th pctile	Max.
Full sample							
Number of donations per page	34.5	25.4	1	1	29	114	370
Number of days	74.8	50.7	0	0	67	204	225
Online donations – all	£30.31	£66.02	£1	£5	£20	£200	£10,000
Total raised online per page	£1,093	£1,401	£1	£20	£778	£5,710	£40,326
Total raised offline per page	£335	£1,115	£0	£0	£0	£3,077	£53,000
Proportion of pages with target	.803						
Prop. of pages with target achieved	.395						
Target amounts	£99,985	£9.9 m	£0.01	£200	£1,500	£9,000	£1 bn
Number of fundraisers	12,750						
Estimation sample							
Number of donations per page	36.7	19.7	10	10	33	91	100
Number of days	79.5	49.5	2	6	73	205	225
Online donations	£29.81	£46.58	£1	£5	£20	£200	£1,000
Total raised online per page	£1,115	£916	£53	£136	£892	£4,458	£12,260
Total raised offline per page	£310	£827	£0	£0	£0	£2,725	£43,897
Proportion of pages with target	.823						
Prop. of pages with target achieved	.420						
Target amounts	£1,511	£832	£200	£200	£1,500	£5,000	£7,000
Number of fundraisers	10,597						

Note: All donation amounts exclude any Gift Aid, i.e. tax relief which the charity can additionally reclaim

Table 2: Peer effects in giving

	Influence on	
Influence of ...	Only some donors	All donors
Large donations (“Shining knights”)	Competition to be the top donor	Crowding in/ out Signalling quality Benchmark for appropriate amount
Small donations (“Widows’ mites”)	Desire to avoiding being the bottom donor	Crowding in/ out Signalling quality Benchmark for appropriate amount
Modal donations (“The herd”)	Following the herd and giving what most other people give	Crowding in/ out Signalling quality Benchmark for appropriate amount

Table 3: Effect of large/ small donation – fixed effects regression results

Dependent variable = £ amount given

a.	**Effect of a "large" donation**			
	One before/ One after	One before/ One after (same day)	Five before/ Five after	Five before/ Ten after
After	12.458**	13.392**	12.611**	12.134**
	(0.789)	(2.609)	(0.661)	(0.496)
N	15,508	6,464	68,926	102,492
b.	**Effect of a "small" donation**			
	One before/ One after	One before/ One after (same day)	Five before/ Five after	Five before/ Ten after
After	-11.411**	-9.493**	-11.169**	-10.232**
	(0.911)	(2.090)	(0.770)	(0.550)
N	14,499	6,600	58,858	91,422
c.	**Effect of an increase in the mode**			
	One before/ One after	One before/ One after (same day)	Five before/ Five after	Five before/ Ten after
After	-0.424	1.755	0.887	1.137*
	(1.211)	(2.818)	(0.961)	(0.671)
N	11,394	7,137	55,272	80,104
d.	**Effect of a decrease in the mode**			
	One before/ One after	One before/ One after (same day)	Five before/ Five after	Five before/ Ten after
After	-3.250*	-2.195	-2.732**	-4.142**
	(1.290)	(3.772)	(0.959)	(0.666)
N	12,665	8,754	55,114	87,904
e.	**Effect of a large donation – excluding other large donations**			
	One before/ One after	One before/ One after (same day)	Five before/ Five after	Five before/ Ten after
After	2.541**	2.724**	3.051**	2.793**
	(0.348)	(1.001)	(0.278)	(0.208)
N	14,690	6,079	6,5386	9,6125
f.	**Effect of a small donation – excluding other small donations**			
	One before/ One after	One before/ One after (same day)	Five before/ Five after	Five before/ Ten after
After	-2.050*	-1.214	-0.610	-1.014*
	(1.124)	(2.751)	(0.830)	(0.606)
N	12,399	5,546	4,8705	7,2011
g.	**Effect of different-sized large donations (five donations before/ five after)**			
	Twice mean	Three times mean	Five times mean	Ten times mean
After	11.154**	10.663**	17.396**	20.327**
	(1.043)	(0.973)	(1.825)	(3.155)
N	27,647	24,585	12,285	4,409

Notes to table

A large donation is twice the page mean and at least £50. A small donation is half the page mean. Columns (III) and (IV) in panel a-f and all columns in panel g include additional controls for place within page (linear trend), indicators for days since page was set up (capped at 100) and indicator variables for two days and one day before the marathon, the day of the marathon and (any) days after the marathon. *p<0.10; **p<0.05

Table 4: Main regression results

Dependent variable: Donation amount (£)

