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Peer effects in charitable giving: Evidence from the (running) field

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## Peer effects in charitable giving: Evidence from the (running) field

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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. We analyse a unique dataset of donations to online fundraising pages to provide evidence on the direction and magnitude of peer effects – we find that a £10 increase in the mean of past donations increases giving by £3.50, on average. We also explore potential explanations for why peers matter. We find no evidence that donations provide a signal of charity quality, nor any role for fundraising targets. Our preferred explanation is that donors benchmark themselves against the distribution of donations from their peers.

**Keywords:** charitable giving; peer effects; donations

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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

In spite of there being a widespread belief that peer effects are important in charitable giving, there is surprisingly little direct evidence on how donors respond in practice to donations made by others in their peer group. Early studies used cross-section data to define generic reference groups in terms of income (Martin Feldstein and Charles Clotfelter, 1976) and other socio-demographic characteristics such as age and education (James Andreoni and Karl 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 (Bruno Frey and Stephan Meier, 2004, Francisco Alpizar et al, 2008 and Jen Shang and Rachel Croson, 2009). There are two studies that have looked directly at peer effects in giving. Jonathan Meer (2009) focused on peer effects in solicitation, looking at whether people give more if the ask comes from someone that they know. Katherine 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 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.<sup>2</sup> The way that individual online fundraising typically works is as follows: An individual fundraiser decides 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 individual fundraiser then sets up a personalized webpage on a fundraising website and invites people – typically their friends,

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<sup>2</sup> For comparison, total donations from individuals in the UK were estimated to be £13 billion in 2010-11.

family and work colleagues – to make donations to their chosen charity. Most of the donations are made online via the fundraising page and are passed directly by the fundraising website to the charity, together with tax relief at the basic rate of tax.<sup>3</sup> All of the donations that have been made online are listed on the fundraising page, with the most recent first. Information on how much has been given, and by whom<sup>4</sup>, 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.

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 (Peter Warr, 1982, Russell Roberts, 1984) but we show that higher donations cause people to increase the amount that they give and, moreover, that these peer effects are economically significant – following a large donation of £100, for example, the donations that follow are £10 higher on average.

Our second contribution is to exploit the richness of our online fundraising dataset – we have more than 300,000 donations given to more than 10,000 fundraising pages and to more than 1,000 different charities – to explore potential 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 (Lise Vesterlund, 2003) nor that peer effects are related

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<sup>3</sup> In the UK, the main form of tax relief for individual donations, known as Gift Aid, works in the following way: Individuals donate out their net of tax income; the charity can reclaim basic rate relief on these donations. Higher-rate taxpayers can reclaim an additional rebate equivalent to the difference between their marginal rate and the basic rate on the grossed up donation. So, for a donation of £1 out of net-of-tax income, the charity can reclaim 25 pence (equivalent to the relief at the basic rate of 20%) and a higher-rate donor can reclaim a further 25 pence (equivalent to the difference between their marginal rate of 40% and the basic rate of 20%). This two-part system is designed for a situation where most taxpayers do not file tax returns.

<sup>4</sup> 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.

to fundraising targets (Andreoni, 1989). We also show that donors do not simply compete to be the top donor, or seek to avoid being the smallest donor. We show that how much donors respond to donations made by others does not depend on the total number of donations on a page, but that it does depend on the ordering within a page. One possible explanation for this could be that donors are looking to benchmark themselves in the distribution of their peers' donations and that individual donations provide less information for this purpose, the more donations there are already on the page.

We face well-known identification problems in estimating peer effects (Charles Manski, 2003). Many previous studies of peer effects in other areas, such as education and neighbourhood, have exploited mechanisms that randomly change the composition of peer groups through the allocation of eg student accommodation or housing vouchers (Bruce Sacerdote, 2001; Lawrence Katz et al, 2001). Looking at online individual fundraising, where most donations to a page are made by fundraisers' friends, family and work colleagues, allows us to study peer effects in charitable giving within naturally-occurring peer groups. This is arguably a better context in this case since it more closely resembles the situation facing fundraisers and policy-makers interested in whether they can exploit peer effects in order to influence the total amount given. The problem we face is that donations made to a page will be correlated precisely because they are made by 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.<sup>5</sup> 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 provide further discussion of our identifying assumptions in the context of our estimation in sections 3 and 4.

The plan of the remainder of the paper is as follows. The next section provides information on our data, which is a subset of fundraising pages set up by runners in the 2010 London marathon. Section

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<sup>5</sup> Alexandre Mas and Enrico 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 worker-specific fixed effects; we do not have sufficient observations to allow us to do this.

3 provides some preliminary evidence on peer effects, focusing on the effect of large and small donations, while section 4 contains our main econometric analysis. Section 5 explores several potential explanations for why donors respond to their peers and section 6 concludes.

