The effect of social information on charitable donations: Evidence from the (running) field[1]

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Abstract

This paper exploits online fundraising, where donors can see the full history of previous donations, to look at the influence of other people's donations on individual giving. We find consistent evidence that early donations crowd in later ones – our results show that a £10 increase in the mean of past donations leads to people giving £3.60 more, on average. We explore differences in "crowd in" across charities. We find no evidence that crowd in is stronger for smaller or newer charities, which might support a signalling story. We do find stronger crowd in among men than women.

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1. Introduction

This paper addresses the question of how donors respond to information on how much other individuals have previously given to a charitable cause. If donors observe that other people have given generously, will they give more or less to the same cause? This is important both for understanding what motivates individual giving to charity, as well as, practically, for informing charity fundraising strategies.

There is a widespread perception that it is good to encourage generous donors to give early and publicly, but there is no unambiguous theoretical prediction for how other donors will respond. There are a number of explanations for why such lead donations could "crowd in" individual giving, i.e. result in people giving more, through signalling effects (Vesterlund, 2003) or social norm effects, eg Sugden's model of reciprocity (Sugden, 1984) or Bernheim's model of conformity (Bernheim, 1994). However, models of "crowd out" which emphasize public good motivations for giving predict that the effect of lead donations could be negative (for example, Warr, 1982 and Roberts, 1984). The question of how an individual's donations are affected by how much other people have given is, therefore, an empirical one.

A number of recent experimental studies have found that social cues – that is, single pieces of information about how much other people have given – have a positive effect on giving. Studies by, among others, Frey and Meier (2004), Alpizar et al (2008), Shang and Croson (2009) find that telling people about a higher level of giving among other donors results in them giving more. This paper addresses the same issue but does so by exploiting a naturally-occurring setting in which donors have full information on previous donations.

We analyse a unique dataset of more than 300,000 donations made on behalf of more than 10,000 individual fundraisers who were running in the 2010 London marathon and were raising money for charity. These donations were made online through two websites – *Justgiving* (www.justgiving.co.uk) and *Virgin Money Giving* (http://uk.virginmoneygiving.com/giving/).[2] These websites work in broadly the same way: Individual runners set up a personal fundraising web page on behalf of a

[2] A previous study by Boeg et al (2008) analysed donations to a small sample of fundraising pages on Justgiving. They looked at the effect of early modes on later donations but did not take account of systematic variation in donations over time.

charity and then appeal to people (often their family, friends and colleagues) to make a donation to their chosen cause. Most donations are made through the website (rather than offline) and both the amount and, usually, the donor's identity are publicly recorded. This information on previously-made donations is then visible to each donor who subsequently visits the website (see Appendix A1). We exploit this set up to look at whether individuals' donations are affected by how much others before them have given.

One of the strengths of our study lies in the sheer scale of the fundraising activity. The claim of the London marathon is that it is the largest annual, one-day fundraising event in the world. Compared to many field experiments which are often small scale and focus on donations to a single charity, the marathon was used to raise many millions of pounds for thousands of charities. We exploit this to explore the effect of previous donations across different charities.

Online fundraising also provide an excellent setting for analysing crowd out/ crowd in because it is a situation where full information on all previous donations is provided to donors when they make their donation. In other studies that have looked at crowd out/in, donors are not necessarily aware of all the funding that the charities have received from elsewhere.

A potential concern with analysing naturally-occurring field data, compared to a field experiment, is that we cannot manipulate the social information. Our main interest in this paper is on the effect of previous donations on how much people give. However, fundraisers will typically seek donations from their family, friends and work colleagues, who are likely to be similar to them and to each other. Finding a positive correlation between previous and subsequent donations may therefore tell us little more than that similar people give in response to people like them. A second problem is endogenous sorting within the page – fundraisers may encourage larger donors to give earlier and close family and family may be among the first to give.

Our identification strategy exploits within-page variation in the observed history that arises as a result of donors arriving at the website at different times. We include a number of controls for systematic variation in how much people give at different points in time. We argue that there is likely to be some random variation in exactly when people come to make an online donation (arising as a result of exactly when they turn on their computer and make an online donation) – and therefore some variation across donors in the previous donations that they see when they arrive at the page.

We find consistent evidence that higher donations crowd in giving. In Section 4, we show that "large" ("small") donations have a significant positive (negative) effect on the donations that follow them. Our regression results, presented in Section 5, indicate that a £10 increase in the mean of past donations increases the amount given by £3.60. In Section 6 we look at how crowd in varies across charities and donors to explore alternative explanations for why crowd in might occur. Section 7 concludes.

2. The effect of past donations on giving

A growing empirical literature, much of it experimental, has looked directly at the effect of information about how much other individual donors have given (referred to as "social information"). These studies mainly find a positive effect – donors give more if the information indicates that other donors have been more generous. For example, Frey and Meier (2004) conducted a field experiment asking students to give to either a hardship fund or a fund to support foreign students. When the students were told that a higher proportion of past students had donated, 64 per cent compared to 46 per cent, this had a small (2.3 percentage point) effect on participation, which was statistically significant once past giving behavior was taken into account. Alpizar et al (2008) tested the effect of revealing different levels of the modal donation on both the propensity to give and the amount given. They found that a low mode increases participation but reduces average donation (compared to no social information) while a higher mode increases the average donation. Finally, Shang and Croson (2009) explored the effect of telling donors how much a single, previous donor had given on the *amounts* given to a public radio station campaign, varying the social reference level across donors. This most closely resembles our own study which is similarly looking only at the intensive margin. They found telling people about a larger donation (drawn from the 90th to 95th percentile of the distribution) significantly increased the amount given. In a separate paper (Croson and Shang, 2008) they also find that information about smaller donations had the opposite effect.

These findings run counter to the predictions of earlier models of public good giving that predicted crowd out (see Warr, 1982, Roberts, 1984). In such models, individuals are assumed to care only about the level of the public good that is going to be financed through voluntary contributions (i.e. they are "pure altruists"); in this case, a higher level of public good provision reduces the marginal value from the donor's own contribution, causing the individual to substitute towards private goods. Incorporating a direct utility effect from giving through "warm glow"[3] (Andreoni, 1989, 1990), reduces the magnitude of crowd out but the predicted effect of others' donations is still negative. Recent studies that find evidence of crowd out of private donations by other funding from government grants include Andreoni and Payne (2009).

A number of possible mechanisms could explain why individual donations crowd in other donations. One set of models incorporates social norms directly or indirectly into individual utility calculations. For example, Sugden (1984) presents a model of reciprocity in which individuals optimise subject to the constraint that they give at least as much as the least generous person is giving. Bernheim's model of conformity (1994) assumes that people care about status which can be harmed by deviations from the social norm, which in turn is defined by how much other people give.