	(I)	(II)	(III)
	OLS	Page fixed effects	Difference GMM
(a)			
Past_mean (£)	0.525**	-0.359**	0.250**
	(0.013)	(0.023)	(0.028)
Arellano-Bond test for AR(1), p-value			*0.000*
Arellano-Bond test for AR(2), p-value			*0.322*
Hansen test, p-value (217 over-id restrictions)			*0.864*
(b)			
Mean, last ten (£)	0.458**	-0.114**	0.202**
	(0.012)	(0.012)	(0.019)
Arellano-Bond test for AR(1), p-value			*0.000*
Arellano-Bond test for AR(2), p-value			*0.313*
Hansen test, p-value (217 over-id restrictions)			*0.397*
(c)			
Mean, last five (£)	0.361**	-0.047**	0.116**
	(0.011)	(0.007)	(0.010)
Arellano-Bond test for AR(1), p-value			*0.000*
Arellano-Bond test for AR(2), p-value			*0.348*
Hansen test, p-value (217 over-id restrictions)			*0.771*
(d)			
Past_donation (£)	0.125**	0.003	0.022**
	(0.005)	(0.003)	(0.001)
Arellano-Bond test for AR(1), p-value			*0.000*
Arellano-Bond test for AR(2), p-value			*0.051*
Hansen test, p-value (217 over-id restrictions)			*0.630*

Notes to table

Sample size: I = 10,597, NI = 364,286. Instruments are the second and third period lag of the (level) independent variable. All regressions include additional controls for place within page (linear trend), indicators for days since page was set up (capped at 100) and indicator variables for two days and one day before the marathon, the day of the marathon and (any) days after the marathon. ****p<0.01**

Table 5: Testing for heterogeneous effects

Difference GMM: Dependent variable: Donation amount (£)

	(I)	(II)	(III)	(IV)	(V)
Past_mean (£)	0.104**	0.160**	0.098**	0.264**	0.214**
	(0.042)	(0.041)	(0.031)	(0.032)	(0.034)
Past_mean * PageWithTarget	0.158**				
	(0.050)				
Past_mean * MediumCharity		-0.043			
		(0.057)			
Past_mean * LargeCharity		0.078			
		(0.056)			
Past_mean * MajorCharity		0.085			
		(0.054)			
Past_mean * CharityAge>10y			0.127**		
			(0.047)		
Past_mean * CharityAge>20y			0.018		
			(0.047)		
Past_mean * OverseasCharity				-0.079	
				(0.045)	
Past_mean * YoungDonors					0.020
					(0.046)
Number of obs = NI	364,286	183,619	280,660	260,362	364,286
Number of pages = I	10,597	5,248	8,208	8,194	10,597

Notes to table: All regressions include additional controls for place within page (linear trend), indicators for days since page was set up (capped at 100) and indicator variables for two days and one day before the marathon, the day of the marathon and (any) days after the marathon. Instruments are the two-period and three-period lag of the past mean. **p<0.01

Medium, large and major charities have incomes of £1m-£5m, £5m-£50m and £50m+, respectively

YoungDonors are defined by the fundraiser being <40

Table 6: Targets

Dependent variable: Donation amount (£)

	(I)	(II)	(III)
	Fixed effects	Difference GMM	Difference GMM
Target donation	53.988**	47.506**	50.554**
	(3.957)	(3.455)	(1.490)
Reached target	-3.517**	-2.563	3.588**
	(0.564)	(1.482)	(1.398)
Past_mean (£)		0.262**	0.268**
		(0.040)	(0.030)
Past_mean * Reachedtarget			-0.191**
			(0.030)
Arellano-Bond test for AR(1), p-value		0.000	0.000
Arellano-Bond test for AR(2), p-value		0.940	0.943
Hansen test, p-value		0.669	0898
(over-id restrictions)		*(205)*	*(395)*
Number of obs = NI	139,201	135,308	135,308
Number of pages = I	3,893	3,893	3,839

<u>Notes to table</u>

All regressions include additional controls for place within page (linear trend), indicators for days since page was set up (capped at 100) and indicator variables for two days and one day before the marathon, the day of the marathon and (any) days after the marathon.

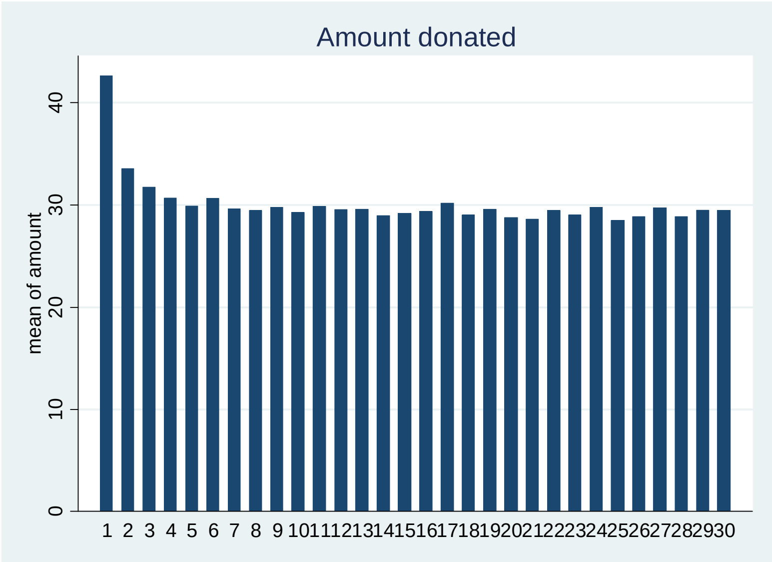
Target donation is the first donation to take the total over the target amount

