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Viral Altruism? Charitable Giving and Social Contagion in Online Networks

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Abstract: How do social media affect the success of charitable campaigns? We show that, despite the promise of online platforms to generate social network effects in generosity through social contagion or peer effects, these platforms may instead stimulate costless (and less impactful) forms of involvement. Online social contagion might thus be limited when it comes to contributing real money to charities. This study relies on both individual-level longitudinal data and experimental evidence from a social media application that facilitates donations while broadcasting donors' activities to their contacts. We find that broadcasting is positively associated with donations, although some individuals appear to opportunistically broadcast a pledge and then delete it. Furthermore, broadcasting a pledge is associated with more pledges by a user's contacts, suggesting the presence of network effects or social contagion. However, results from a field experiment where broadcasting of the initial pledges was randomized suggest that the observational findings were likely due to homophily rather than genuine contagion effects. The experiment also shows that, although the campaigns reached approximately 6.4 million users and generated considerable attention in the form of clicks and "likes," only 30 donations were made. Finally, an online survey experiment indicates that both the presence of an intermediary and a fee contributed to the low donation rate.

Keywords: social contagion; charitable giving; social media

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ORGANIZATIONS have long relied on social forces such as "contagion" and network effects to promote their products, services, or causes. In recent years, the Internet has been an increasingly used instrument for marketing and outreach strategies that exploit these social forces. In addition to the fact that the World Wide Web allows for reaching a large number of customers at virtually zero marginal cost, the advent of social media in the last decade has the potential to compound social network and contagion effects, thus further increasing the reach of promotional campaigns. The optimism about the potential of the Internet, and social media in particular, to expand the consumer base has spread from for-profit companies to charitable and other nonprofit organizations.

In this article, we study, with both observational and field-experimental data, the performance of online fund-raising campaigns, with a focus on social network effects for donations to charities. Charitable giving is a widespread activity involving millions of individuals and organizations and provides essential resources to cover a vast array of needs, from disaster relief to food and shelter provision to the support of agencies and organizations engaged in different forms of prosocial activities (e.g., volunteering or donating blood). U.S. households and companies, for example, give more than $300 billion annually to charities, and charitable giving

amounts to more than £10 billion in the United Kingdom (Charity Aid Foundation 2012; Giving USA 2013).

Online social networks offer charities an opportunity to efficiently reach a large number of individuals in a short time, and network effects can further boost donations. Studies showed that peer effects and social pressure do affect charitable giving (Burt 1983; DellaVigna, List, and Malmendier 2012; Galaskiewicz and Burt 1991; Meer 2011; Shang and Croson 2009). Castillo, Petrie, and Wardell (2014) and Smith, Windmeijer, and Wright (2015) recently found similar patterns for online giving in particular. There is also evidence of incentives positively affecting the propensity to share support to a cause in social networks (Naroditskiy et al. 2014). Social media could boost these dynamics and benefit especially smaller, less-known organizations that cannot afford the high fixed costs of standard, offline promotional campaigns and rely on an initial smaller base of contributors. Charitable organizations indeed increasingly use these channels to attract and retain donors and to generate social contagion (Blackbaud 2013). Examples of pro-social causes that went "viral" through social media include the Kony2012 and the Bullied Bus Monitor campaigns, the Facebook feature that allows broadcasting one's status as an organ donor (Cameron et al. 2013), and the "ice bucket challenge" in summer 2014.

Despite this potential, online fund-raising currently accounts for less than 10 percent of total donations (Blackbaud 2013). This amount is bound to increase given the current trends; however, the small incidence of online fund-raising might also be due to some limitations of the online environment and, in particular, to some features of the social media that make it difficult, or costly, for charities to raise funds. Expressions such as "slacktivism" or "illusion of activism," for example, indicate that, although many people express support for a cause by, for example "liking" or "favoring" a post on Facebook or Twitter, most of them do not follow up with an actual donation or active engagement (Kristofferson, White, and Peloza 2014; Lewis, Gonzalez, and Kaufman 2012; Lewis, Gray, and Meierhenrich 2014). If social-image concerns motivate pro-social behavior, then the possibility provided by social media to costlessly express support for a cause and display it in public might satisfy individuals' desire to "look good" without them having actually to engage in costly activities such as donating money or volunteering (Kristofferson et al. 2014). Similarly, individuals might obtain some personal utility or "warm glow" from costless activities on social media, or they may feel that their effort is not needed when they observe donations in their social network (Tsvetkova and Macy 2014), thus substituting more costly alternatives such as actual contributions. Collective action problems are likely to characterize the online environment; given the large number of individuals potentially involved, incentives to participate actively are low (Lewis et al. 2012; Lewis et al. 2014). Also, an explicit reference to the pro-social behavior (or lack thereof) of one's contacts on social media might generate a sense of intrusiveness and lead to less pro-social behavior by peers (Tucker 2012). Finally, ad click-through rates on social media sites are notoriously low (Kim 2012); thus a large number of users need to be reached for any meaningful effects to be obtained. One implication is that the impact of online campaigns, if any, might be short-lived, thus further increasing fund-raising costs. After the immediate increase in organ

donor registrations following the introduction of the donor status on Facebook, for example, registrations rates rapidly reverted to baseline levels (Cameron et al. 2013); and the Kony2012 Cover the Night campaign was not as successful as expected, despite the viral success of the online video.[1] More recently, a survey study of residents in the United Kingdom found that even though one in six people participated in the ice bucket challenge, only 10 percent of these actually made a donation (Charities Aid Foundation 2014).

Thus, because of some peculiarities of online social interactions and of charitable activities, it is challenging to apply theories and findings from offline charitable activities and to extrapolate insights from studies of online dynamics such as contagion and network effects as they apply to other contexts, such as product adoption and sales. The relatively scant literature on online charitable giving thus calls for more empirical analyses. Fortunately for researchers, the use of online channels by charities offers new possibilities to exploit these platforms as laboratories to better understand donation behavior and the effects of certain fund-raising strategies.

In this study we investigate the effectiveness of these tools in generating users' engagement and donations, as well as their ability to originate network effects. We collaborated with HelpAttack! (HA), the developer of an application that allowed users to donate to charities through Facebook status updates and Twitter tweets. The HA application allows users to broadcast their initial pledge and subsequent donations to some or all of their contacts. The following section provides further details on HA.

Our empirical analysis consists of three parts. First, we analyzed HA's full historical data set of 3,460 pledges made by 820 unique Twitter or Facebook users to 343 charities in the period from August 2010 to December 2012 to assess the role of broadcasting one's pledge on the actual fulfillment of the pledge. On one hand, broadcasting might function as a "soft" (i.e., nonbinding) commitment (Bryan, Karlan, and Nelson 2010) to make an actual donation, possibly because of reputational or psychological costs of not following through. On the other hand, making one's involvement public might substitute for donating higher amounts. Because HA broadcasts the initial pledge, a user's social image is immediately affected at the time the pledge is made, irrespective of whether any payment is ultimately made to the charity. Approximately 16 percent of pledges made through HA were subsequently deleted, and the proportion of deleted pledges was higher for users who broadcasted their initial pledges. Regression analyses that control for unobserved individual heterogeneity show that broadcasting is positively correlated with the share of a pledge that is actually fulfilled and negatively associated with the probability of deleting a pledge. The difference between the raw correlations and the regression results indicates that individuals who are more likely to delete a pledge also choose to broadcast their pledges, on average. This is consistent with the presence of a subset of users displaying some opportunism in their use of the app.

Moreover, approximately 5 percent of initial pledges resulted in additional pledges by contacts (friends or followers) of the original users, and most of these additional pledges were from contacts of users who broadcasted their activity.

However, the occurrence of additional pledges by contacts of the original donors is hard to interpret as evidence of network effects from observational data (Shalizi and Thomas 2011). These pledges may be driven by homophily, that is, the fact that individuals tend to interact with similar people,[2] or by common shocks.

To overcome these problems, the second part of our analyses consisted in a natural field experiment conducted during June–August 2012. We used a combination of Facebook ads and sponsored stories that invited users to make donations through HA to Heifer International, a nonprofit organization whose mission is to fight poverty in developing countries. The experimental manipulation consisted of randomly turning off (control) and on (treatment) the broadcasting feature of the application for each individual adopter. Thus, for users in the control group, any donation activity was private to the individual, whereas for users in the treatment group, any donation activity was automatically notified to their contacts. This strategy enabled us to causally identify and quantify the social multiplier or network effect in the number and dollar amounts of pledges and donations. The campaigns reached a total of about 6.4 million Facebook users and generated a considerable number of reactions by users but only a very small number of actual donations. Almost 6,000 users clicked on the ads (roughly in line with Facebook click-through rates for nonprofit ads [Kim 2012]); support was expressed through "likes" (2,008), "shares" (303), and comments (213), whereas only 30 users (16 in the treatment and 14 in the control group) installed the application and pledged some money. Moreover, we did not find evidence, in this controlled setting, of network effects. Of the treatment group's 2,275 contacts, none made further pledges.

A concern about the very limited number of actual donations in our experiment is that the initial sample size was too small, thus not allowing for reliable detection of effects. However, our marketing campaigns were on a large scale, and the diffused reaction, although mostly in the form of costless activities, indicates that the campaigns did not go unnoticed. We therefore interpret our findings as evidence of the limited engagement of potential donors in online social networks in terms of making actual donations. It can further be argued that an even bigger intervention would have generated more initial pledges, and in turn, this would have increased the likelihood of network effects. However, conducting these campaigns on Facebook is costly; in our study, for each dollar raised for the charity, we spent $13.50 to pay for the Facebook ads. There is little value in estimating an effect that is economically very small, especially when the cost of statistical precision is so high.

Thus, although there is evidence of the success of promotional campaigns and of peer influence through social media in other contexts (Aral and Walker 2011; Bapna and Umyarov 2014), in our study, both the direct and indirect (network) responses were very limited, if existent at all. We attribute this difference to two key characteristics of our setting: first, users were invited to make actual monetary contributions; second, in the case of altruistic behavior, current social media platforms do offer costless alternatives to actual donations (such as "likes" and "shares"), which are less useful for a charity or for social welfare more generally but may fulfill some of the motives of donors, such as a desire for social recognition or warm glow. In fact, we believe that there is value in reporting "null" results like ours, as a way to provide boundary conditions to the role of certain social processes

and the effectiveness of certain strategies, and more generally as a healthy scientific practice.