Other explanations for giving can incorporate an effect of other people's donations. For example, where giving is assumed to attract an extrinsic reward by signalling wealth (Glazer and Konrad, 1996) or generosity (Harbaugh, 1998), this reward may depend not on the absolute level of the donation, but on the level relative to some socially determined reference level which depends on how much other people are giving.

An alternative set of explanations for crowd in focuses on the information value in other people's donations. Vesterlund (2003) presents a model in which past contributions signal the quality of a charity, in which case higher early donations would tend to crowd in later donations. Potters et al (2005) show that donors with an informational advantage will select to make lead donations in order to signal quality.

Finally, 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. In this case, announcing lead donations provides donors with an inexpensive method of coordinating on positive provision and early donations can crowd in later ones, at least up to the threshold. The possible effects of thresholds are highly relevant to the London marathon

[3] Warm glow refers to the increase in utility that individuals derive directly from their donation. Here, we assume that it captures the intrinsic reward that individuals derive from giving to charity.

fundraising pages, the majority of which have target levels of fundraising and we look at whether these targets have an effect on individual donations in practice.

This paper adds to the existing empirical literature in a number of ways. Like previous studies, we test directly whether previous donations affect how much people give to a charitable cause and we add to the growing body of evidence that there is crowd in – higher donations result in people giving more. We are also able to exploit a rich dataset with information on many thousands of donors giving to hundreds of different charities to explore variation across donors and charities, allowing us to shed some light on alternative explanations for why crowd in might occur.

3. Data

Our sample consists of people running in the 2010 London marathon who raised money for charity and who set up fundraising pages on the two main giving websites in the UK – Justgiving and Virgin Money Giving (see Appendix A1).

We have information from more than 12,000 fundraising pages. The information was 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 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 was captured and the full history of donations to the website and the donors' names (where available) and the amount given. In Section 6 we describe how we are able to merge in additional information on the fundraisers and the charities.

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.[4]

<< Table 1 near here>>

The mean online donation is £30.31. The distribution of donations is heavily "spiked" 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.

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

As shown in Table 1, the distributions are quite skewed by the presence of a few very successful fundraisers[5] and generous donors. In the regression analysis, we exclude 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). Finally, we exclude the first five donations to each page because these are likely to be made by close family and friends who may be atypical and tend to give more than later donors (see Figure A3.2 in the Appendix). The effect of this sampling is shown in Table 1.

3. "Large" and "small" donations as a natural experiment

In this section, we provide some preliminary descriptive evidence of crowd in, focusing on the effects of "large" and "small" donations (defined below) on subsequent amounts given. Our identification strategy exploits the fact that exactly when donors arrive at the page – and hence whether they arrive just before or just after a large or small donation – is likely to be random. For example there might be some random timing arising as a result of exactly when people find a moment in their day to make an online donation.

Within a narrow window, we would argue that it seems plausible to treat arriving just after a large/small donation as an exogenous "treatment" and to identify a crowd in (or crowd out) effect by comparing mean amounts given before and after.

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 ignore large/small donations made within the first five donations to a page.

Figure 1 shows mean amounts donated before and after the first large/small donation to a page, providing clear evidence that both large and small donations are associated with a change in subsequent amounts given. The effects appear to be fairly persistent, at least up to twenty donations after the large/small donation, although at longer intervals the assumption of an exogenous treatment may be less plausible. Figure 1 also shows the flow of donations. Although we cannot

[5] 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.

look directly at the extensive margin, this evidence does not suggest any obvious effect of large/small donations on whether or not people donate.

<< Figure 1 near here>>

To control for changing sample composition over donations observed before and after, we run fixed effects regressions of the following form:

$$d_{in} = \alpha + \beta T_{in} + \lambda_n + \delta_t + u_{in}$$

where d_{in} = refers to the n^{th} donation to fundraising page i (in pounds) and T_{in} is an indicator equal to one if the donation follows a large/small donation and equal to zero otherwise. λ_n and δ_t are 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 that removes the effect on donations of the page-specific unobservable factors.

Our identification strategy relies on there being some random variation in the timing of donations within a narrow window (after controlling for systematic within-page variation), i.e. $E(v_{in} \mid T_{in}) = 0$. In this case, then the coefficient β will identify the average effect of a large/small donation on the amount subsequently given.[6]

The regression results are summarized in Table 2. For both large and small donations we vary the size of the window before and after – looking at narrow windows of three donations before/after and five donations before/after and also longer after-periods of ten and twenty donations. (More detailed results, containing individual lead and lag terms are reported in Table A3.1 in the Appendix.) The results confirm that there is a significant change in how much subsequent donors give following both large and small donations and that the effects appear to be fairly persistent. The

[6] One possible violation of this would be if the fundraiser targets groups of potential donors by type. In this case the first large (or small) donation would mark the first in a group of similar people to come to a page. The evidence that there is no change in flow and that the effect persists for a long time suggests that this is not the explanation.

coefficients indicate fairly sizeable effects. Within a narrow window of three donations, large donations are associated with a £12 increase in donation size (compared to a previous mean of £20), while a small donation reduces donation size by £5 (compared to a previous mean of £33).

<<Table 2 near here>>

We also show results for large donations of different sizes (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) there is evidence that larger donations produce a greater response from subsequent donors.

Finally in this section, we look at whether there is evidence of any spillover effect from donors giving more in response to a large donation on one fundraising page to how much they give to 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 estimate an equation of the following form:

$$d_{di} = \alpha + \beta_1 T_i + \beta_2 T_j + \omega_{di}$$

where d_{di} refers to the donation of donor *d* to fundraising page i. T_i is an indicator equal to one if the donation to page *i* is made after a large donation to that page, while T_j is an indicator equal to one if the donation to page *i* is made after a large donation to another page ($i \neq j$) that the donor has given to. β_1 captures the own-page effect of a large donation (the difference in how much the donor gives following a large donation on that page compared to their earlier donations to other pages), while β_2 captures any spillover effect on donations to other pages (the difference in how much the donor gives after going to another page with a large donation, compared to their earlier donations to other pages). We also include a trend to allow for the fact that donors may reduce their donations as they are asked to sponsor more people.

After dropping donations made on the same day (where we cannot establish the order in which they occurred) and donors who make fewer that three donations in total, our estimation sample consists of 1,626 donors who make an average of 4 donations to different pages.