## 2. The setting – online fundraising in the 2010 London marathon

In this paper, we focus on a subset of all online individual fundraising webpages. In particular, we analyze 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. The London marathon claims to be the biggest single fundraising event in the world and of the approx 35,000 runners who line up, an estimated 20,000 are raising money for charity.

Our initial sample contained information from more than 12,000 fundraising pages set up on the UK's two main fundraising websites – *Justgiving* ([www.justgiving.co.uk](http://www.justgiving.co.uk)) and *Virgin Money Giving* (<http://uk.virginmoneygiving.com/giving/>). The data were captured on 30<sup>th</sup> 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 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.<sup>6</sup>

<< 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.

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<sup>6</sup> 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<sup>7</sup> and generous donors. In our analysis, we exclude pages which have 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. Estimates of peer effects – a natural experiment approach

Our identification strategy 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 A3.2). In our analysis we exclude the first five donations to a page since these early donors may behave differently. We also include a number of controls for systematic within-page variation in how much people give.

However, looking at a randomly selected sub-sample of pages (illustrated in Figure A3.2), it is clear that there is also a considerable amount of non-systematic variation in the size of donations within a page that causes the within-page mean to vary. This observed within-page variation motivates our first piece of evidence on peer effects in giving which focuses on the effect of “large” and “small” donations on subsequent amounts given. Essentially we look at whether a “large”/ “small” donation is associated with a change in the size of donations to a page, i.e:

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

where  $d_{in}$  refers to the  $n^{\text{th}}$  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. 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

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<sup>7</sup> 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.

is £8.61.  $z_{in}$  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 that removes the effect on donations of the page-specific unobservable factors.

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  $\beta$  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 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 on 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, but as shown in Figure 1, the arrival of a large/small donation is not associated with a statistically significant change in the distribution of arrival rates (the p-values for the kolmogorov-smirnov statistics are 0.163 and 0.224 for large and small donations respectively) although it is clearly associated with a statistically significant change in the distribution of donation amounts (the p-value for the kolmogorov-smirnov statistic is 0.000 in both cases).

<< Figure 1 near here >>



Figure 2 provides further information on donation amounts before and after, 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, although at longer intervals the assumption of an exogenous treatment may be less plausible.

<< Figure 2 near here >>

Our regression results are summarized in Table 2. 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 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 coefficients indicate fairly sizeable effects. Within a narrow window of one donation either side, large donations are associated with a £10.50 increase in donation size, compared to a previous mean of £20, while a small donation reduces donation size by £6.50, compared to a previous mean of £33. (More detailed results, containing individual lead and lag terms are reported in Table A3.1 in the Appendix.)

<<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, at least up to very large donations of ten or more times the page mean.

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:

$$d_{si} = \alpha + \beta_1 T_{si} + \beta_2 T_{sj} + \omega_{si}$$

where  $d_{si}$  refers to the donation of donor  $s$  to fundraising page  $i$ .  $T_{si}$  is an indicator equal to one if the donor visits page  $i$  after a large donation has been made to that page, while  $T_{sj}$  is an indicator equal to one if the donor has visited another page  $j \neq i$  after a large donation has been made to that page.  $\beta_1$  captures the own-page effect of a large donation, while  $\beta_2$  captures any spillover effect on 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 than three donations in total, our estimation sample consists of 1,626 donors who make an average of four 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 (7.25, SE 4.14) 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 (2.59), but insignificant (SE 1.80), implying that there is no evidence that the crowd in effect of a large donation to one page is associated with a crowd out of donations to other fundraising pages.

#### 4. Estimates of peer effects – econometric analysis

In this section, we extend the empirical analysis to look more widely at the effect of past donations by estimating the following reduced-form model:

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

As before  $d_{in}$  refers to the  $n^{\text{th}}$  donation to fundraising page  $i$  while  $\bar{d}_{i,n-1}$  is the mean of all donations made online to the fundraising page up to the point at which the  $n^{\text{th}}$  donor arrives at the page.<sup>8</sup> This is included to capture potential peer effects. In practice, donors are not provided with information on the mean of past donations when they arrive at a page; it is also unlikely that they would calculate the mean themselves directly and we are not assuming that they do. Our assumption

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<sup>8</sup> 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.

is that donors respond to information on the past donations made to a page and we include the mean because it provides a simple summary statistic of the information on the distribution of past donations that is available to them. We do not rule out that other moments of the distribution of donations may also be relevant – for example the mode or median donation. However, we have already seen that donors respond to single large and small donations and this kind of response will be better captured by the mean than by the mode or median. As well as looking at the effect of the mean of all past donations, 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 before,  $z_{it}$  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  $\gamma$  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  $\gamma$  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.  $u_{it} = \eta_i + v_{it}$ . 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.<sup>9</sup> 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  $\gamma$  because the mean-differenced error term,  $u_{it} - \frac{1}{N-1} \sum_{j=2}^N u_{ij}$ , 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

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<sup>9</sup> 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.

and we observe many pages with 50 or more donations), unlike the standard case of “Nickell bias” (Steven Nickell, 1981). We show this formally in Appendix A2.