The third part of the analysis was a computerized survey experiment to further investigate some potential reasons for the very small donation rates. Approximately 1,600 U.S. respondents on Amazon Mechanical Turk were asked about their willingness to donate $5 out of a hypothetical endowment of $10 to a charity. The survey used the *item count technique* to allay concerns for social desirability bias (Coffman, Coffman, and Ericson 2013; Miller 1984), and respondents were randomly assigned different versions of the questions, where the manipulations were meant to capture the key features of the HA app and of our experiment: the target charity (Red Cross, Heifer, or a charity of choice), the presence of a fee, and the presence of a third party (an intermediary) to collect the fee. The presence of a fee, the mention of an intermediary, and the focus on a lesser-known charity (i.e., Heifer) combined to depress the stated donation rates significantly.

Overall, the results also suggest that much of what might seem to be network effects in charitable giving from the observational data is due to confounding factors. An implication for charitable organizations that aim to leverage the power of online promotional campaigns to generate social multiplier effects is that they might need to be explicit in asking for actual monetary support through online social media to reduce users' reliance on substitute, "costless" activities (such as a "like" or "share").[3] Moreover, although in principle, online campaigns might substitute for large, traditional offline campaigns and thus favor smaller and less recognizable charities, in fact, offline recognition appears as a necessary complement to the success of online initiatives.

HelpAttack!

HA developed an application through which Facebook and Twitter users could donate to a charity of their choice via Facebook updates, tweets, or blog posts. The user pledges an amount of money (e.g., $20) and decides the rate per update (e.g., $0.20 per Facebook update). Each time the user updates her Facebook status, the application records a donation to the charity. The HA application allows users to broadcast their initial pledges and subsequent donations to their Facebook friends or Twitter followers. The default is that the "broadcasting" feature of the application is turned on, unless the user decides to turn it off (by checking a box). Pledges can be either fulfilled or deleted by the user without penalty. Once a pledge has been completed, users are requested to enter their credit card information.[4] The application automatically sends several broadcasting messages of the donation activity to the users' friends: one at the moment of the initial pledge, one after a few days, one after the user reaches half of the total amount pledged, and one at the end of the period. Once users install the HA application and make a pledge to a charity, they also give permission to the app to monitor their donation activity and download information from their public profile. The company keeps 8.25 percent of each donation (also to cover credit card fees and administrative costs). HA began operations in August 2010 and closed in December 2012, when it was acquired by We-Care.com.[5]

Table 1: Most popular charities on HelpAttack!, by status of the pledge

Charity Name	Total Pledges N	Fulfilled %	Partially Fulfilled %	Deleted %	Inactive %	Active %
American Red Cross	714	48.9	25.5	21.8	1.1	2.7
Best Friends Animal Society	357	69.5	11.5	14.6	1.4	3.1
Fenix281	158	65.8	22.8	9.5	0.6	1.3
Mobile Loaves & Fishes	114	85.1	0	12.3	0	2.6
Arthritis Foundation	98	73.5	0	14.3	0	12.2
NTEN: Nonprofit Technology Network	72	66.7	0	20.8	2.8	9.7
U.S. Fund for UNICEF	71	77.5	5.6	7	4.2	5.6
Autism Society of America	67	4.5	83.6	11.9	0	0
People for the Ethical Treatment of Animals (PETA)	67	43.3	0	17.9	1.5	37.3
Lights. Camera. Help.	59	91.5	0	8.5	0	0
Homes for Our Troops Inc	53	7.5	79.2	13.2	0	0
1736 Family Crisis Center	51	19.6	66.7	11.8	0	2
Total	3,461	64.1	12.5	15.8	1.4	6.2

Notes: The table shows the distribution of pledges by outcome, in total and for the most popular charities in the database, i.e. organizations with more than 50 pledges total. Fulfilled indicates pledges with a payment processed for (at least) the pledged amount; Partially fulfilled indicates pledges with a payment processed for an amount smaller than the amount pledged; Deleted indicates pledges that were deleted before being paid and that therefore did not result in an actual donation; Inactive pledges were started but there was no subsequent activity on the users' Facebook or Twitter profiles; Active pledges are the ones that were still open when the company was acquired in December 2012.

We have access to HA's (anonymized) database of pledges and donors, and we used the application to implement the randomization for our field experiment. Figure 1A shows an example of HA's pledge page, Figure 1B the pledge page where the user can customize the viral features of the HA broadcast, and Figure 1C some examples of broadcasted messages as they appear on the user's Facebook timeline.

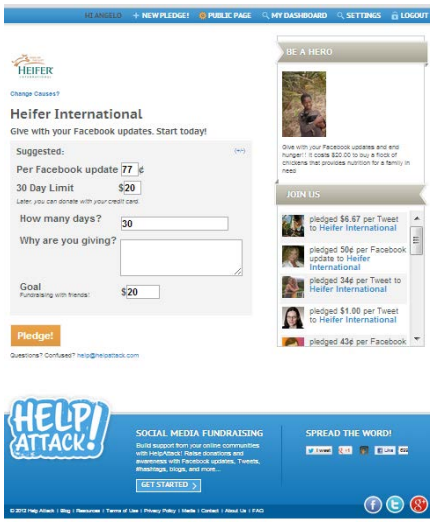
Analysis of the Observational Data

Descriptive Statistics

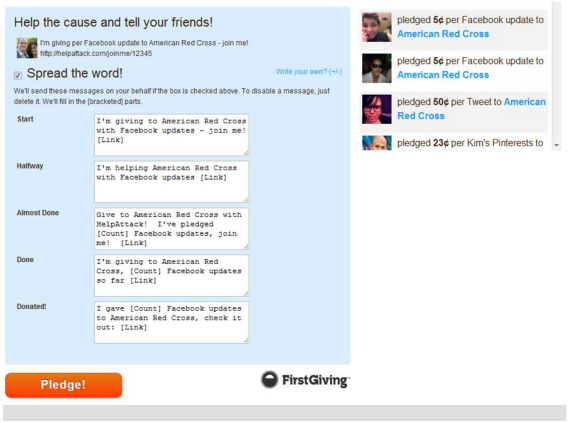
The historical data contain the entire database of pledges for 820 unique users in the period August 2010–December 2012. There are 3,460 pledges in total, almost $200,000 pledged, and donations of about $81,000. The most popular charities (i.e., those with at least 50 pledges) are shown in Table 1. More than half of the pledges were concentrated in 10 charities, with the American Red Cross being the most popular organization, with 714 pledges (20.63 percent of the total), followed by Best Friend Animal Society, with 357 pledges.[6]

As shown in Table 2, about 43 percent of pledges were made through Facebook and 57 percent via Twitter. The average amount pledged on Facebook is slightly

1A: Sample pledge page



1B: Viral features–Details



1C: Examples of broadcasted messages

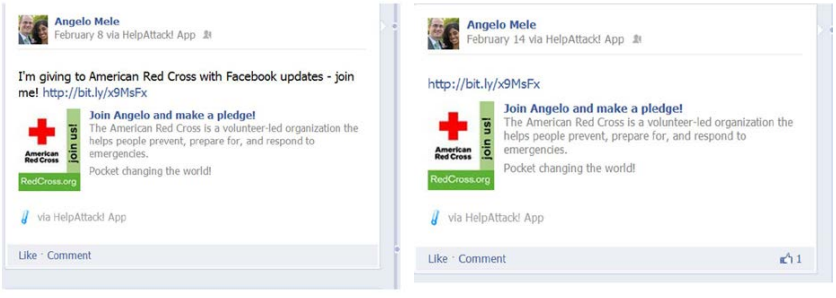


Figure 1: Note: the figures have been edited to conceal users' identifiable information

Table 2: Pledges and Donations—Summary Statistics by Medium

		Pledges			
Medium	Number	Mean amount ($)	Mean rate (cents)	Median amount ($)	Median rate (cents)
Facebook	1,366	65.5	94.3	40	50
Feed	22	24.8	69.2	20	29
Twitter	1,629	57.3	50.2	40	10
Twitter Proxy	76	28.9	30.2	40	25
Twitter Tag	103	31.2	22.1	20	10
Total	3,196	59.1	67.8	40	25
		Donations			
Medium	Number	Mean amount ($)	Mean rate (cents)	Median amount ($)	Median rate (cents)
Facebook	1,186	34.9	94.9	31.05	50
Feed	3	12	34.3	11.73	23
Twitter	1,367	27.1	48.8	20	10
Twitter Proxy	32	16.6	22.3	15	25
Twitter Tag	62	24.4	24.3	19.9	17.5
Total	2,650	30.4	68.5	20	25

Notes: The table compares mean and median rate, amount pledged and amount donated of pledges made through Facebook and Twitter. Inactive and Active pledges were dropped.

larger than that pledged on Twitter ($66 vs. $57), although the median amounts are the same ($40). As for actual donations, both the average and median amounts are larger for Facebook than for Twitter ($35 vs. $27 for the mean, and $31 vs. $20 for the median).[7] The rate per update/tweet (i.e., the amount of money that goes toward the goal of the pledge every time the user updates her Facebook status or makes a tweet on Twitter) are larger on Facebook than on Twitter (about $1 vs. $0.50 on average, and $0.50 vs. $0.10 for the median). Table 3 reports mean and median amounts pledged and donated as well as the rates-per-update separately for each of the most popular charities on HA. There is substantial heterogeneity across charities along all dimensions.

The examination of the timeline of donations reveals spikes in new pledges on certain dates, some of which coincide with catastrophic events and, presumably, fund-raising campaigns. For example, Figure 2 shows the new pledges for the American Red Cross by starting date. In 2011, several spikes coincide with the Japanese Earthquake/Tsunami in March and with the tornado outbreak in the United States, culminating with the EF5 tornado in Joplin (May).