The results confirm the crowd in effect of large donations. Donors give more when they come to a page which has a large donation, compared to their earlier donation(s). The estimated effect (7.250, SE 4.138) is lower than the previous estimates of crowd in of large donations but is defined for a group of donors who give to multiple pages. The estimated spillover effect is positive (2.588), but insignificant (SE 1.804), implying that there is no evidence that the crowd in effect of a large donation to one page is also associated with a crowd out of donations to other fundraising pages.

5. Identifying the effect of past donations – regression analysis

In this section we look at the effect of the full, past history of all donations to a fundraising page. We estimate the following reduced-form model:

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

As before d_{in} = refers to the n^{th} donation to fundraising page *i*. $\bar{d}_{i,n-1}$ 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. This is a summary measure of all the information on previous donations that the donor sees when they arrive at the page.[7] We are interested in the coefficient γ which measures the extent to which a higher level of past donations is associated with people giving more or less.

As before, λ_n is a set of indicators for the order in which the donation occurs on the page and δ_t is a set of date controls, including indicators for the days since the page set up (capped at 100) and also for the days in the immediate run up to the day of the marathon.

The OLS estimate of γ is 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.[8] For this reason, we cannot identify the effect of past

[7] 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.

[8] The fact that fundraiser characteristics may influence all donations to a page means that it may not be possible to obtain an unbiased estimate of the effect of past donations by exploiting multiple donations by the same donor to different pages.

donations from variation across pages, but only from variation within pages over time. (This variation is illustrated in Figure A3.2).

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, $u_{in} - (u_{i2} + ... u_{iN}) / (N-1)$, will be negatively correlated with the mean-differenced lagged dependent variable, $\overline{d}_{i,n-1} - (\overline{d}_{i1} + ... \overline{d}_{iN-1}) / (N-1)$. 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 – this bias will not be negligible, 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 – Bond (1991) GMM estimator[9] i.e the page-specific effect η_i is eliminated by first-differencing:

$$\Delta d_{in} = \alpha + \gamma \Delta \overline{d}_{i,n-1} + \lambda_n + \delta_t + \Delta v_{in}$$

In this first-differenced model there is now an endogeneity problem due to the correlation between $\overline{d}_{i,n-1}$ and $v_{i,n-1}$. 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 does not reject the null of no second-order serial correlation, implying that the two-period lag is valid. The Hansen test (with 214 over-identifying restrictions) does not reject that the instrument set is valid. The main coefficient estimate is robust to alternative instruments sets, including using the second and third lags as only two instruments, i.e. with the same reduced form per donation order.and equivalently for the third and fourth lags. The Hansen test rejects the null that the instruments are excludable in the collapsed case with lags 2 and 3, but not in the case of using lags 3 and 4. Both these sets of instruments are strong predictors of the lagged change in the mean donations. The results from a number of alternative specifications are reported in Table A3.2.

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[9] We estimate the GMM model using xtabond2, see Roodman, 2006.

Our main results are presented in Table 3. For comparison, we show both the upward biased OLS and the downward biased fixed effects results. Our main GMM result lies between these two. The GMM estimate of γ is positive and significant – the coefficient implies that a £10 increase in the mean of past donations – eg from £10 to £20 – leads to people giving £3.60 more on average. This is slightly smaller than the results from the previous section: The GMM results imply that a donation of £100 in fifth place on the page which raised the mean from £25 to £40 would increase donations by £5. However, the GMM results provide confirmation of the main finding from the previous section that past donations have a sizeable "crowd in" effect on later giving

<< Table 3 near here >>

The final columns of Table 3 contain the results of some robustness checks. Column IV excludes pages with any offline donations since we do not have information on the exact amount that has been given offline when each donor comes to the page (we only know the total offline donations at the point at which the data were captured). The magnitude of the estimated coefficient in this specification is very similar. Column V replaces the mean of all previous donations to the page with a rolling average based on the last ten donations. The coefficient on the mean of the past ten donations is smaller, but still positive and significant.

6. Testing for differential effects across charities and donors

One of the potential advantages of looking at the fundraising data from the London marathon is that it covers a wide range of fundraisers, charities and donors, allowing us to test whether the effect of social information varies across groups. However, the fundraising pages themselves contain relatively little information apart from the donations given. We therefore match additional information from other sources.

We obtain information on the fundraisers by matching each fundraiser by name to their race results on the official marathon website.[10] This provides information on the runners' gender, their age (banded), nationality and marathon time. We also assign a gender to the donors on the basis of their first name using a database of 18,881 names. We can do this for 76 per cent of donors; for the remainder, either the name is not gender-specific or the donation is made by more than one person

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[10] http://www.virginlondonmarathon.com/marathon-centre/race-results/race-results/

– for this reason the mean donation among the matched sample is lower than among the full estimation sample. We tested our assignment process on the sample of fundraisers for whom gender is known, and predicted correctly in 99 per cent of cases.

For information on charities, 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. However, even where we do match, key variables such as the charities' date of birth, location of activity and income are missing from the Register data. In the case of income, for example, only charities with annual income greater than £10,000 a year are required to submit an annual return. Table A3.3 provides summary statistics on the sub-samples for which data are available.

For information, Table A4.4 summarizes differences in mean donations across different fundraiser, donor and charity characteristics: the key focus in this section, however, is in whether there is a differential response to past donations by any of these characteristics. Table 4 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 (defined by an annual income cut-off of £10 million[11]), the age of the charity (defined by a cut-off of ten years old), 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) and the gender of the donors.

<< Table 4 near here>>

One possible explanation for crowd in, discussed in Section 2, is that donors extract some information about the quality of the charity from large, early donations. However, the results provide little support for this signalling story. In this case, we would expect the information content of past donations to be more important for smaller and younger charities (Heutel, 2009) and for those operating overseas and for younger donors. However, the results show that crowd in is actually stronger for larger charities and for older charities (although the difference is not statistically significant in the latter case). There is no difference in crowd in between overseas and UK-based

[11] Alternative specifications which included charities with missing income as smaller charities produced similar results.

charities. We do find a stronger crowd in effect for younger donors (proxied by the age of the fundraiser), but this is not statistically significant.

Interestingly, we find a statistically significant difference between the size of the crowd-in effect between men and women. Past donations positively influence giving for both, but the estimated effect is significantly greater for men than for women. While we cannot completely rule out that this may be driven by other characteristics that are correlated with gender, this suggests a new finding in relation to gender differences in altruistic behaviour (eg Andreoni and Vesterlund).

Finally, we explore whether there are threshold effects. Andreoni (1998) shows that lead donations can provide donors with an inexpensive method of coordinating on positive provision where there is a threshold level of donations – or a target as is the case for around 80 per cent of London marathon fundraising pages. In practice, however, we find evidence of crowd in for pages both with and without a fundraising page – as shown in Table 4, the coefficient on the interaction term is insignificantly different to zero. The "threshold effect" cannot explain all observed crowd in.