Our preferred approach, therefore, is to estimate  $\gamma$  using the Manuel Arellano and Stephen Bond (1991) GMM estimator,<sup>10</sup> i.e. the page-specific effect  $\eta_i$  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 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, shown in Table A3.2.

Our main results are presented in Table 3. 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. As demonstrated in 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 3 near here >>

Across all specifications, the GMM estimate of  $\gamma$  is positive and significant, implying positive peer effects. The past mean has the largest coefficient – a £10 increase in the mean of past donations leads to people giving £3.50 more on average. To compare the magnitude more directly across these specifications – and with the analysis in the previous section, consider the effect of a £100 donation following four donations of £20. The predicted increase in the subsequent donation is £5.58 for the past mean of all donations, £4.29 for the mean of the past ten, £2.08 for the mean of the past five

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<sup>10</sup> We estimate the GMM model using xtabond2, see David Roodman, 2006.

and £1.90 for the lagged dependent variable. For a £100 donation following nine donations of £20, the predicted increases would be the same for the lagged dependent variable and the mean of the past five, but would be £2.14 for the mean of the past ten donations and £2.79 for the past mean.

These results illustrate that the past mean of all donations tends to have a bigger effect on subsequent donations, but also that the effect of a single donation diminishes the later it occurs on a page. This seems 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 £1.25 when it occurs after ten or more donations and by £2.67 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.

## **5. Inside the black box – exploring why peers matter**

We would like to understand why peers matter. The existing literature suggests a number of potential explanations and in this section we look at the extent to which these are supported by the evidence.

**Signal of charity quality** – Vesterlund (2003) suggests that peer donations provide a signal of the quality of the charity, with higher donations indicating that the particular cause is more worthy of support. In practice we would expect the information content of past donations to be more important for smaller charities and for younger charities (Garth Heutel, 2009), for charities operating overseas whose activities are less easy to observe directly and for younger donors. To explore 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 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, 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 a stronger crowd in effect for younger donors (proxied by the age of the fundraiser), but this is not statistically significant.

<< Table 4 near here >>

**Link to fundraising targets** – we also find no evidence that the observed effect of past donations can be explained purely by donor behaviour around fundraising targets. 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 very relevant to the London marathon fundraising pages, the majority of which have fundraising targets. However, targets cannot provide an explanation for the observed peer effects since we cannot reject that the effects of past donations are the same for pages with and without a target (column (V), Table 4).

However, further analysis reveals some interesting differences in behaviour around the target. Regression analysis, summarised in Table 5, 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 £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 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'>>

**Social effects** – There is a broad class of alternative explanations for giving that could explain peer effects that we group together under the heading “social effects”. The common element is that these explanations incorporate other people’s donations directly or indirectly into individual utility calculations. Gary Becker (1976) argued early on that charitable giving may be motivated by individuals’ desire for social acclaim, or by the desire to avoid stigma, which may in turn be linked to how much other people have given. Amihai Glazer and Kai Konrad (1996) and William Harbaugh (1998) emphasize prestige motives for giving in which individual donations (relative to those made by others) provide a signal of wealth or generosity. Douglas 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.

We cannot provide a direct test of these different explanations but looking at the behaviour of donors on the online fundraising websites can help to shed some light on which are more or less likely to be empirically relevant in this context:

- Our finding that small donations are associated with a change in the amount given rules out an explanation that donors are (just) aiming to be the most generous donor to a page. Similarly, the finding that large donations are associated with a change in the amount given is inconsistent with the idea that donors are simply trying to avoid being the least generous donor to a page. Both findings are also inconsistent with a story in which donors seek to conform by aligning themselves with the median or mode donation.
- We find no evidence that the responsiveness of donations to how much other people have given depends on the total number of donations on a page.<sup>11</sup> Assuming that donors are aware of the size of the donor pool, this provides further evidence (together with the finding

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<sup>11</sup> Regressions not reported but available on request.

on small donations) that donors do not (just) care about prestige from being observed by others to give more than their peers.

- As already discussed, the effect of large and small donations (and the past mean) diminishes across the page, i.e. donors respond less to individual donations when there is more information on the page. This is consistent with donors looking to benchmark the amount that they give against the distribution of donations to a page (rather than a single moment such as the maximum, minimum, mode or median) since subsequent single donations contribute less information on the distribution. One plausible story is that donors may care about social acclaim/stigma but that this is defined relative to a personal reference level of what the donor thinks he is expected to give. This reference level is likely to be donor- (and possibly fundraiser-) specific and determined by the amounts that previous donors have given to the page as well as by the donor's own characteristics such as the proximity of their relationship to the fundraiser and their income (and what their peers know about their income).