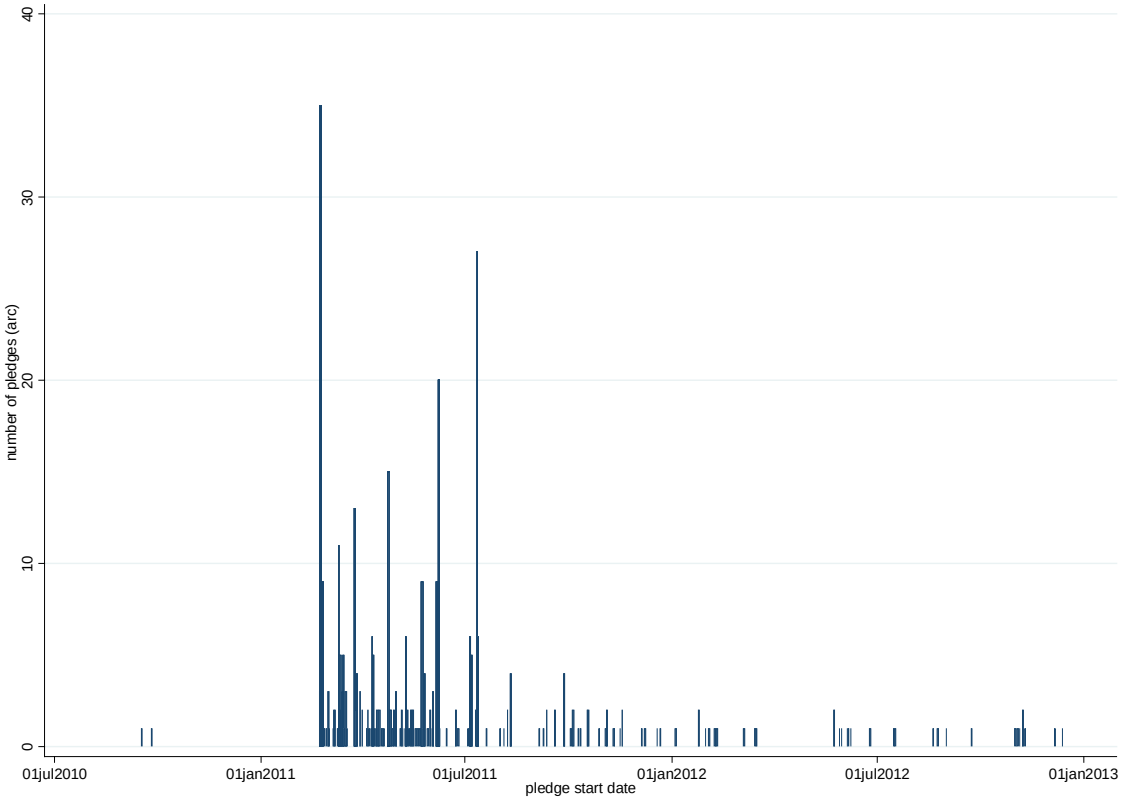


Figure 2: New pledges for the American Red Cross, by starting date. The graph shows the number of pledges by starting date for the American Red Cross.

Donation Activities on HA

It is difficult to establish if a total of 3,460 pledges and $81,000 collected are large or small amounts. We do analyze, however, *how much* of the activity and traffic on HA's webpage was generated by actual engagement through pledges and donations. During the period August 2010–December 2012, the HA website had stable traffic of about 2,500 unique visitors per month. Thus the 820 users who made at least one pledge correspond to approximately 1 percent of the total number of users who accessed the website.

Table 3 shows that 64 percent of pledges were fulfilled (i.e., they were honored with a payment to the selected charity of at least the amount pledged), and 12.5 percent were partially fulfilled (i.e., a payment was made for an amount smaller than the amount pledged).[8] In approximately 16 percent of cases, pledges were deleted before being paid and therefore did not result in an actual donation.[9] The fact that a substantial share of pledges are deleted clearly reduces the proceeds generated though the HA application and, as such, warrants some attention. There is also substantial heterogeneity across charities in the share of pledges fulfilled (totally or partially) and deleted. For example, Habitat for Humanity International received 39 pledges, but only 1 of those was processed and paid to the organization,

Table 3: Pledges and Donations—Summary Statistics by Charity

		Pledges			
Medium	Number	Mean amount ($)	Mean rate (cents)	Median amount ($)	Median rate (cents)
American Red Cross	687	53.2	39.3	40	10
Best Friends Animal Society	341	48.8	72.5	40	39
Fenix281	155	98.4	86.8	40	66
Mobile Loaves & Fishes	111	40	106.5	40	30
Arthritis Foundation	86	38.1	67.8	40	26
Autism Society Of America	67	39.1	68.7	40	69
U.S. Fund for UNICEF	64	33.6	62.4	40	25
NTEN: Nonprofit Technology Network	63	38.6	13.7	25	6
Lights. Camera. Help.	59	79.5	30.0	40	25
Homes for Our Troops Inc	53	44.5	75.0	0	75
1736 Family Crisis Center	50	97.1	151.2	40	69
People For The Ethical Treatment of Animals (PETA)	41	24	77.3	20	13
Total	3,197	59.1	67.8	40	25
		Donations			
Medium	Number	Mean amount ($)	Mean rate (cents)	Median amount ($)	Median rate (cents)
American Red Cross	531	30.4	44	21.4	10
Best Friends Animal Society	289	33.9	64.5	34.1	40
Fenix281	140	60.4	86.7	40	66
Mobile Loaves & Fishes	97	24	105.9	20	30
Arthritis Foundation	72	29.1	74.5	20.75	26
Autism Society Of America	59	39	68.5	40	69
U.S. Fund for UNICEF	59	22.8	65.8	20.7	25
Lights. Camera. Help.	54	21.9	26.5	20	25
NTEN: Nonprofit Technology Network	48	19.2	11.6	18.79	7.5
Homes For Our Troops Inc	46	40.4	75.7	40	75
1736 Family Crisis Center	44	66.8	163.6	40	69
People For The Ethical Treatment of Animals (PETA)	29	18.5	95	20	7
Total	2,650	30.4	68.5	20	25

Notes: The table compares mean and median rates, amount pledged and amount donated of all pledges, and separately for charities with more than 50 pledges (inactive and active pledges were not included).

whereas Mobile Loaves and Fishes received a total of 114 pledges, and 97 of them were processed and paid.

Whether a pledge is fulfilled presents additional elements of interest in this context. First, this can be informative about different motivations for pro-social

behavior. In particular, HA users can, in principle, behave opportunistically by pledging to donate some money, broadcasting their pledge to their contacts, and subsequently deleting the donation, without any repercussions on their reputation. It is also possible, however, that broadcasting a pledge could act as a form of "soft commitment" (Bryan et al. 2010) that might make it more likely for the user to go through with the donation. Second, it is important to consider the deleted pledges when estimating network effects, because the HA application posts a message on the Facebook (or Twitter) timeline when a pledge is started. Even when the pledge is deleted later on, this initial message may be sufficient to trigger a network effect, attracting new donors.

In Table 4, we report the estimates from this linear regression model of the relationship between whether a user's activity was broadcasted and two outcome variables, namely, the share of a pledge that is fulfilled and the likelihood of a pledge being deleted:

$$y_{ict} = \alpha + \beta \,\text{BROADCAST} + \gamma X_{ict} + \delta_c + \eta_i + \varepsilon_{ict}. \quad (1)$$

In Equation (1), y_{ict} is either the share of a pledge that was actually fulfilled (average = 0.62) or an indicator equal to 1 if a pledge by an individual i to a charity c at time t was deleted, and 0 otherwise (average = 0.17).[10] The vector X includes control variables related to the characteristics of the pledge (its amount and time duration) as well as past pledging and donation behavior of the user (the total number of pledges made in the past and the total amount of money actually donated to charities through HA up to the date of the current pledge). We then added charity and individual fixed effects (δ_c and η_i) to account for unobserved heterogeneity.[11] When individual fixed effects are included, we estimate a positive association between broadcasting and the share of pledges actually fulfilled.

As shown in column 4 of Table 4A, broadcasting a pledge leads to a 7.8 percentage point increase in the share of the pledge that is fulfilled, or 12.6 percent of the baseline fulfillment rate of 62 percent. Controlling for charity and individual unobserved heterogeneity is even more crucial for the interpretation of the results when we analyze the correlates of the likelihood of deleting a pledge (Table 4B). Regressions that do not include charity and individual fixed effects (column 1) estimate a positive and statistically significant association between broadcasting a pledge and deleting it. The association between broadcasting and deleting a pledge could be due to broadcasting the pledge *causing* users to subsequently delete it (Kristofferson et al. 2014) but could also be driven by omitted variables and, more generally, unobservable individual heterogeneity. For instance, if users who are intrinsically opportunistic choose to use the HA app to satisfy their desire to "look good" by making a pledge, broadcasting it, and subsequently deleting it (with no penalty or negative publicity), this might create a positive correlation in the data between broadcasting and deleting. Also, in Table 1, we noted that different charities varied considerably in the share of pledges that were subsequently deleted, suggesting potential heterogeneity among charities potentially related to the association between broadcasting and deleting. The addition of charity and individual fixed effects leads to negative and significant estimates on the coefficient of interest, larger when individual fixed effects are included. This indicates that individual-

Table 4: Broadcasting and Donation Behavior: Regression Analysis

Panel A Outcome variable = Share of Pledge Fulfilled	(1)	(2)	(3)	(4)
Pledge Broadcasted	0.45	6.54†	2.18	7.79†
	(1.31)	(1.45)	(1.43)	(1.49)
Pledge Length (Days)	0.01	0.08†	0.02	0.09†
	(0.01)	(0.01)	(0.01)	(0.02)
Pledge Amount ($)	−0.03†	−0.09†	−0.07†	−0.13†
	(0.003)	(0.02)	(0.007)	(0.03)
N. Past Pledges	−0.60†	−0.39†	−0.56†	−0.37†
	(0.02)	(0.03)	(0.02)	(0.03)
$ Donated In The Past	0.02†	0.005†	0.01†	0.002∗
	(0.001)	(0.001)	(0.001)	(0.001)
User Fixed Effects		X		X
Charity Fixed Effects			X	X
Observations	3,196	3,196	3,196	3,196
Adjusted R^2	0.190	0.465	0.280	0.498

Panel B Outcome variable = 1 if pledge deleted, 0 otherwise	(1)	(2)	(3)	(4)
Pledge Broadcasted	2.38	−8.15†	−3.34∗	−10.85†
	(1.25)	(1.51)	(1.39)	(1.56)
Pledge Length (Days)	−0.03∗	−0.03	−0.02	−0.03
	(0.01)	(0.01)	(0.01)	(0.02)
Pledge Amount ($)	0.01†	0.04∗	0.02†	0.03
	(0.003)	(0.02)	(0.006)	(0.03)
N. Past Pledges	0.67†	0.65†	0.65†	0.66∗
	(0.02)	(0.03)	(0.02)	(0.03)
$ Donated In The Past	−0.01†	−0.01†	−0.01†	−0.01†
	(0.001)	(0.001)	(0.001)	(0.001)
User Fixed Effects		X		X
Charity Fixed Effects			X	X
Observations	3,196	3,196	3,196	3,196
Adjusted R^2	0.241	0.399	0.298	0.436

Notes: In Panel A, the dependent variable is the share of a pledge that was fulfilled, and in Panel B the dependent variable is equal to 1 if a pledge was deleted, and 0 otherwise. We present results from linear probability models. The unit of observation is a pledge. The sample excludes pledges that were "active" or "inactive" as of December 31, 2012. Robust standard errors are reported in parentheses. All coefficient estimates and standard errors are multiplied by 100 for ease of presentation.
* $p < 0.05$; † $p < 0.001$.

level heterogeneity also exists among users who give to the same charity. Our fully specified model (column 4) implies that broadcasting one's pledge is associated with a 10.85 percentage point reduction in the probability of subsequently deleting it. Essentially, once charity and user heterogeneity are accounted for, the probability of deleting a pledge is almost entirely removed. One interpretation of this effect is that broadcasting acts as form of "soft commitment," whereby failure to comply with the promise made carries a psychological cost (e.g., loss of self-esteem) that induces users to follow through with the donations they publicly pledged to make (Bryan et al. 2010).