However, further analysis reveals differences in behaviour around the target. Figure 2 plots the profile of donations around the target – twenty donations on each side where zero represents the first donation to take the total over the target. The target appears to have two main effects – donors give more to hit the target and give slightly less once the target has been reached. This is borne out by regression analysis, summarised in Table 5, cols (1) and (II), where the results indicate that donations are £3 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.

<< Figure 2 near here>>

Finally, col (III) of Table 5 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 it is not possible to reject that there is no crowd in effect of past donations once the target has been reached. While the threshold effect cannot explain crowd in across all fundraising pages, these results are consistent with Andreoni (1989) that, for pages with targets, crowd in is only empirically relevant below the target.

<<Table 5 near here>>

6. Discussion

In an online survey of nearly 18,000 Justgiving donors carried out between October 2010 – June 2011, donors were asked to rate the importance of a number of different factors in deciding how much to give. The results (summarised in Table A3.5) showed that "how much other people had given" was cited as very important by 3 per cent and as somewhat important by 21 per cent. The evidence in this paper adds to the growing evidence base that donations are responsive to social information and that how much other people have given has a positive effect on giving.

Online fundraising provides a rich environment to look at the effect of social information because of the numbers of fundraisers, donors and different types of charity. It is important to acknowledge that there are some distinctive features that might affect the results (and hence their external validity). In particular, there are often personal connections between the fundraisers and the charities they are raising money for and personal relationships between the fundraisers and the people who give to charity on their behalf. The fact that many donors are likely to be friends, family and colleagues of the fundraiser (and know other donors) may affect the extent to which crowd in occurs.

However, assuming that this effect is common to the online fundraising environment, we are able to look at whether there are differences in crowd in behaviour across different types of charity and donors and to shed new insights on what might explain observed crowd in. Our analysis provides little support for a signalling story – crowd in is not stronger for smaller and newer charities or for younger donors. And, while there are interesting differences in behaviour around fundraising targets, the presence of these targets can also not explain all observed crowd out. This leaves a set of explanations which emphasize crowd in as a social phenomenon.

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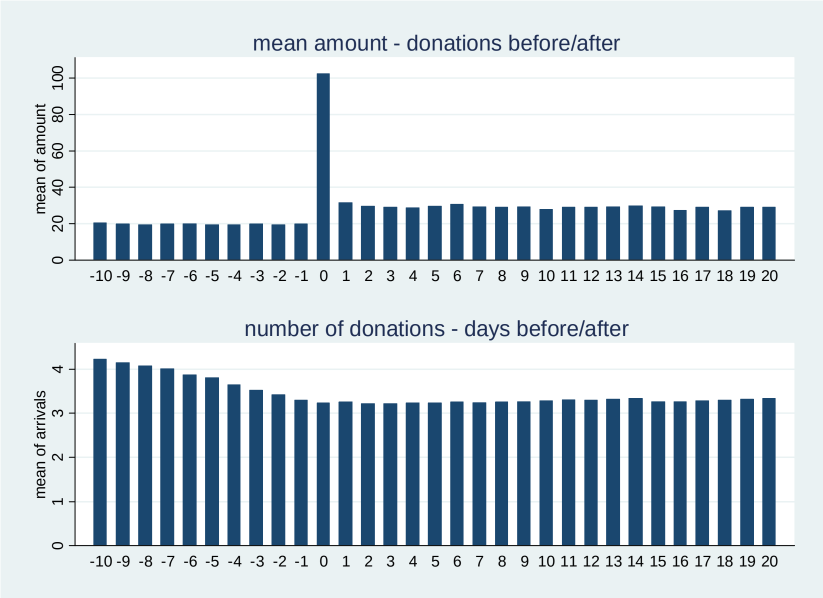
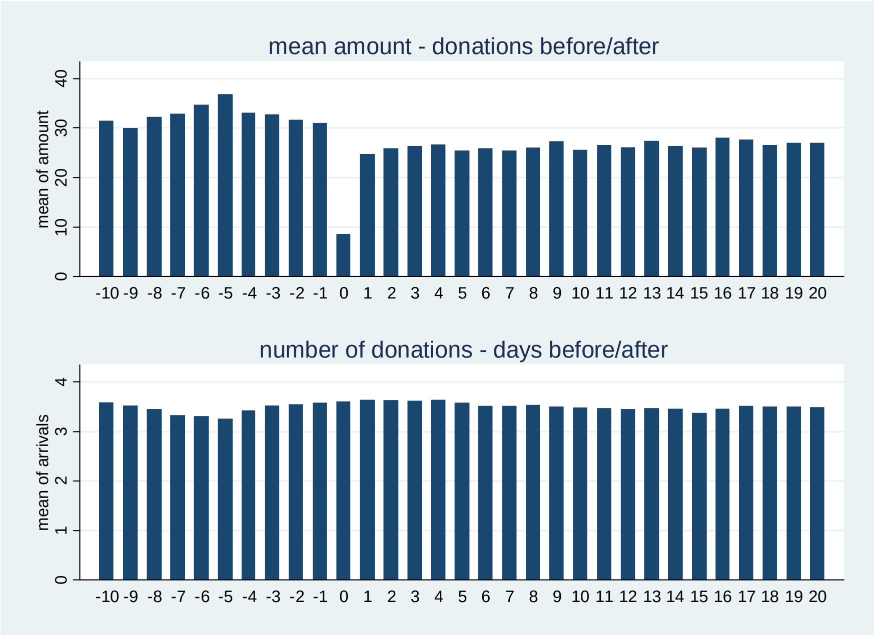
Figure 1: Effect of large/ small donations