## **6. Discussion**

This paper adds to the empirical literature on what James 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 occurring 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.

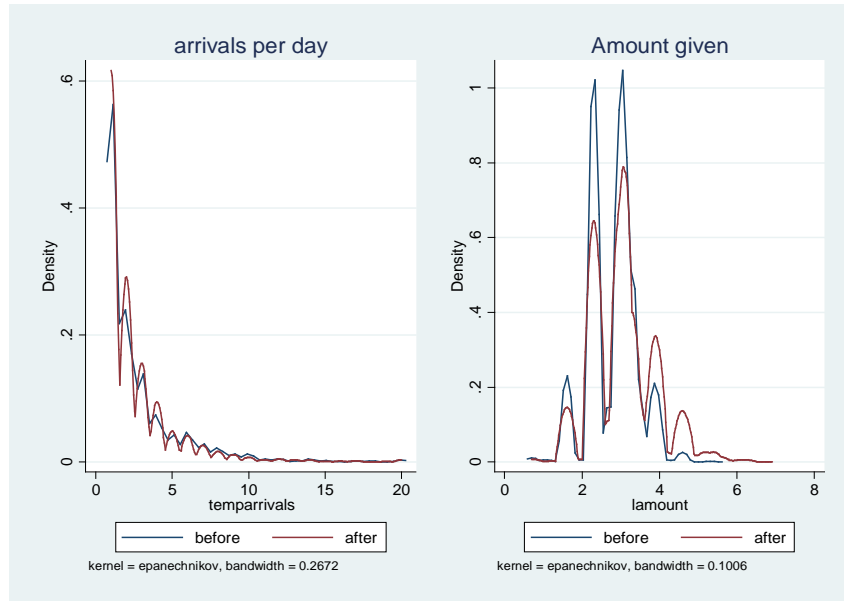
In this paper we have analysed only a small sub-sample of the population of online fundraising pages that are potentially available. Going forward, information from online fundraising pages, particularly matched with social network data, has the potential to yield even further insights into how donors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

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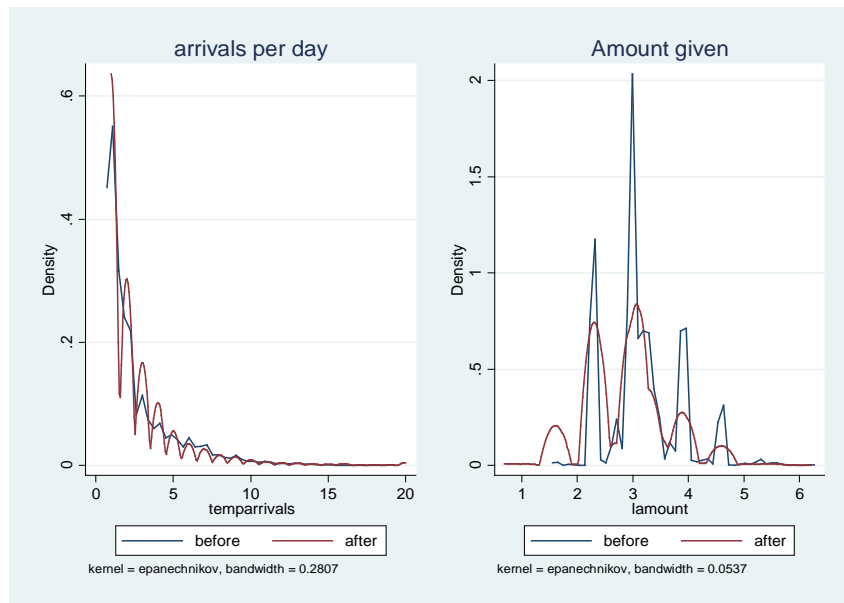
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**Figure 1: Distributions of arrivals and donations  
Before and after a large donation**



**Before and after a small donation**

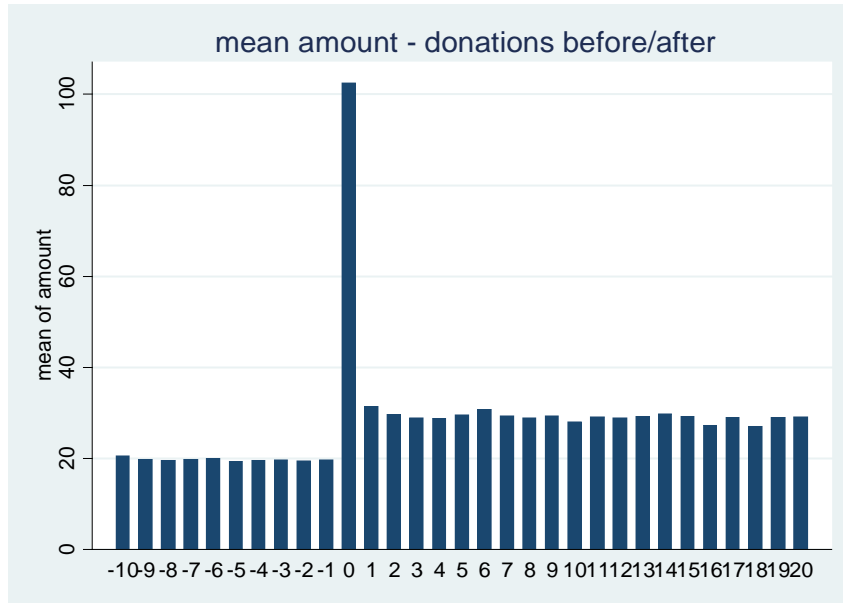


Notes to figure:

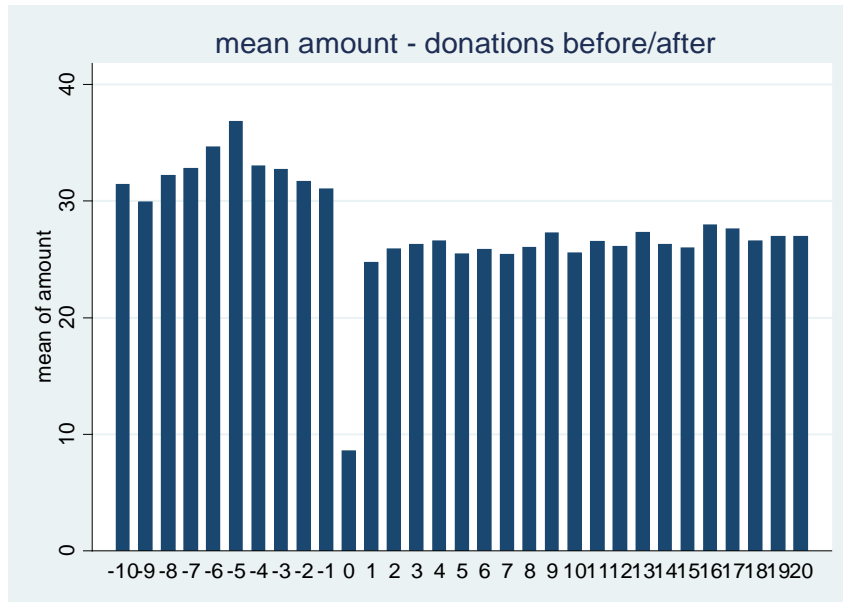
A large donation is defined as twice the page mean and at least £50. A small donation is half the page mean. We focus on the first large/small donation on a page, excluding those within the first five donations.

**Figure 2: Mean amounts given**

### Before and after a large donation



### Before and after a small donation



**Table 1: Sample summary statistics**

	Mean	St. dev.	Min.	1 <sup>st</sup> pctile	Med.	99 <sup>th</sup> pctile	Max.
<b>Full sample</b>							
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
Number of fundraisers	12,750						
<b>Estimation sample</b>							
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
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**

	(I)	(II)	(III)	(IV)
<b>a. First large donation</b>				
Dependent variable = £ amount given				
	One before/ One after	One before/ One after (same day)	Five before/ Five after	Five before/ Ten after
After	10.89** (0.85)	10.45** (2.59)	11.17** (0.75)	10.52** (0.56)
NI	10,115	4,122	44,895	67,429
<b>b. First small donation</b>				
Dependent variable = £ amount given				
	One before/ One after	One before/ One after (same day)	Five before/ Five after	Five before/ Ten after
After	-6.54** (0.93)	-5.02** (1.97)	-4.50** (0.80)	-5.72** (0.60)
NI	6,157	2,761	30,328	41,287
<b>c. Different sized large donations (five before/after)</b>				
Dependent variable = £ amount given				
	Twice mean	Three times mean	Five times mean	Ten times mean
After	9.39** (1.13)	10.30** (1.16)	15.18** (1.95)	15.20** (3.32)
NI	17,213	16,720	8,024	2,938

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. Columns (III) and (IV) in panel a and b and all columns in panel c 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)
	OLS	Page fixed effects	Difference GMM
(a)			
Past_mean (£)	0.567** (0.013)	-0.541** (0.032)	0.354** (0.043)
<i>Arellano-Bond test for AR(1), p-value</i>			0.000
<i>Arellano-Bond test for AR(2), p-value</i>			0.539
<i>Hansen test, p-value (214 over-id restrictions)</i>			0.865
(b)			
Mean, last ten (£)	0.483** (0.012)	-0.147** (0.012)	0.239** (0.022)
<i>Arellano-Bond test for AR(1), p-value</i>			0.000
<i>Arellano-Bond test for AR(2), p-value</i>			0.516
<i>Hansen test, p-value (214 over-id restrictions)</i>			0.345
(c)			
Mean, last five (£)	0.368** (0.011)	-0.065** (0.008)	0.117** (0.011)
<i>Arellano-Bond test for AR(1), p-value</i>			0.000
<i>Arellano-Bond test for AR(2), p-value</i>			0.562
<i>Hansen test, p-value (214 over-id restrictions)</i>			0.793
(d)			
Past_donation (£)	0.122** (0.005)	-0.000 (0.004)	0.020** (0.001)
<i>Arellano-Bond test for AR(1), p-value</i>			0.000
<i>Arellano-Bond test for AR(2), p-value</i>			0.039
<i>Hansen test, p-value (214 over-id restrictions)</i>			0.749