Exploring Network Effects

The broadcasting feature of HA could potentially trigger additional donations for the charitable organizations. If a Facebook or Twitter contact of a user starts a pledge by clicking on the notification, the application records the user's identification number, and we are able to track this donation. We can then distinguish the *direct pledges* of the original adopters and the *network pledges* by their contacts. A simple way to compute the network effect is thus given by

$$\text{Network effect} = \frac{\text{Network pledges}}{\text{Direct pledges}}. \tag{2}$$

Out of a total of 3,461 pledges, the direct pledges were 3,287, thus the estimated network effect is $\frac{3{,}461-3{,}287}{3287} = \frac{174}{3287} = 5.3\%$. If we only consider the pledges that were processed and paid to the charitable organizations, the raw network effect is 5.1 percent. These figures are shown in Table 5, overall and by charity. There is, again, heterogeneity across charities. For example, the American Red Cross has a network effect of 3.3 percent, whereas PETA's pledges imply a network effect of 13.6 percent.

The magnitudes of the network effects are similar for pledges broadcasted in Facebook and Twitter.[12] We also measured the network effects in terms of amount pledged and donated (Table 6). The users pledged a total of $197,333, and $9,059 was generated through the broadcasting feature (Table 6A). This implies a network effect of 4.8 percent for the amount pledged. There is heterogeneity across the charitable organizations: whereas 1736 Family Crisis Center has a network effect of 21.6 percent, the pledges for American Red Cross consist of a 2.7 percent network effect. In Table 6B, we consider the amount actually donated by the users. The total amount donated through the network is $2,956, over a total of $80,913, implying a 3.8 percent network effect, again with substantial heterogeneity across charities.

In Table 7, we report estimates from regression analyses of the relationship between broadcasting one's pledge and network pledges:

$$\text{CREDIT\_USER}_{ict} = \alpha + \beta\ \text{BROADCAST} + \gamma X_{ict} + \delta_c + \eta_i + \varepsilon_{ict}. \tag{3}$$

The outcome variable CREDIT_USER_{ict} is a 0/1 indicator for whether a given app adopter/donor generated a network pledge, that is, if other donors installed the HA app after having clicked on a post by the original user. There is, not surprisingly, a

Table 5: Network Effects—Number of Pledges and Actual Donations

	Pledges		
Charity Name	Total	Network	Network Effect (%)
American Red Cross	714	23	3.3
Best Friends Animal Society	357	11	3.2
Fenix281	158	1	0.6
Mobile Loaves & Fishes	114	6	5.6
Arthritis Foundation	98	4	4.3
NTEN: Nonprofit Technology Network	72	7	10.8
U.S. Fund for UNICEF	71	2	2.9
Autism Society Of America	67	0	0.0
People For The Ethical Treatment of Animals (PETA)	67	8	13.6
Lights. Camera. Help.	59	3	5.4
Homes For Our Troops Inc.	53	1	1.9
1736 Family Crisis Center	51	2	4.1
Total	3,461	174	5.3
	Donations		
Charity Name	Total	Network	Network Effect (%)
American Red Cross	349	12	3.6
Best Friends Animal Society	248	9	3.8
Fenix281	104	0	0.0
Mobile Loaves & Fishes	97	6	6.6
Arthritis Foundation	72	2	2.9
NTEN: Nonprofit Technology Network	48	3	6.7
U.S. Fund for UNICEF	55	2	3.8
Autism Society Of America	3	0	0.0
People For The Ethical Treatment of Animals (PETA)	29	4	16.0
Lights. Camera. Help.	54	3	5.9
Homes For Our Troops Inc.	4	0	0.0
1736 Family Crisis Center	10	1	11.1
Total	2218	107	5.1

Notes: The table shows the most popular charities and the "network effect" generated. The network effect was computed as (Network pledges)/(total pledges − network pledges) = (Total pledges-direct pledges)/(total pledges − network pledges).

positive and statistically significant correlation between broadcasting and network pledges being generated, and the magnitude and statistical significance of the estimated coefficient are robust to inclusion of charity and user fixed effects.

Although these findings are consistent with the presence of a network effect in charitable giving, we worry about several identification challenges that may affect the estimates and their interpretation. In particular, the broadcast feature of the application is a decision variable of the user. To the extent that social networks in Facebook and Twitter display homophily, users who broadcast their activity

Table 6: Network effects—Amounts donated and pledged

Panel A

Charity Name	Total amount Pledged	Amount Pledged from Network (%)	Network Effect
American Red Cross	37,470	990	2.7
Best Friends Animal Society	17,148	1,365	8.6
Fenix281	15,365	40	0.3
Mobile Loaves & Fishes	4,543	181	4.1
Arthritis Foundation	3,560	125	3.6
NTEN: Nonprofit Technology Network	2,677	165	6.6
U.S. Fund for UNICEF	2,317	65	2.9
Autism Society Of America	2,620		0.0
People For The Ethical Treatment of Animals (PETA)	1,515	235	18.4
Lights. Camera. Help.	4,692	145	3.2
Homes For Our Troops Inc	2,360	40	1.7
1736 Family Crisis Center	5,856	1,039	21.6
Total	197,333	9,059	4.8

Panel B

Charity Name	Total amount Pledged	Amount Pledged from Network (%)	Network Effect
American Red Cross	16,210	475	3.0
Best Friends Animal Society	9,856	369	3.9
Fenix281	8,452	40	0.5
Mobile Loaves & Fishes	2,328	115	5.2
Arthritis Foundation	2,092	63	3.1
NTEN: Nonprofit Technology Network	922	48	5.4
U.S. Fund for UNICEF	1,390	48	3.6
Autism Society Of America	2,300		0.0
People For The Ethical Treatment of Animals (PETA)	557	72	15.0
Lights. Camera. Help.	1,181	69	6.2
Homes For Our Troops Inc	1,857	40	2.2
1736 Family Crisis Center	2,939	65	2.3
Total	80,913	2,956	3.8

Notes: The table shows the most popular charities and the "network effect" generated in terms of money pledged (or donated). The network effect was computed as (Amount pledged by network)/(total amount pledged − amount pledged by network) = (Total amount pledged − Amount directly pledged) /(total amount pledged − amount pledged by network).

might be those with contacts who are more responsive, or they may even decide to broadcast to a selected group of individuals, for example. the ones who are more likely to donate.[13] This would confound the interpretation of the social multiplier effect. In addition to the endogeneity of the broadcast, users in the same

Table 7: Broadcasting and Network Pledges: Regression Analysis

Outcome variable = 1 if a pledge generated a network pledge, 0 otherwise	(1)	(2)	(3)	(4)
Pledge broadcasted	6.46†	6.77†	6.76†	7.48†
	(0.68)	(0.81)	(0.86)	(0.91)
Pledge length (days)	−0.01	−0.007	−0.005	−0.002
	(0.01)	(0.007)	(0.009)	(0.01)
Pledge amount ($)	−0.000	0.005	−0.001	−0.004
	(0.001)	(0.004)	(0.01)	(0.01)
N. past pledges	0.02	0.02	0.06∗	0.05∗
	(0.01)	(0.015)	(0.02)	(0.02)
$ donated in the past	−0.001	−0.000	−0.001	−0.001
	(0.001)	(0.000)	(0.001)	(0.000)
Partially fulfilled	−4.67†	−4.46†	−2.84	−1.42
	(1.20)	(1.35)	(2.43)	(2.66)
Deleted	−2.19∗	−1.70	−3.77†	−2.85∗
	(1.02)	(1.13)	(1.26)	(1.36)
User Fixed Effects		X		X
Charity Fixed Effects			X	X
Observations	3,196	3,196	3,196	3,196
Adjusted R^2	0.032	0.003	0.179	0.189

Notes: The table shows regression estimates where the unit of observation is a pledge (N = 3,160). The dependent variable is equal to 1 if a pledge generated a network pledge (i.e., a pledge by one of the original user's Facebook friends or Twitter followers), and 0 otherwise. Linear probability models are employed. Robust standard errors are reported in parentheses. Coefficient estimates and standard errors have been multiplied by 100 for ease of presentation.
* $p < 0.05$; † $p < 0.01$.

social circles are exposed to similar events and influences that make them behave similarly; for example, fund-raising campaigns and natural disasters may influence the volume of new pledges and could change the magnitude of network effects in either direction. These empirical challenges cannot be addressed using the HA database. For this reason, we turn to an experimental design where we have clean control and treatment groups: the treated users have the broadcast feature turned on, automatically broadcasting to all of their Facebook friends; the control group does not have any broadcasting opportunity. By randomizing this feature, we generate exogenous variation among users, and we can thus limit the identification problems discussed previously.

Field Experiment

In collaboration with HA, we conducted a field experiment where users were invited to donate to Heifer International (http://www.heifer.org), a charity whose mission is to "end poverty and hunger."[14] We chose to work with only one charity to decrease the costs of coordination. Heifer is a relatively small charity with fast decision-making processes, which allowed us to obtain immediate feedback on the marketing campaign and flexibly change it so we could experiment with different strategies. In addition, allowing the users to choose the charity would make the identification of social contagion more challenging even within a randomized controlled framework.[15]

Design

Figure 3 shows the HA pledge page for Heifer International as seen by the users in our experiment. The experiment started with a marketing campaign on Facebook, with a mix of sponsored stories and ads that asked users to donate to Heifer International using the HA application. If a user clicked on the ad or sponsored story, she was redirected to the web page of Heifer International on the HA website.