Before/ after "large" donation

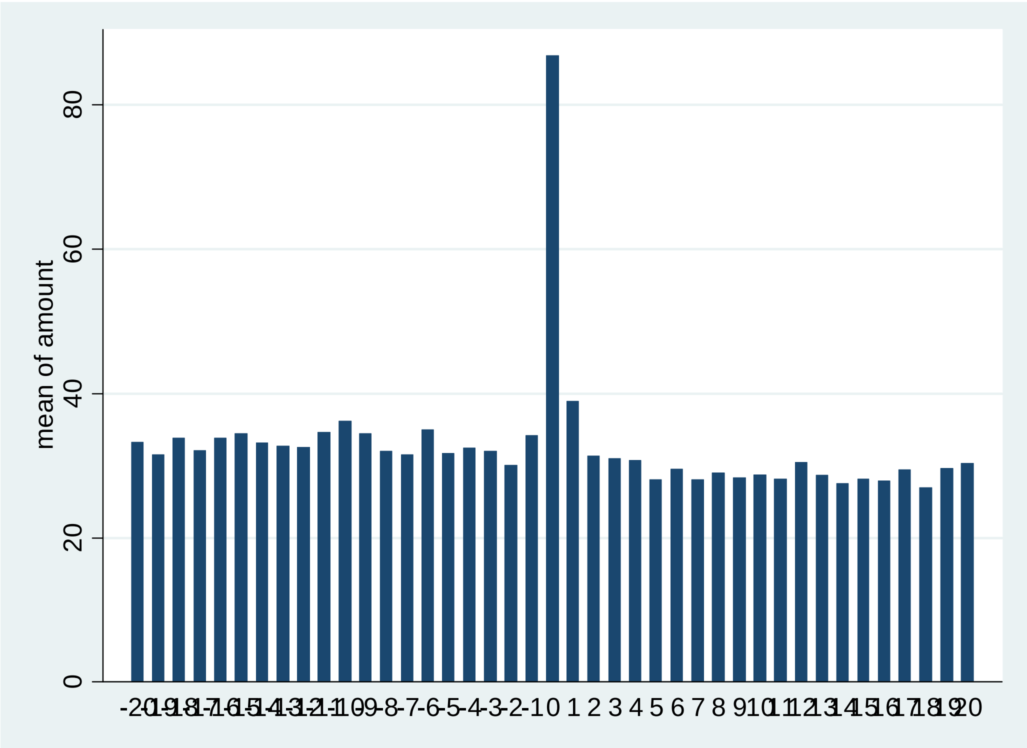


Before/ after "small" donation



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 on a page, excluding those within the first five donations.

Figure 2: Profile of donations around the target



Notes to figure:
This shows twenty donations above/ below the target. Zero represents the first donation to take the total over the target amount.

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
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
Proportion of donors who are male	.513						
Number of fundraisers	12,750						
Estimation sample							
Number of donations per page	36.7	19.7	10	10	33	91	100
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
Proportion of donors who are male	.512						
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: Effect of large/ small donation – fixed effects regression results

a. First large donation

Dependent variable = £ amount given

	Three before/ Three after	Five before/ Five after	Five before/ Ten after	Five before/ Twenty after
After	12.622**	11.171**	10.517**	9.797**
	(1.034)	(0.746)	(0.562)	(0.391)
N	17,213	16,720	8,024	2,938

b. Different sized large donations (five before/after)

Dependent variable = £ amount given

	Twice mean	Three times mean	Five times mean	Ten times mean
After	9.394**	10.304**	15.184**	15.203**
	(1.133)	(1.166)	(1.957)	(3.329)
N	17213	16720	8024	2938

c. First small donation

Dependent variable = £ amount given

	Three before/ Three after	Five before/ Five after	Five before/ Ten after	Five before/ Twenty after
After	-5.567**	-5.591**	-3.589**	-2.987**
	(0.764)	(0.565)	(0.488)	(0.451)
N	35,051	59,187	109,118	298,872

Notes to table

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 on a page, excluding those within the first five donations.

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 3: Main regression results

Dependent variable: Donation amount (£)

	(I)	(II)	(III)	(IV)	(V)
	OLS	Page fixed effects	Difference GMM	Difference GMM Excl offline	Difference GMM Last 10
Past_mean (£)	0.567**	-0.541**	0.356**	0.373**	0.239**
	(0.013)	(0.032)	(0.043)	(0.059)	(0.023)
Instruments			$\bar{d}_{i,n-2}, \bar{d}_{i,n-3}$	$\bar{d}_{i,n-2}, \bar{d}_{i,n-3}$	$\bar{d}_{i,n-2}, \bar{d}_{i,n-3}$
Arellano-Bond test for AR(1), p-value			0.000	0.000	0.000
Arellano-Bond test for AR(2), p-value			0.539	0.964	0.516
Hansen test, p-value *214 over-id restrictions*			0.865	0.685	0.345
Number of obs = NI	343,092	343,092	343,092	166,537	343,092
Number of pages = I	10,597	10,597	10,597	5,321	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.

$^{**}p<0.01$

Table 4: Testing for heterogeneous effects

Difference GMM regression results

Dependent variable: Donation amount (£)

	Definition of group					
	Larger charity	Older charity	Overseas charity	Pages w/ target	Younger donors	Male donors
Past_mean (£)	0.191**	0.247**	0.362**	0.420**	0.283**	0.284**
	(0.062)	(0.070)	(0.050)	(0.094)	(0.062)	(0.032)
Past_mean * Group	0.356**	0.119	0.004	-0.075	0.099	0.157**
	(0.091)	(0.084)	(0.079)	(0.105)	(0.081)	(0.011)
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	0.560	0.581	0.593	0.542	0.544	0.616
Hansen test, p-value	0.762	0.752	0.863	0.970	0.908	0.397
Number of over-identifying restrictions						(619)
Number of obs = NI	173,123	264,256	263,974	343,092	343,092	343,092
Number of pages = I	5,248	8,202	8,194	10,597	10,597	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

Larger charities have income > £10m

Older charities were born ten or more years ago

Younger donors are identified from the age of the fundraiser (< 40)

Differential effects by gender also includes indicators for "male" and "gender missing", as well as an additional interaction term between past_mean and "gender missing"

****p<0.01**

Table 5: Targets

Dependent variable: Donation amount (£)

	Fixed effects	Difference GMM	Difference GMM
Target donation	54.255**	47.471**	50.323**
	(3.881)	(0.059)	(1.476)
Reached target	-2.892**	-2.838	7.365**
	(0.544)	(1.489)	(1.772)
Past_mean (£)		0.338**	0.327**
		(0.059)	(0.039)
Past_mean * Reachedtarget			-0.303**
			(0.046)
Arellano-Bond test for AR(1), p-value		0.000	0.000
Arellano-Bond test for AR(2), p-value		0.581	0.593
Hansen test, p-value		0.752	0.863
(over-id restrictions)		(201)	(389)
Number of obs = NI	139,732	127,522	127,522
Number of pages = I	4,221	3,839	3,839

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

$^{**}p<0.01$

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[12]) 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.

[12] As well as enabling people to give online, one of the potential attractions of the websites for donors and charities is that they make it easier for people to get tax relief on their donations. The main system of tax relief on individual donations in the UK, known as Gift Aid, allows charities to reclaim tax relief on donations made by taxpayers at the basic rate of tax (currently 20%). For every £1 given out of net of tax income, charities can claim 25 pence in tax relief[12] – but to do this, individual donors have make a declaration that they are UK taxpayers. This process is automated when donations are made online; JG and VMG reclaim the tax relief and pass it on to the charity.