Reached target is an indicator variable if the total is greater than the target

Instruments are the two-period and three-period lag of the past mean. ****p<0.01**

Figure 1

a. Mean amount, by order of donation on page



b. Within page variation in past mean (randomly selected sub-sample)

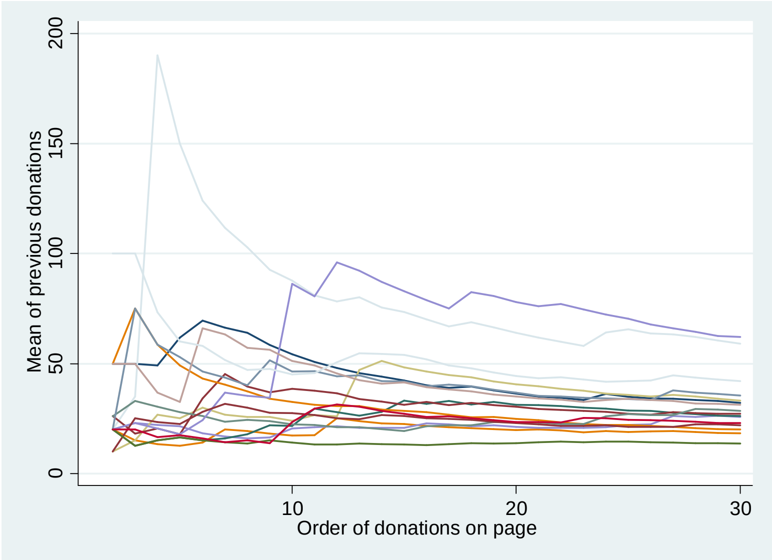
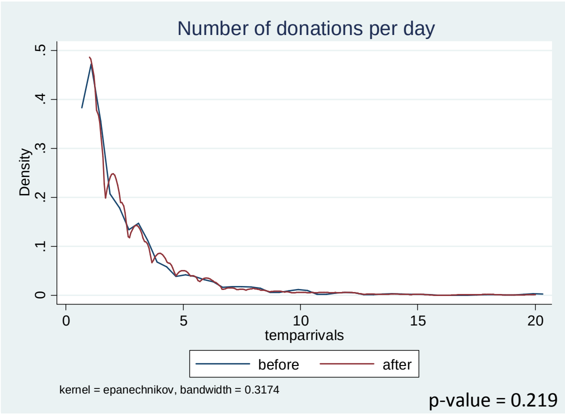
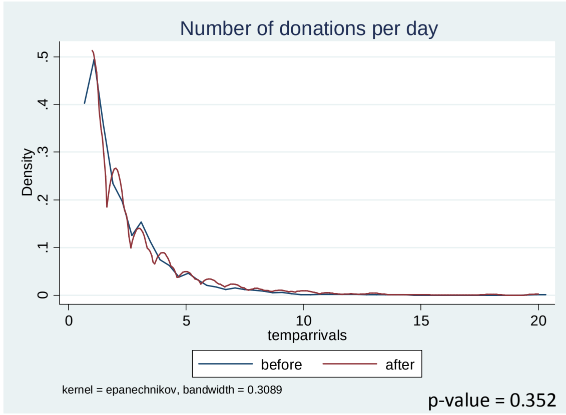