The design (Figure 4) consisted of randomly turning on and off the broadcasting feature of the application (in Figure 1B, the checkbox "Spread the word!"). Thus we have two conditions:

1. C1: Broadcasting "off." Any donation activity is private to the individual user.

2. C2: Broadcasting "on." Any donation activity is automatically notified to all of the user's contacts.

Figure 1B shows the details of the HA viral features on the pledge webpage. Our intervention randomized the availability of the "Spread the word!" option at the time of pledging. Treated users automatically broadcasted their donation activity, whereas control users did not have that option. We then tracked the donation activity of the user and the donation activity of her contacts, if any. If a contact of the initial user started a new pledge with HA, we were able to track her activity and link it to the initial user's activity. The comparison of the donation activity for the list of contacts in the two experimental conditions allows us to determine the presence, if any, of a causal link from the broadcasting feature of the application being turned on to the number of donors and the amount pledged to Heifer International.

The advantage of our design is that it allows us to track the diffusion starting from a set of seeding nodes, that is, the initial users. The randomization provides the exogenous variation necessary to estimate causal effects of the broadcasting feature of the application. The use of the application is crucial to track the diffusion; we would not be able to track the social contagion without the initial users' friends lists, which is something that HA does, whereas the charities do not normally do this. A limitation of our setting is that we cannot obtain data on individuals who do not install the application and pledge some money to the charity. So, for example, we cannot observe users' friends' characteristics until they become users of the

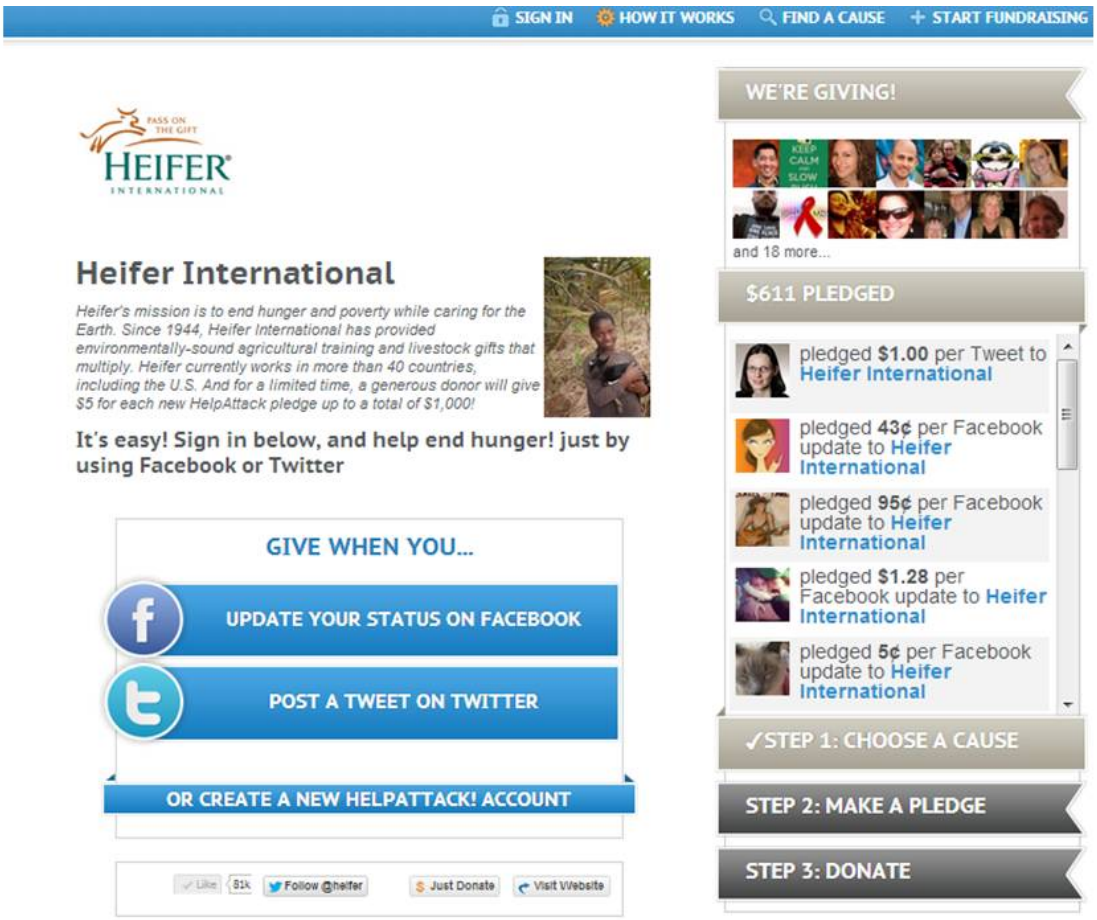


Figure 3: Helpattack! Pledge page for Heifer International

HA application. This is due to the legal requirements of the application, which cannot collect data from users' Facebook profiles without users' permission (see also Aral and Walker 2011). As a consequence, we cannot track those friends' "likes," "shares," and so on. An alternative design would collect the entire network and individual characteristics before the randomization and follow the behavior of all the potential users (Banerjee et al. 2012). However, in online social networks, we would need to collect the entire universe of users.

Implementation and Results

The initial recruitment of the participants is crucial and proved to be challenging in our experiment. We relied on a mix of Facebook ads and sponsored stories, in collaboration and coordination with HA and Heifer International. The campaign was executed in three stages. The first stage started on June 7, 2012, with the sponsored story shown in Figure 5A and a Facebook ad that mimicked the sponsored story. Our target audience for the campaign was the U.S. population aged 18–65 years.

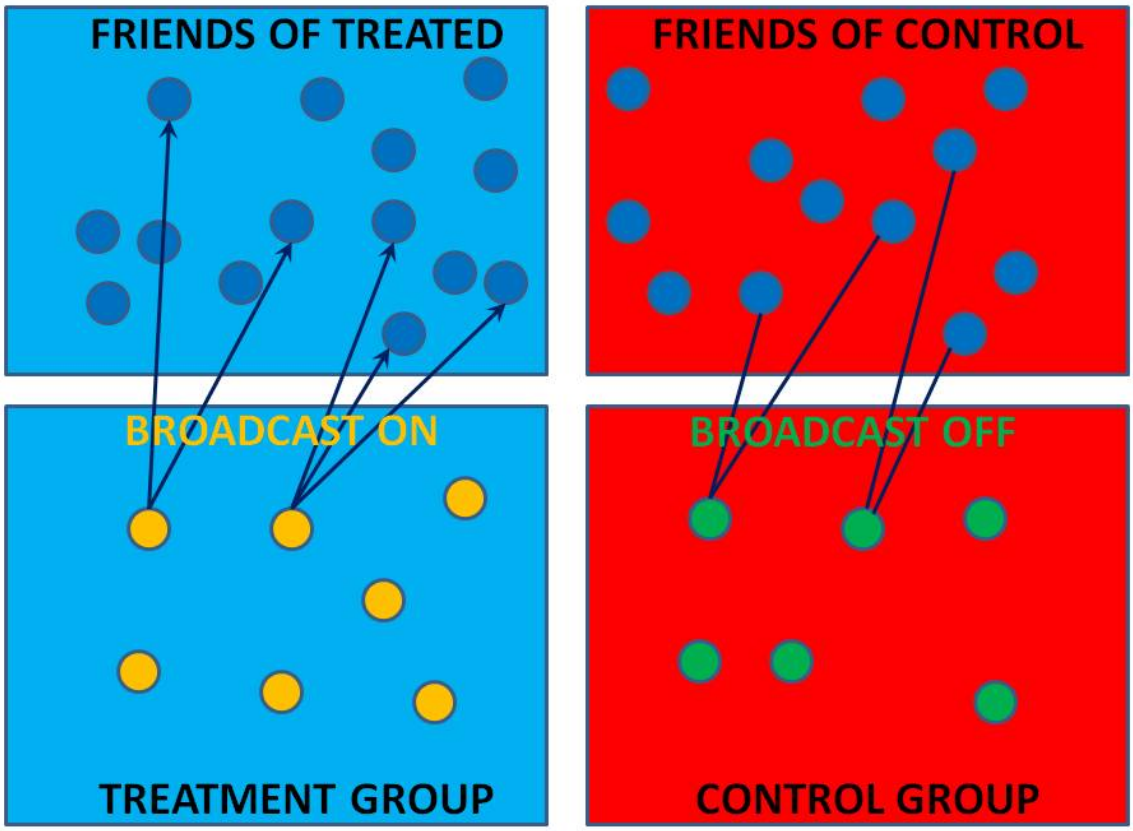


Figure 4: Experimental Design. The treated group of initial users broadcasts the information about the charity and the donation activity to their friends. The control group of initial users has the broadcasting feature of the application turned off.

During the first week (June 7–13), the sponsored story, which reached more than 484,000 Facebook users, was "liked" by 254 people, was "shared" by 34, and prompted 42 comments on the Heifer Facebook page; 611 users clicked on the link, to be redirected to the HA page. The ads were ineffective in terms of number of installations and pledges: with a total reach of 2,860 and 1,354, respectively, they generated only one click. This first campaign thus generated only three new Facebook pledges. In the second stage, started on June 22, 2012, we used a similar sponsored story and ads (Figure 5B) but increased the bid per click, which would give the ads greater visibility. The second campaign reached a significantly higher number of Facebook users: the total reach for the sponsored story was 3,742,000, with a total of more than 9 million impressions in 10 days. The story received 1,512 "likes," generated 164 comments, and was shared by 236 Facebook users. The total number of clicks was 4,859. Yet the ads generated in total only 235 clicks, even though the number of impressions was beyond 1 million. Overall, the second campaign generated an additional 19 pledges: 15 Facebook pledges and 4 Twitter pledges. Thus the first two stages of the campaign generated a total of 18 usable Facebook pledges (and 4 Twitter pledges). In the third stage, started on July 27, 2012,

we offered to match the pledge of initial users with a $5 donation (Figure 5C). This is a common scheme used by many charitable organizations to promote donations and has been found to increase not only the revenue per solicitation but also the response rate (Karlan and List 2007). Specifically, for each user's pledge, an extra $5 would be given to Heifer by an anonymous "generous donor." The third campaign lasted two weeks, and only seven additional Facebook pledges were made. The time series of likes, shares, and comments are shown in Figure 6 for the period that includes our marketing activity (February–November 2012). The red vertical dashed lines represent the dates of the sponsored story publications: we observe several spikes of activity that correspond to our campaign's initial dates, especially during the second wave. Descriptive details on the outcomes of our three promotional campaigns are displayed in Table 8.