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

PhabKids!

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

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

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money giving

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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!

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 »

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

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 »

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

$$\text{Model LDep: } y_{it} = \alpha y_{i,t-1} + \eta_i + v_{it}$$

for $t = 2,..,T$ and $i = 1,...,n$, it is well known the fixed effects estimator for α 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:

$$\text{Model LAvg: } y_{it} = \alpha \bar{y}_{i,t-1} + \eta_i + v_{it}$$

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

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

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

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

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

We present the biases of the fixed effects estimators of α in the two models LDep and LAvg in Table A1, for different values of T, α and σ_η^2, for 1,000 Monte Carlo replications.

Table A1. Bias of the Fixed Effects Estimator

		$T=5$		$T=20$		$T=40$	
α	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

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 T 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 $T=40$, for $\alpha=0.5$ 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 $x_{it}=y_{i,t-1}$ for the LDep model and $x_{it}=\bar{y}_{i,t-1}$ for the LAvg model, we can write the generic model as

$$y_{it}=\alpha x_{it}+\eta_i+v_{it}$$

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

$$\hat{\alpha}_{FE} = \frac{\sum_{i=1}^{n}\sum_{t=2}^{T}(x_{it}-\bar{x}_i)(y_{it}-\bar{y}_i)}{\sum_{i=1}^{n}\sum_{t=2}^{T}(x_{it}-\bar{x}_i)^2}$$

$$= \alpha + \frac{\sum_{i=1}^{n}\sum_{t=2}^{T}(x_{it}-\bar{x}_i)(v_{it}-\bar{v}_i)}{\sum_{i=1}^{n}\sum_{t=2}^{T}(x_{it}-\bar{x}_i)^2}$$

where $\bar{y}_i = \frac{1}{T-1}\sum_{t=2}^{T} y_{it}$, $\bar{x}_i = \frac{1}{T-1}\sum_{t=2}^{T} x_{it}$ and $\bar{v}_i = \frac{1}{T-1}\sum_{t=2}^{T} v_{it}$.

This can be further simplified to

$$\hat{\alpha}_{FE} - \alpha = \frac{\sum_{i=1}^{n}\sum_{t=2}^{T} x_{it}(v_{it}-\bar{v}_i)}{\sum_{i=1}^{n}\sum_{t=2}^{T}(x_{it}-\bar{x}_i)^2}$$

and hence

$$\text{plim}(\hat{\alpha}_{FE} - \alpha) = \frac{\text{plim}\frac{1}{n}\sum_{i=1}^{n}\sum_{t=2}^{T} x_{it}(v_{it}-\bar{v}_i)}{\text{plim}\frac{1}{n}\sum_{i=1}^{n}\sum_{t=2}^{T}(x_{it}-\bar{x}_i)^2}$$

$$= -\frac{\text{plim}\frac{1}{n}\sum_{i=1}^{n}\sum_{t=2}^{T} x_{it}\bar{v}_i}{\text{plim}\frac{1}{n}\sum_{i=1}^{n}\sum_{t=2}^{T}(x_{it}-\bar{x}_i)^2}$$

as $E[x_{it}v_{it}] = 0$.

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

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

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

It is clear, that the bias decreases more rapidly in the LDep model because the variance term $\frac{1}{n}\sum_{i=1}^{n}\sum_{t=2}^{T}\left(x_{it}-\bar{x}_i\right)^2$ increases more rapidly with T. This is of course expected, as $\bar{y}_{i,t-1}$ eventually converges to a constant. The covariance terms $\frac{1}{n}\sum_{i=1}^{n}\sum_{t=2}^{T} x_{it}\left(v_{it}-\bar{v}_i\right)$ are of the same order and magnitude.

Appendix A3 – Further figures and tables

Figure A3.1 Distribution of amounts given

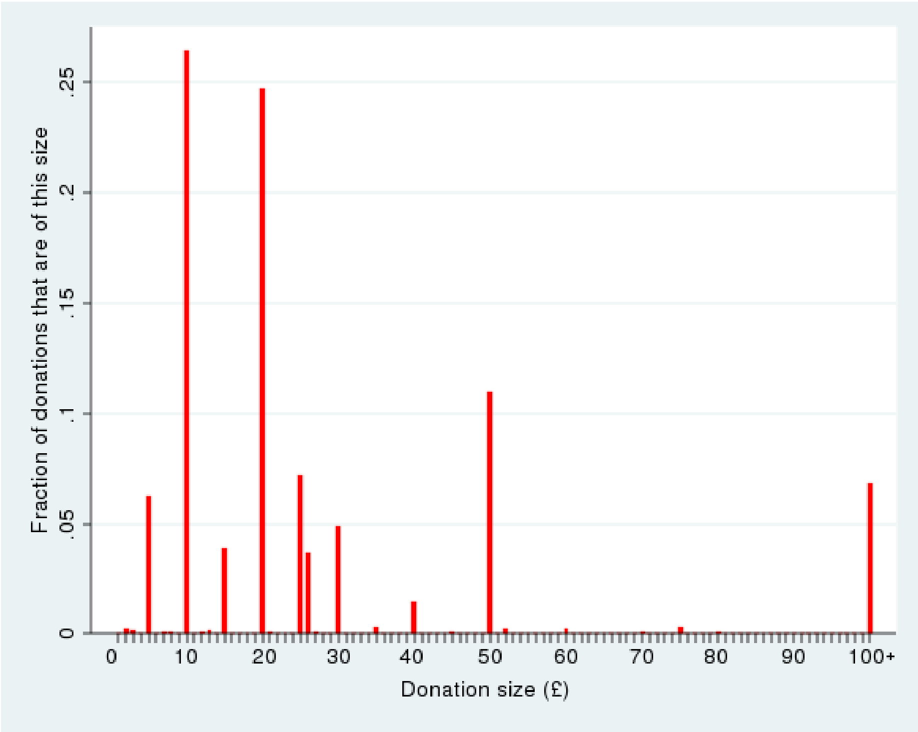
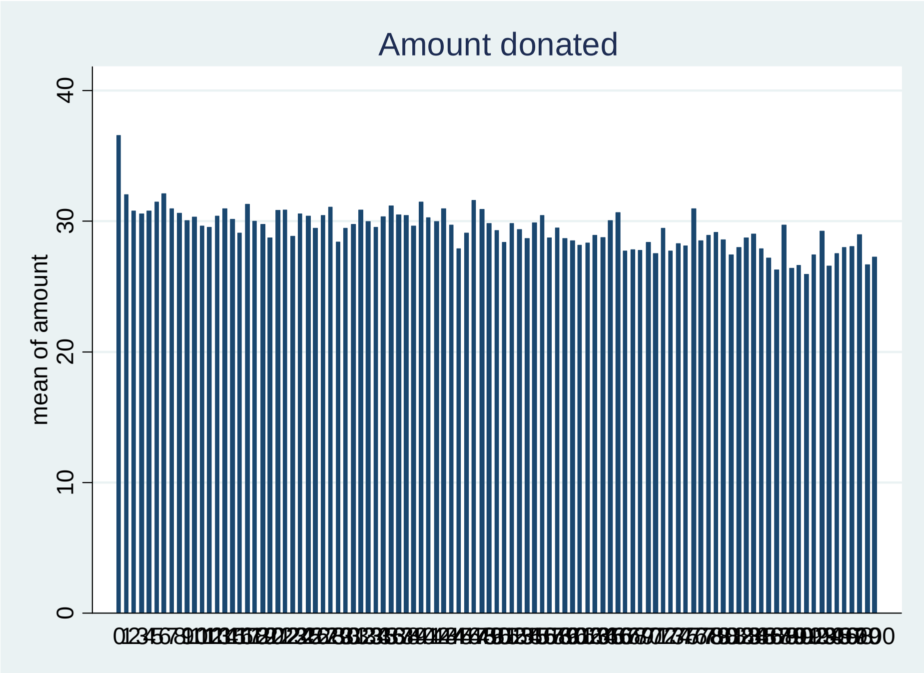