Notes to table

Sample size: I = 10,597, NI = 343,092. 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 4: Testing for heterogeneous effects**

**Difference GMM: Dependent variable: Donation amount (£)**

	(I)	(II)	(III)	(IV)	(V)
Past_mean (£)	0.204** (0.084)	0.229** (0.076)	0.375** (0.052)	0.272** (0.064)	0.438** (0.104)
Past_mean * MediumCharity	-0.056 (0.113)				
Past_mean * LargeCharity	0.175 (0.109)				
Past_mean * MajorCharity	0.143 (0.099)				
Past_mean * CharityAge>10y		0.039 (0.099)			
Past_mean * CharityAge>20y		0.084 (0.088)			
Past_mean * OverseasCharity			-0.037 (0.052)		
Past_mean * YoungDonors				0.107 (0.084)	
Past_mean * PageWithTarget					-0.095 (0.104)
Number of obs = NI	173,123	264,246	263,974	343,092	343,092
Number of pages = I	5,248	8,202	8,194	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. \*\*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 5: Targets**

**Dependent variable: Donation amount (£)**

	(I)	(II)	(III)
	Fixed effects	Difference GMM	Difference GMM
Target donation	54.255** (3.881)	47.471** (0.059)	50.323** (1.476)
Reached target	-2.892** (0.544)	-2.838 (1.489)	7.365** (1.772)
Past_mean (£)		0.338** (0.059)	0.327** (0.039)
Past_mean * Reachedtarget			-0.303** (0.046)
<i>Arellano-Bond test for AR(1), p-value</i>		0.000	0.000
<i>Arellano-Bond test for AR(2), p-value</i>		0.581	0.593
<i>Hansen test, p-value (over-id restrictions)</i>		0.752 (210)	0.863 (389)
<i>Number of obs = NI</i>	139,732	127,522	127,522
<i>Number of pages = I</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.

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**

## Appendix A1 – Online fundraising

Justgiving (JG) [www.justgiving.com](http://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.

**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](#)

 [Remind me to donate later](#)

[Page owner](#)

Target: **£1,500.00**  
Raised so far: **£1,564.00**



[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



### Charity



### 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.



## 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 charities 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

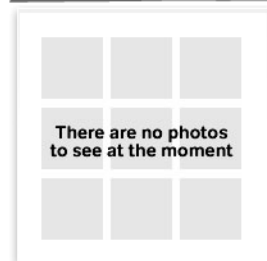
### Running total

£205.00



Donate now »

### Photos



### Other fundraising

[Sarah runs 26.2 miles for Action](#)

## 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  $i = 1, \dots, I$  and  $n = 1, \dots, N$ , it is well known the fixed effects estimator for  $\gamma$  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  $\gamma$ .

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

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

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  $\gamma$  in the two models LDep and LAvg in Table A2.1, for different values of  $N$ ,  $\gamma$  and  $\sigma_\eta^2$ , for 1,000 Monte Carlo replications.

**Table A2.1 Bias of the Fixed Effects Estimator**

$\gamma$	$\sigma_\eta^2$	$N = 5$		$N = 20$		$N = 40$	
		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, especially for jointly smaller values of  $\alpha$  and  $\sigma_\eta^2$ . 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  $n = 2, \dots, N$  and  $i = 1, \dots, I$ . The fixed effects estimator is given by

$$\begin{aligned}
\hat{\gamma}_{FE} &= \frac{\sum_{i=1}^I \sum_{n=2}^N (x_{in} - \bar{x}_i)(d_{in} - \bar{d}_i)}{\sum_{i=1}^I \sum_{n=2}^N (x_{in} - \bar{x}_i)^2} \\
&= \gamma + \frac{\sum_{i=1}^I \sum_{n=2}^N (x_{in} - \bar{x}_i)(v_{in} - \bar{v}_i)}{\sum_{i=1}^I \sum_{n=2}^N (x_{in} - \bar{x}_i)^2}
\end{aligned}$$