Overall, our campaigns generated 30 pledges. However, some of these users deleted their pledges after a few days, or were inactive, and some were Twitter users. We focus here on the 25 "usable" Facebook pledges. These were the initial users from whom we tracked the diffusion: 13 initial users were randomly assigned to treatment group, broadcasting "on," and 12 were assigned to the control group, broadcasting "off." The former group had a total of 2,275 friends and the latter 1,897 friends. Table 9 reports descriptive statistics for the 25 Facebook users and the results of the experiment.[16] Of these 25 users, 22 were women and only 3 were men. Most pledges were based on the default HA pledge (maximum amount $20, one-month period). The rate per Facebook update was quite variable. There are no substantial differences between the control and treatment groups in terms of observable actions and characteristics.

The campaigns, therefore, generated interest and attention; stories were liked, shared, and commented upon by a nonnegligible share of users (see Figure 7 and Table 8). However, most of the attention was expressed in the least costly way, that is, simply by liking a story, followed by sharing, and then by commenting, which is a little more costly in terms of time and effort. However, but somewhat consistently with the decline of expressions of interest as they become more costly, the actual donation rates were very low. In addition, social contagion did not take place; of the 4,172 friends of our initial users, none pledged to Heifer International. Recall that the HA application automatically sends several broadcasting messages of the donation activity to the friends of the treated group (one at the moment of the initial pledge, one after few days, one after the user reaches half of the total amount pledged, and one at the end of the period). Even though this reinforcement mechanism was in place, no additional pledges were generated through the network of the treated users. One might be concerned that donors could have donated to the charity directly, that is, without going through the HA app. However, communications with Heifer International revealed that the charity did not experience higher donation rates in the weeks after our promotional campaigns were launched, which indicates the lack of an effect of our campaigns on donations through HA is genuine.

5A: Sponsored story for campaign (1st stage)

5B: Sponsored story for campaign (2nd Stage)

5C: Sponsored story for campaign (3rd Stage)

Figure 5: Stages of Sponsored Stories

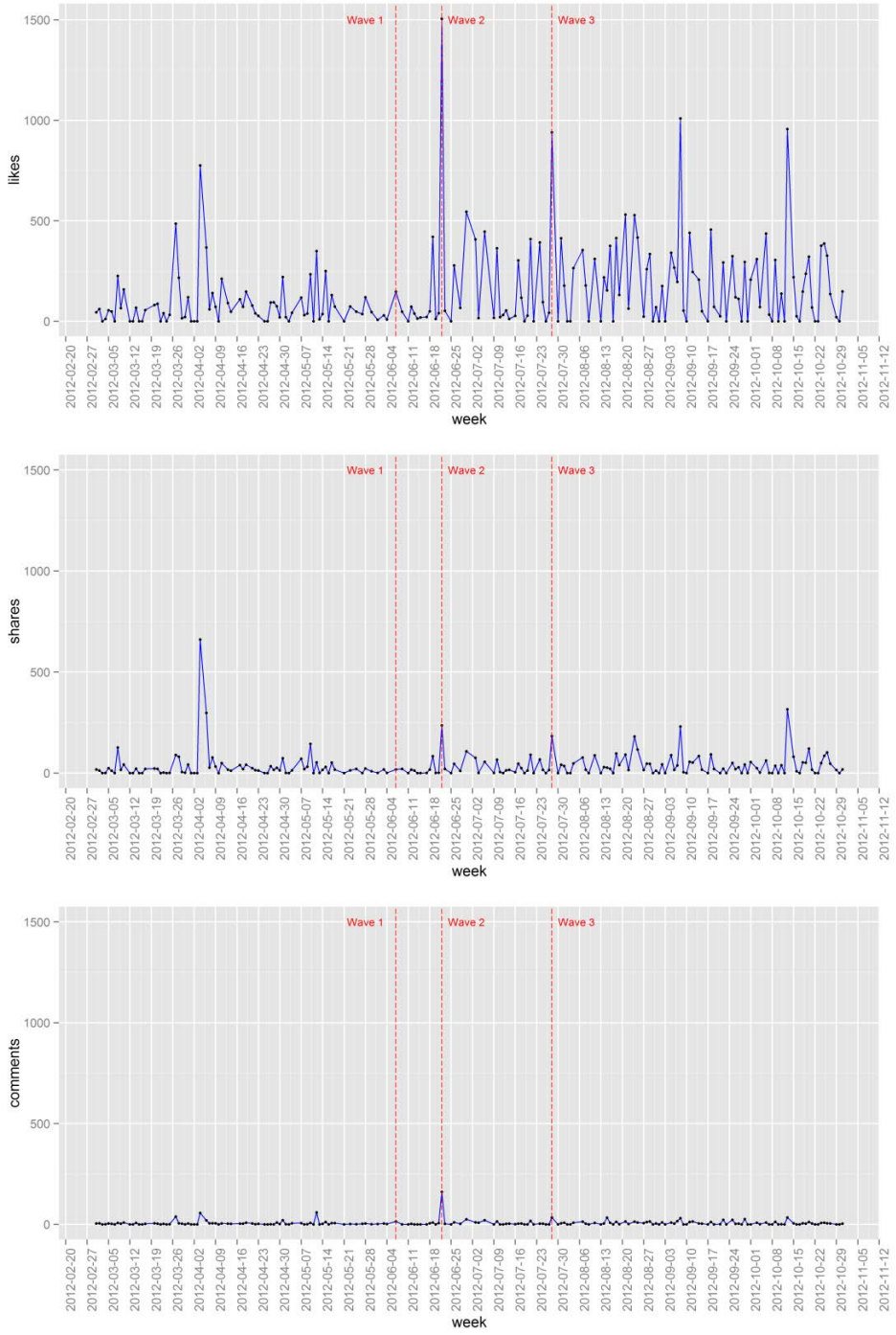


Figure 6: Field Experiment–Likes, Shares and Comments on the Heifer International FB Page

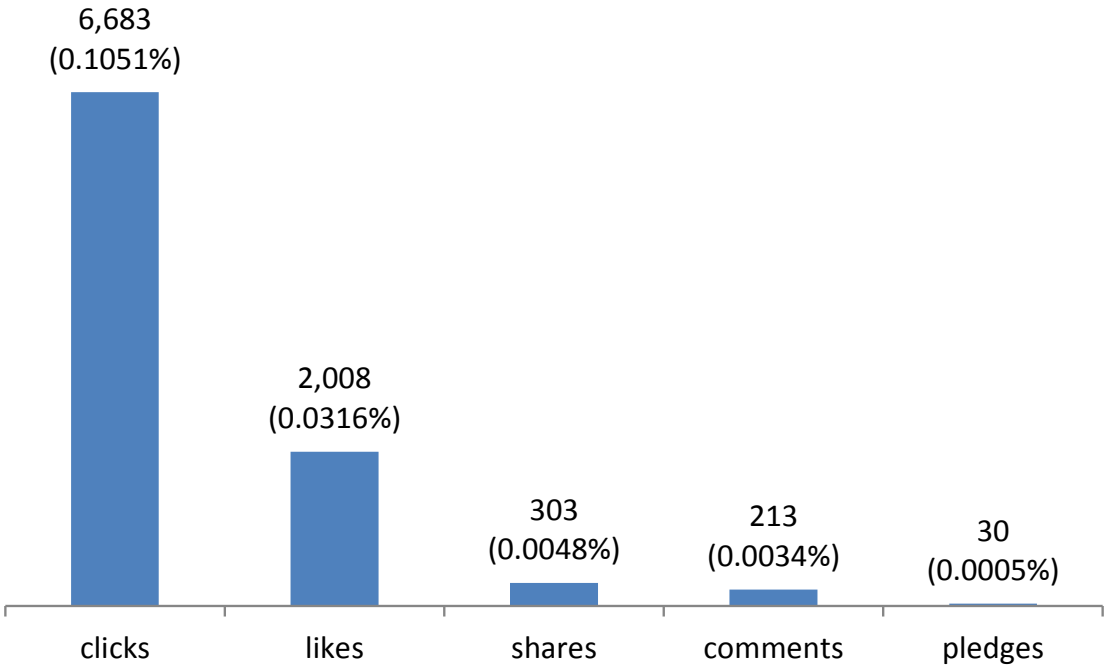


Figure 7: Field Experiment–Responses to the Sponsored Stories and Facebook Ads. This figure displays the reactions to the sponsored stories and Facebook ads that were part of our field-experimental intervention.

Survey Experiment

Our field experiment and, to some extent, the historical HA data show that actually making a donation on this platform is relatively rare and, it can be inferred, is considered more costly than other forms of less active engagement, such as "likes" and comments. To further investigate the potential sources of the small donation rates that we found, we ran a computerized, online survey experiment where respondents were asked about their willingness to make a small donation to a charity. We asked 1,605 U.S.-based participants on Amazon Mechanical Turk (mTurk) to state their willingness to donate $5 to charity if they were given $10. We manipulated the question to study the impact on the willingness to donate of the identity of the charity, the presence of processing fees, and the presence of an intermediary between the donor and the charity. The presence of a fee and an intermediary were prominent features of HA's business model, whereas specifying a charity was somewhat specific to our field experiment (HA allowed donors to choose from a variety of charities).

Design

We presented the key survey questions to the respondents using the item count technique (ICT) in our survey. The ICT is based on not asking a question directly (e.g., "If you were given $10, would you donate $5 to charity?") but instead having

Table 8: Field experiment—Campaign Reach

	Stage 1	Stage 2	Stage 3	Total
Facebook users reached	484,738	3,742,773	2,128,462	6,355,973
# of "likes"	254	1,512	242	2,008
# of "shares"	34	236	33	303
# of comments	42	164	7	213
# of "clicks" (redirected to HA page)	611	4,859	1,213	6,683
# of pledges (Facebook)	3	15	7	25
# of pledges (Twitter)	0	4	1	5
Total # of pledges	3	19	8	30
# deleted or inactive	0	1	1	2
# processed	3	13	4	20

Notes: This table presents the outcomes of our field-experimental promotional campaigns conducted between June and August, 2012 in collaboration with HelpAttack! and Heifer International. The campaigns consisted of a combination of Facebook ads and sponsored stories, as described in Section 4 in the text. Stage 1 started on June 7 2012, stage 2 on June 22, and Stage 3 on July 27.

respondents report the number of descriptive phrases, from a list that they are given, that they believe apply to them. A control group is given a list of N "neutral" phrases (i.e., nonsensitive in nature), whereas the treatment group is given $N+1$ sentences, of which N are the same as for the control, and the additional item is the one of main interest. The researcher cannot infer if a given respondent answered positively or negatively to a given item; this preserves the privacy of the respondents and, together with the anonymity of the online survey, allays the concern that they might give what they perceive to be the "socially correct" answer.[17] In our case, the hypothetical framework might lead to an upward bias if most respondents believe that donating $5 is more socially acceptable and is what the researchers expect. With subjects assigned randomly to various experimental conditions, and a large enough sample size, the difference in the average counts between treatment and control gives an estimate of the share of individuals in the treatment group to which the phrase of interest applies (Coffman et al. 2013; Miller 1984). The key question in our survey asked the respondents to indicate how many of the listed statements applied to them. In the control condition, four statements were reported, and in the various treatment conditions, the fifth statement was a sentence indicating that, if the respondent was to receive $10, he or she would make a $5 charitable donation.