Figure A3.2: Donation profiles

By order of donation on page



By day since page was set up (0 = first day)

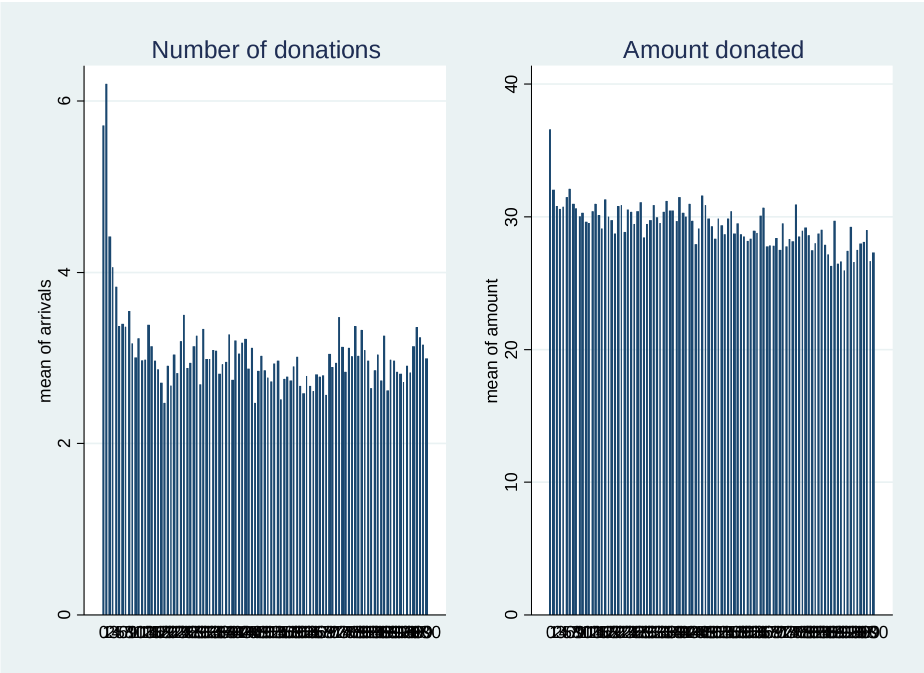


Figure A3.3: Within page variation in past mean (randomly selected sub-sample)

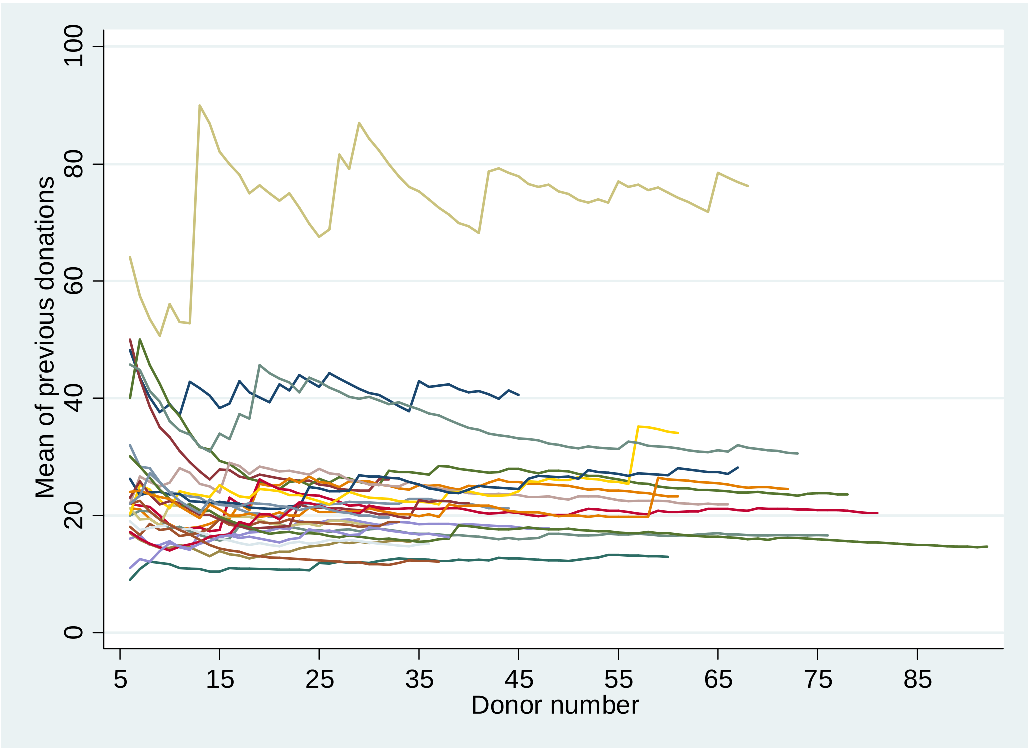


Table A3.1: Lead/lag analysis of large/small donation (FE regression)