Figure 2: Distributions of arrivals

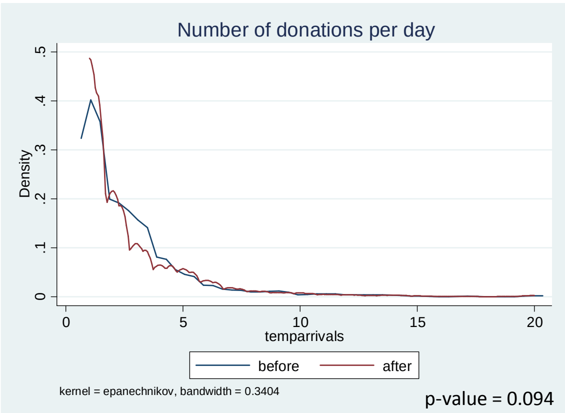
“Large” donation



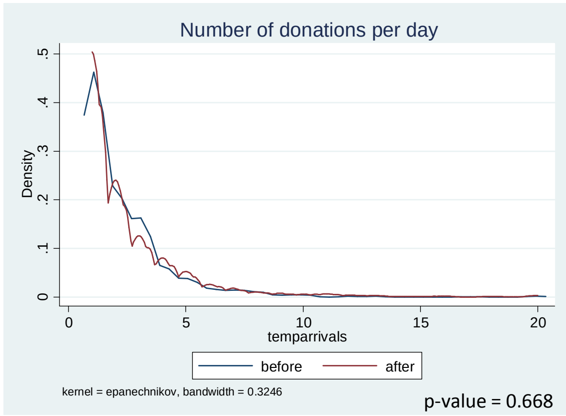
“Small” donation



Increase in mode



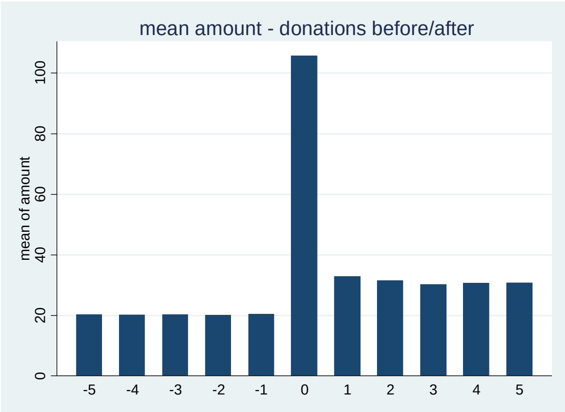
Decrease in mode



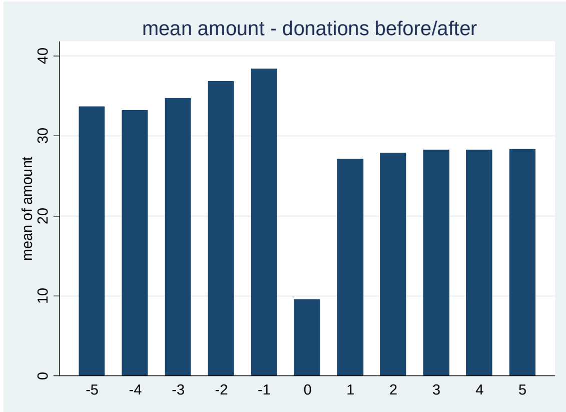
Notes to figure:
A large donation is defined as twice the page mean and at least £50. A small donation is half the page mean. We focus on the first large/small donation or change in mode to occur on a page, excluding those within the first three donations. P-value is for test of equality of distributions (kolgomorov-smirnov).

Figure 3: Mean amounts given

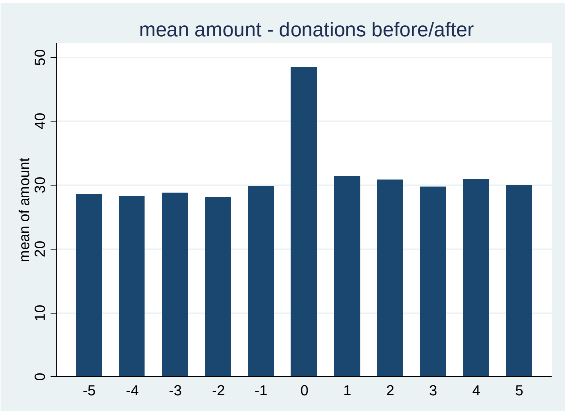
“Large” donation



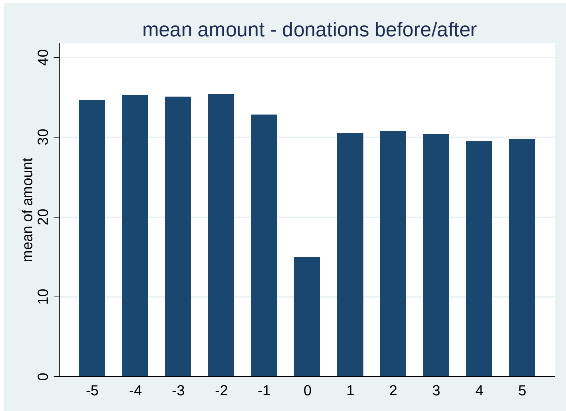
“Small” donation



Increase in mode



Decrease in mode



Notes to figure:

A large donation is defined as twice the page mean and at least £50. A small donation is half the page mean. We focus on the first large/small donation or change in mode to occur on a page, excluding those within the first three donations.