The treatment conditions were defined by the presence and the wording of the fifth sentence assigned to the subjects (Table 10), with the aim of identifying potential determinants of the donation rates and, in particular, given the findings from the experiment, to identify factors that drive donation rates down.

Presence of a fee. First, the presence of a processing fee might inhibit donations, regardless of the identity of the receiving organizations. Some studies and the popular press alike, for example, point to "overhead" costs as driving potential

Table 9: Field experiment—Pledges and Network Effects

Panel A–Facebook

	All Subjects Intitial pledges = 25 # of contacts= 4,172		Treatment Intitial pledges = 13 # of friends = 2,275		Control Intitial pledges = 12 # of friends = 1,897	
Variable	Obs	Mean	Obs	Mean	Obs	Mean
Female	25	0.88	13	0.85	12	0.92
		(0.33)		(0.38)		(0.29)
Facebook Friends	25	166.88	13	175.00	12	158.08
		(127.14)		(147.79)		(106.20)
Cents per Update	25	34.32	13	32.46	12	36.33
		(36.41)		(39.73)		(34.09)
Amount Donated	17	14.73	8	15.27	9	14.26
		(4.26)		(4.41)		(4.32)
Amount Pledged	25	19.8	13	18.08	12	21.67
		(7.14)		(3.84)		(9.37)
Length of Pledge	25	98.4	13	113.08	12	82.5
		(92.27)		(104.75)		(77.94)
Amount per day	17	0.41	8	0.49	9	0.35
		(0.21)		(0.18)		(0.21)
Additional pledges through network effect		0		0		0
Additional amount donated through network effect		0		0		0

Panel B–Twitter

	All Subjects Intitial pledges = 5 # of contacts= 2,844		Treatment Intitial pledges = 3 # of friends = 2,409		Control Intitial pledges = 2 # of friends = 435	
Variable	Obs	Mean	Obs	Mean	Obs	Mean
Friends	5	444.6	3	703.67	2	56
		(499.57)		(497.43)		(5.66)
Followers	5	568.8	3	803.00	2	217.5
		(823.67)		(1066.26)		(169.00)
Cents Per Update	5	178.4	3	247.33	2	75.00
		(274.36)		(363.46)		(35.36)
Amount Donated	3	18.21	2	17.31	1	20.00
		(3.11)		(3.80)		
Amount Pledged	5	36	3	20.00	2	60.00
		(35.78		0.00		(56.57)
Length of Pledge	5	72	3	30.00	2	135
		(93.91)		0.00		(148.49)
Amount per day	3	0.61	2	0.58	1	0.67
		(0.10)		(0.13)		
Additional pledges through network effect		1		0		1
Additional amount donated through network effect		20		0		20

Notes: This table shows the results of the field experiment in terms of initial pledges and network effects, separately for Facebook (Panel A) and Twitter (Panel B) users.

Table 10: Survey experiment—wording of the key question in the control condition and in each of the treatment

Question: Please read the statements below and indicate how many apply to you.

Statements common to control and treatment conditions:
There are several operating systems for smartphones. I am familiar with the Google Android operating system.

Suppose the Government increases income taxes by 0.5%. I would support using the proceedings to improve the public school system.

If I had to replace my phone today, I would buy an iPhone.

I am in favor of expanding offshore drilling to reach energy independence.

Additional statements added in each treatment condition:

ARC, No fee	If I was given $10 and could either keep the full amount or donate $5 to the American Red Cross, I would choose to donate $5 to the American Red Cross.
ARC, With fee	If I was given $10 and could either keep the full amount or donate $5 to the American Red Cross, I would choose to donate $5 to the American Red Cross (8.25% of your donation will be used to cover processing fees)
ARC, With fee and intermediary	If I was given $10 and could either keep the full amount or donate $5 to the American Red Cross, I would choose to donate $5 to the American Red Cross (8.25% of your donation will be used to cover processing fees by an intermediary agent organization)
Heifer, No fee	If I was given $10 and could either keep the full amount or donate $5 to Heifer International, I would choose to donate $5 to Heifer International.
Heifer, With fee	If I was given $10 and could either keep the full amount or donate $5 to Heifer International, I would choose to donate $5 to Heifer International (8.25% of your donation will be used to cover processing fees)
Heifer, With fee and intermediary	If I was given $10 and could either keep the full amount or donate $5 to Heifer International, I would choose to donate $5 to the Heifer International (8.25% of your donation will be used to cover processing fees by an intermediary agent organization)
Charity of choice, No fee	If I was given $10 and could either keep the full amount or donate $5 to a charity of my choice, I would choose to donate $5 to a charity of my choice.
Charity of choice, With fee	If I was given $10 and could either keep the full amount or donate $5 to a charity of my choice, I would choose to donate $5 to a charity of my choice (8.25% of your donation will be used to cover processing fees)
Charity of choice, With fee and intermediary	If I was given $10 and could either keep the full amount or donate $5 to a charity of my choice, I would choose to donate $5 to a charity of my choice (8.25% of your donation will be used to cover processing fees by an intermediary agent organization)

Notes: The order of the statements was randomized in two different versions. In particular, the treatment statements appeared in either the 2nd or 4th position.

donors away from supporting a given cause or organization, as opposed to when the entire amount donated is believed to be fully used for the cause (Ellis 2013; Roderick Williams 2007; Rooney and Frederick 2007). We set out to test for this possibility by providing three additional versions of the main sentence on donating $5, where we indicated, for each of the three charity options described, that a processing fee would be applied. We set the fee to be 8.25 percent of the donated amount, to match the fee actually charged by HA.

Presence of an intermediary. Second, a fee might have a negative effect on the willingness to donate if it is collected and used by a third, intermediary organization, as in the business model of HA. Potential donors might be discouraged from contributing if they perceive an increased "distance" between their action and the ultimate receiver. We included a condition that specified that the 8.25 percent fee associated with donating $5 to the charity would go to an (unspecified) intermediary.

Identity and salience of the charity. Third, we wanted to investigate whether donation rates were affected by the salience of the receiver. Especially in an environment where information is added at a fast pace (such as Facebook), it is plausible that the attention of a user to each single piece of information is limited. Low salience may be due to the type of message[18] or the identity of the receiver. This latter case might occur, as, for example, is the case for Heifer International, if the charitable organization is not widely known (Heifer had received only a few pledges in HA prior to our field experiment). In the key treatment sentence, we therefore assigned, as the organization that would hypothetically receive $5 from the respondent, one between Heifer International, the American Red Cross, or a generic "charity of choice." We chose the American Red Cross because of its wide popularity, in contrast to the more limited popularity of Heifer (in general and also in terms of donation activity via HA, as discussed earlier), and we also added a "choice" option to test whether the indication itself of a precise charity would have an impact (HA does in fact offer a wide range of charities for users to support).[19]

Each subject was assigned to only one treatment; the nine versions of the sentence that constitute our treatment conditions are in Table 10.[20]

Data and Findings

We used data from 1,605 unique respondents.[21] The sample was well balanced by conditions, and therefore the randomization was successful (Tables 11 and 12), and the respondents, although not fully representative of the overall U.S. population, are comparable to those in other studies relying on mTurk (e.g., Coffman et al. 2013; Weinberg, Freese, and McElhattan 2014).

We estimate the share of individuals who would be willing to donate $5 through the following model:

$$Y_i = \alpha + \sum_{j=1}^{T} \beta_j \tau_j + \gamma X_i + \varepsilon_i, \tag{4}$$

where Y_i, the outcome variable, is the count of statements that subject i indicated to apply to him; thus the variables takes integer values between 0 and 4 in the control condition and between 0 and 5 in each of the treatment conditions. The average

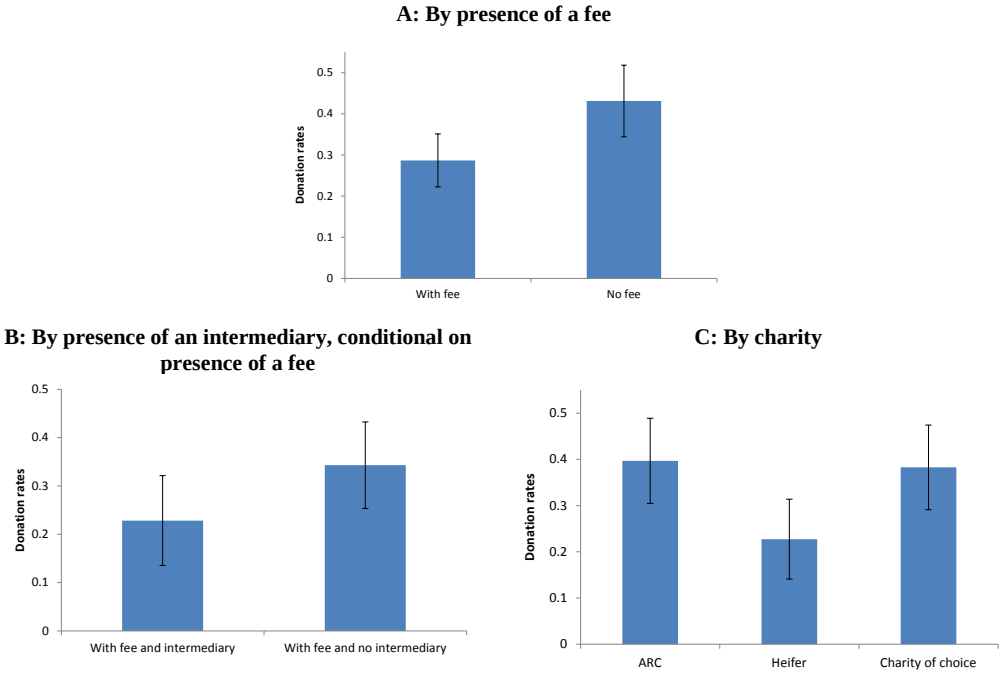


Figure 8: Survey experiment–Donation rates by charity, presence of a fee, and presence of an intermediary. The graphed values were obtained as differences between the average counts between the relevant treatment condition and the control in the main survey question. 95% confidence intervals are also reported.

count for the control condition is expressed by the ordinary least squares estimate of the parameter α. The indicators τ_j assume a value of 1 if a subject i is assigned to treatment j, and 0 otherwise. The estimates of the parameters β_j represent the differences in average response counts between the control and a given treatment condition j. We first combine the nine conditions into three groups as given by the indication of the three different charities: American Red Cross, Heifer, and a charity of choice. Second, we distinguish between versions of the treatment sentence indicating or not indicating the presence of a fee (with or without the indication of an intermediary). Third, limited to the cases where a fee was indicated, we separate the cases where the presence of an intermediary was not indicated and the cases where it was indicated. Finally, we also run the regression with the full set of disaggregated conditions (equivalently, we can think of these as interactions among the more aggregated conditions). The vector X_i includes the control variables from the other responses to the survey.