	Before/after large donation		Before/ after small donation	
	amount	arrivals	amount	arrivals
N – 3	0.368	-0.053	-1.578*	0.356**
	(0.281)	(0.037)	(0.742)	(0.044)
N – 2	0.189	-0.088	-2.316**	0.431**
	(0.314)	(0.052)	(0.893)	(0.062)
N – 1	0.605	-0.118	-3.110**	0.480**
	(0.366)	(0.065)	(0.907)	(0.078)
N	82.699**	-0.083	-25.656**	0.523**
	(1.473)	(0.078)	(0.942)	(0.095)
N + 1	12.315**	0.038	-9.887**	0.511**
	(0.737)	(0.090)	(1.134)	(0.110)
N + 2	10.793**	0.103	-9.103**	0.475**
	(0.758)	(0.103)	(1.302)	(0.126)
N + 3	10.335**	0.170	-9.112**	0.433**
	(0.768)	(0.115)	(1.420)	(0.141)
N + 4	10.427**	0.255*	-9.149**	0.399*
	(0.826)	(0.128)	(1.547)	(0.157)
N + 5	11.365**	0.314*	-10.764**	0.267
	(0.929)	(0.140)	(1.654)	(0.173)
N + 6	12.914**	0.379*	-10.798**	0.164
	(1.062)	(0.153)	(1.782)	(0.191)
N + 7	11.470**	0.410*	-11.317**	0.128
	(0.980)	(0.165)	(1.882)	(0.207)
N + 8	11.563**	0.457*	-11.221**	0.088
	(1.046)	(0.178)	(2.061)	(0.223)
N + 9	12.166**	0.515**	-10.508**	0.019
	(1.118)	(0.190)	(2.232)	(0.238)
N + 10	11.217**	0.559**	-12.823**	-0.059
	(1.118)	(0.202)	(2.296)	(0.255)
N + 11	12.397**	0.621**	-11.925**	-0.136
	(1.242)	(0.215)	(2.471)	(0.269)
N + 12	12.604**	0.653**	-12.722**	-0.188
	(1.278)	(0.227)	(2.589)	(0.286)
N + 13	13.071**	0.702**	-11.788**	-0.215
	(1.340)	(0.240)	(2.755)	(0.301)
N + 14	13.813**	0.749**	-13.544**	-0.257
	(1.391)	(0.251)	(2.836)	(0.318)
N + 15	13.688**	0.712**	-14.273**	-0.416
	(1.458)	(0.265)	(2.951)	(0.334)
N + 16	12.188**	0.759**	-12.734**	-0.430
	(1.432)	(0.277)	(3.168)	(0.350)
N + 17	14.152**	0.799**	-12.951**	-0.427
	(1.531)	(0.289)	(3.281)	(0.366)
N + 18	12.520**	0.842**	-14.394**	-0.471
	(1.548)	(0.302)	(3.372)	(0.383)
N + 19	14.822**	0.901**	-14.455**	-0.529
	(1.703)	(0.315)	(3.514)	(0.399)
N + 20	15.325**	0.925**	-14.541**	-0.600
	(1.712)	(0.327)	(3.690)	(0.416)
N	119827	119827	77287	77287
R^2	0.131	0.189	0.038	0.086

Table A3.2: Additional GMM regression results

	(I)	(II)	(III)	(IV)	(V)	(VI)
Past_mean (£)	0.355** *(0.043)*	0.353** *(0.077)*	0.259** (0.042)	0.307** (0.077)	0.294** *(0.039)*	0.382 0.061
Instruments	$\bar{d}_{i,n-2}, \bar{d}_{i,n-3}$	$\bar{d}_{i,n-2}, \bar{d}_{i,n-3}$ Collapsed	$\bar{d}_{i,n-3}, \bar{d}_{i,n-3}$	$\bar{d}_{i,n-3}, \bar{d}_{i,n-4}$ 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
rellano-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	0.539	0.544	0.544	0.545	0.542	0.543
Hansen test, p-value	0.865 (214)	0.003 (1)	0.786 (214)	0.390 (1)	0.980 (318)	0.865 (214)
Number of obs = NI	343,092	343,092	343,092	343,092	343,092	343,092
Number of pages = I	10,597	10,597	10,597	10,597	10,597	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

Larger charities have income > £10m

Older charities were born ten or more years ago

Younger donors are identified from the age of the fundraiser (< 40)

$^{**}p<0.01$

Table A3.3: Information on samples

	Number of fundraising pages	Number of donations	Mean donation
Estimation sample	10,597	396,077	£29.85
Information on gender of donor	8,003	302,265	£28.72
Matched to charities register	8,225	306,109	£29.80
Non-missing charity income information	5,248	199,363	£30.04
Non-missing charity age information	8,202	305,266	£29.80
Non-missing overseas/ uk information	8,194	304,944	£29.79

Table A3.4: Differences in donations

	Total online donations			Mean donation amount		
	0	1	t-ratio	0	1	t-ratio
Charity size 0 = <£10m, 1 = £10m+	£1,506	£1,460	9.257	£30.25	£29.79	2.143
Charity age 0 = <10 years, 1 = 10 years+	£1,386	£1,461	14.905	£29.58	£29.85	1.204
Charity type 0 = UK based, 1 = overseas	£1,447	£1,406	3.139	£29.75	£31.25	2.616
Fundraiser age 0 = 40+, 1 = < 40	£1,590	£1,400	50.370	£33.43	£28.48	30.015
Pages with a target 0 = no target, 1 = target	£1,312	£1,477	34.175	£30.03	£29.82	0.976
Donor gender 0 = female, 1 = male				£24.07	£33.15	57.373

Table A3.5: Determinants of amount given

Sample Size: 17,989	Very important	Somewhat important	Not very important	Not at all important	Not applicable
A sense that my money will be used efficiently/ effectively	56.1%	35.0%	6.9%	1.6%	0.6%
The charity's cause or mission	45.1%	44.1%	8.4%	1.9%	0.6%
My income and what I can afford	45.3%	42.3%	9.0%	2.5%	0.8%
A personal connection to the fundraiser	41.5%	43.4%	10.6%	3.5%	1.1%
The fundraiser's reason for fundraising	38.0%	48.0%	10.1%	3.0%	1.0%
The reputation of the charity	32.7%	47.5%	15.3%	3.4%	1.0%
Tax relief (e.g. Gift Aid)	21.7%	34.8%	23.5%	14.3%	5.8%
Type of fundraising event	14.4%	45.8%	29.8%	8.6%	1.5%
The name of the charity	14.1%	39.4%	32.5%	12.1%	1.9%
The total amount the fundraiser is seeking to raise	3.3%	28.0%	38.9%	24.9%	5.1%
How much other people have given to the fundraiser	2.7%	21.6%	39.0%	33.1%	3.7%
An individual amount suggested by the fundraiser	1.4%	15.9%	39.6%	29.9%	13.2%

Sample: 17,989 donors who had recently given through Justgiving, contacted Oct 2010 – June 2011