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

This can be further simplified to

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

and hence

$$\begin{aligned}
\text{plim}(\hat{\gamma}_{FE} - \gamma) &= \frac{\text{plim} \frac{1}{I} \sum_{i=1}^I \sum_{n=2}^N x_{in} (v_{in} - \bar{v}_i)}{\text{plim} \frac{1}{I} \sum_{i=1}^I \sum_{n=2}^N (x_{in} - \bar{x}_i)^2} \\
&= - \frac{\text{plim} \frac{1}{I} \sum_{i=1}^I \sum_{n=2}^N x_{in} \bar{v}_i}{\text{plim} \frac{1}{I} \sum_{i=1}^I \sum_{n=2}^N (x_{in} - \bar{x}_i)^2}
\end{aligned}$$

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

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
$\frac{1}{I} \sum_{i=1}^I \sum_{n=2}^N x_{in} (v_{in} - \bar{v}_i)$	-1.06	-0.91	-1.79	-1.49	-1.90	-1.64
$\frac{1}{I} \sum_{i=1}^I \sum_{n=2}^N (x_{in} - \bar{x}_i)^2$	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

$\frac{1}{I} \sum_{i=1}^I \sum_{n=2}^N (x_{in} - \bar{x}_i)^2$  increases more rapidly with  $N$ . This is of course expected, as  $\bar{d}_{i,n-1}$  eventually

converges to a constant. The covariance terms  $\frac{1}{I} \sum_{i=1}^I \sum_{n=2}^N x_{in} (v_{in} - \bar{v}_i)$  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  $\bar{d}_{i,n-2}$  and  $\bar{d}_{i,n-3}$  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	GMM
		First Differences	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 figures and tables

Figure A3.1 Distribution of amounts given

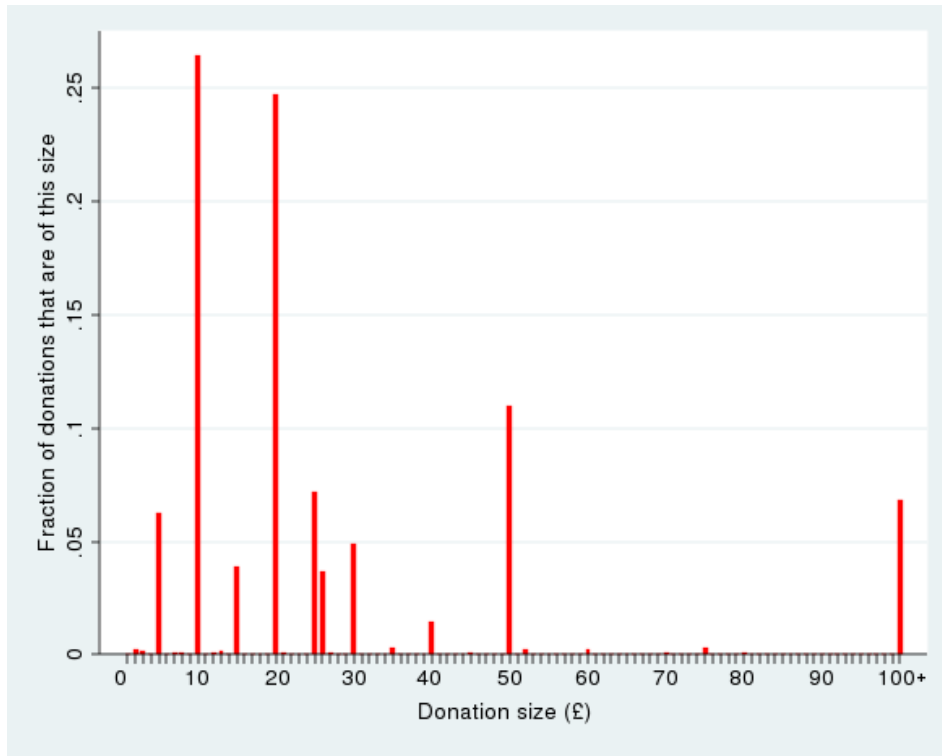
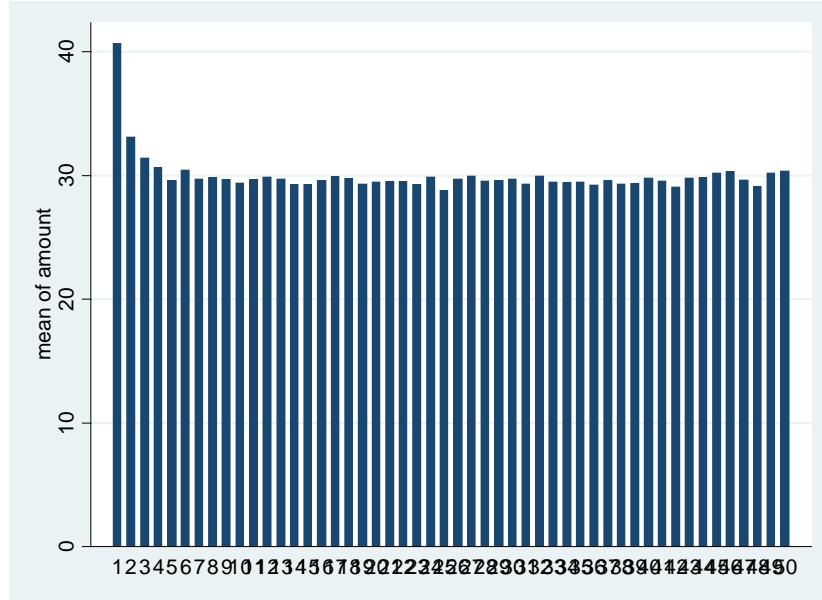
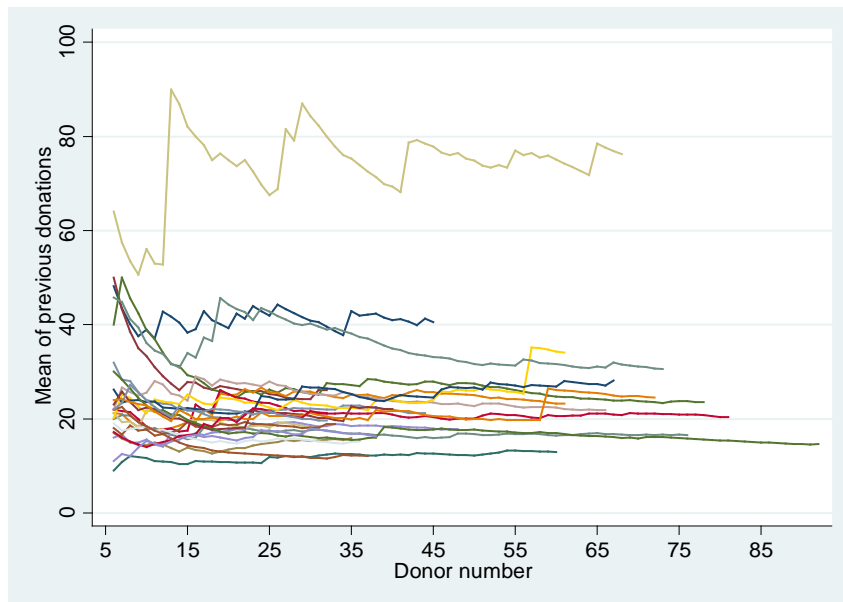


Figure A3.2: Donation profiles

Mean amount, by order of donation on page



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



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

Dependent variable: Donation amount (£)		
	Before/after large donation	Before/after small donation
N - 3	0.368 (0.281)	-1.578* (0.742)
N - 2	0.189 (0.314)	-2.316** (0.893)
N - 1	0.605 (0.366)	-3.110** (0.907)
N	82.699** (1.473)	-25.656** (0.942)
N + 1	12.315** (0.737)	-9.887** (1.134)
N + 2	10.793** (0.758)	-9.103** (1.302)
N + 3	10.335** (0.768)	-9.112** (1.420)
N + 4	10.427** (0.826)	-9.149** (1.547)
N + 5	11.365** (0.929)	-10.764** (1.654)
N + 6	12.914** (1.062)	-10.798** (1.782)
N + 7	11.470** (0.980)	-11.317** (1.882)
N + 8	11.563** (1.046)	-11.221** (2.061)
N + 9	12.166** (1.118)	-10.508** (2.232)
N + 10	11.217** (1.118)	-12.823** (2.296)
N + 11	12.397** (1.242)	-11.925** (2.471)
N + 12	12.604** (1.278)	-12.722** (2.589)
N + 13	13.071** (1.340)	-11.788** (2.755)
N + 14	13.813** (1.391)	-13.544** (2.836)
N + 15	13.688** (1.458)	-14.273** (2.951)
N + 16	12.188** (1.432)	-12.734** (3.168)
N + 17	14.152** (1.531)	-12.951** (3.281)
N + 18	12.520** (1.548)	-14.394** (3.372)
N + 19	14.822** (1.703)	-14.455** (3.514)
N + 20	15.325** (1.712)	-14.541** (3.690)
N	119827	77287
R <sup>2</sup>	0.131	0.038

**Table A3.2: Additional GMM regression results**

	(I)	(II)	(III)	(IV)	(V)	(VI)
Past_mean ( $\lambda$ )	0.355** (0.043)	0.353** (0.078)	0.259** (0.042)	0.307** (0.077)	0.295** (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	$\bar{d}_{i,n-3}, \bar{d}_{i,n-4}$	$\bar{d}_{i,n-3}, \bar{d}_{i,n-4}$ 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
<i>Arellano-Bond test for AR(1), p-value</i>	0.000	0.000	0.000	0.000	0.000	0.000
<i>Arellano-Bond test for AR(2), p-value</i>	0.539	0.544	0.545	0.544	0.542	0.543
<i>Hansen test, p-value (over-id restrictions)</i>	0.865 (214)	0.003 (1)	0.786 (214)	0.386 (1)	0.563 (318)	0.865 (214)

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