The estimated donation rate in all conditions is significantly greater than zero: on average, mean response counts over all treatment conditions are 2.48 over 2.13 for the controls, implying an average donation rate of 35 percent. The differences among treatment conditions are reported graphically in Figure 8, whereas the regression results are in Table 13.

A first finding is that the presence of a fee inhibits donations by about 15 percentage points, or about 33 percent of the effect with no fees (Figure 8A and Table 13, columns 1 and 2).[22]

Table 11: Survey experiment—sample distribution across treatments and randomization check

Condition	N	Age	Female	No children	Highest educ. (1-6)	Employ. status	Income (1-5)	Has volunteered	Religion	Political views
Control	158	33	0.4	0.7	4.5	2.7	2.7	0.7	1.7	2.1
ARC, No fee	152	32.1	0.4	0.6	4.4	2.7	2.7	0.6	1.5	2.2
ARC, With fee	166	31.7	0.4	0.7	4.5	2.9	2.7	0.7	1.6	2.1
ARC, With fee and intermediary	154	33.1	0.4	0.7	4.3	2.7	2.7	0.8	1.7	2.1
Heifer, No fee	161	32.2	0.4	0.6	4.3	2.7	2.8	0.7	1.7	2.2
Heifer, With fee	172	30.3	0.4	0.7	4.5	2.7	2.8	0.7	1.7	2.2
Heifer, With fee and intermediary	161	30.8	0.5	0.8	4.2	3.2	2.4	0.6	1.6	2.2
Charity of choice, No fee	162	30.6	0.4	0.7	4.5	3	2.5	0.7	1.6	2.2
Charity of choice, With fee	158	30.2	0.4	0.7	4.4	3.1	2.6	0.7	1.6	2.2
Charity of choice, With fee and intermediary	161	32.3	0.4	0.7	4.3	3	2.5	0.6	1.8	2.2

Notes: The table reports the number of subjects per conditions as well as the average values of the responses to the various questions in the survey, by treatment condition. Note that in some case these means are meaningful (e.g. for age or for binary responses such as gender and whether the subject has children or has volunteered in the past). In other cases, averages are taken over categorical variables. Within the categorical variables we report the value ranges for the cases where the options were following some plausible order (educational attainment and income) but not for those where there is no ranking (employment status, religion, and political views).

Table 12: Survey experiment—descriptive statistics on additional questions (control variables)

Age		Employment status	
30 and below	59.8%	Private Employee	36.0%
31-50	32.7%	Public Employee	13.9%
Above 50	7.5%	Self-employed/Entrepreneur	15.7%
Average	31.2	Unemployed	13.3%
		Housekeeper	4.4%
Gender		Student	15.0%
		Retired	1.8%
Male	59.6%		
Female	40.4%		
Race/ethnicity		Approximate monthly income	
White/caucasian	77.3%	Not currently earning any income	12.1%
African American	6.5%	Less than $1.500	39.1%
Hispanic	6.0%	Between $1.50 and $2.500	24.9%
Asian	8.60%	Between $2.500 and $5.000	19.0%
Other	1.6%	More than $5.000	4.9%
Relationship status		Religion	
Single	41.4%	Atheist/Agnostic	51.6%
Unmarried in a relationship	24.0%	Christian	39.4%
Married	29.2%	Jewish	1.6%
Separated/divorces	4.8%	Muslim	6.6%
Other	0.6%	Other	0.8%
Highest educational level attained		Political views	
Completed primary school	0.0%	Conservative	16.6%
Some high school	0.9%	Liberal	52.0%
Completed high school	13.3%	Moderate	27.9%
Some college	39.1%	Other	3.5%
Completed college	37.9%		
Postgraduate	8.7%		
Has children		Donated or volunteered in the past 2 years	
Yes	31.7%	Yes	68.9%
No	68.3%	No	31.1%

Note: N = 1,605 subjects.

Second, a further negative effect on donation rates arises when the fee is presented to pertain to an intermediary organization; we observe a decline of 11 percentage points as compared to a scenario with a fee, but where there is no mention of an intermediary (Figure 8B, columns 3–4 of Table 13).

Third, the identity of the charity does affect donation rates; in particular, the fact that naming the American Red Cross leads to almost twice as high stated donation rates as mentioning Heifer (40 vs. 23 percent; Figure 8A and columns 1 and 2 of Table 13) is consistent with lower recognizability of the charity limiting the subjects'

willingness to contribute to it. Interestingly, leaving the charity choice open led about 38 percent of respondents to express willingness to donate, very similar to the level for ARC.

Columns 7–8 of Table 13 show that the presence of a fee and, in addition, the presence of an intermediary depresses the willingness to donate, especially so when the charity mentioned is Heifer.

Overall, the findings are consistent with the various hypotheses that we stated earlier: the salience or recognizability of a charity or cause, the presence of a fee, and the involvement of the intermediary all contribute to affect donation rates; in particular, the limited recognizability of a charity, and the fact that a fee is charged through the involvement of a third party, all play against obtaining high donation rates.

Conclusion

Our field experiment showed very limited engagement of users through actual donations in response to online fund-raising efforts, despite considerable responses to the promotional campaigns in terms of "costless" activities such as "likes" or "shares." In addition, although the observational data from application adoption and donation activities were consistent with the presence of social contagion and network effects in charitable giving, the pledges generated by our field experiment did not lead to any further donations by the user's contacts. Also, the findings from our survey experiment imply that the presence of fees, especially if administered through an intermediary, contributes to inhibit the willingness to donate. Moreover, consistent with what we observed in HA's historical data, charities with a strong offline presence and visibility (e.g., the American Red Cross) appear to have an advantage at raising funds online compared to lesser-known charities. These findings from the survey offer insights that generalize beyond the particular context that we studied; if, on one hand, the low donation rates that we documented may be partly due to the particular features of the HA application, on the other hand, the insights about the role of third-party fees and offline visibility of a charity apply more broadly.

Our findings are consistent with the presence of behaviors and phenomena such as "slacktivism" or "illusion of activism" (Kristofferson et al. 2014; Lewis et al. 2012; Lewis et al. 2014); this suggests that, at least for now, many people may see online social networks as essentially free platforms for personal exchange and much less as vehicles for costly activities. The provision of "free" forms of participation made available in online contexts defines a different choice set as compared to offline participation. In traditional "social movements," participation typically implies a costly action associated with a tangible contribution to a cause. In contrast, online platforms introduce opportunities for activism consisting of nearly costless actions without actual contributions to the cause.

Moreover, although social contagion through online social networks may occur when free activities are concerned, even relatively small costs may discourage individuals or shield them from peer pressure.

Table 13: Survey experiment—regression analyses

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ARC combined	0.40†	0.40†						
	(0.09)	(0.09)						
Heifer combined	0.23*	0.23†						
	(0.09)	(0.09)						
Charity of choice combined	0.38†	0.39†						
	(0.09)	(0.09)						
With fee combined			0.29†	0.29†				
			(0.09)	(0.08)				
No fee Combined			0.43†	0.44†				
			(0.09)	(0.09)				
With fee and intermediary combined					0.23*	0.24†		
					(0.09)	(0.09)		
With fee and no intermediary combined					0.34†	0.33†		
					(0.09)	(0.09)		
ARC, No fee							0.52†	0.54†
							(0.11)	(0.11)
ARC, With fee							0.37†	0.36†
							(0.11)	(0.11)
ARC, With fee and intermediary							0.30†	0.29†
							(0.11)	(0.11)
Heifer, No fee							0.34†	0.34†
							(0.11)	(0.11)
Heifer, With fee							0.16	0.15
							(0.11)	(0.11)
Heifer, With fee and intermediary							0.18	0.22*
							(0.11)	(0.11)
Charity of choice, No fee							0.43†	0.44†
							(0.11)	(0.11)
Charity of choice, With fee							0.51†	0.50†
							(0.11)	(0.11)
Charity of choice, With fee and intermediary							0.21	0.23*
							(0.11)	(0.11)
Controls		X		X		X		X
Observations	1,605	1,604	1,605	1,604	1,130	1,130	1,605	1,604
Adjusted R^2	0.013	0.052	0.013	0.051	0.011	0.042	0.019	0.057

Notes: The table reports the parameter estimates from Equation (1), limited to the main parameters of interest. The bottom section of the table displays the estimated differences of the effects between some conditions of interest. Standard errors are in parentheses.
ARC - Heifer: 0.17†
No fee - With fee: 0.14†
With fee, no intermediary -With fee and intermediary: 0.11*
Charity of choice - ARC: (0.02)
* $p < 0.05$; † $p < 0.01$.

Consistent with previous studies showing that networks on social media are largely based on homophily (Lewis et al. 2012), finally, the different estimates of network effects (or lack thereof) in the observational and controlled experimental analyses imply that social contagion in online charitable giving may be limited or require additional effort by organizations.

More broadly, the results provide some insight into the motivations for charitable giving. In particular, the fact that, when cheaper but visible alternative forms of support are present, individuals do use them much more frequently than offering actual monetary donations is consistent with self or social-image concerns being a factor that motivates giving.

A further contribution of our study, together with others that rely on increasingly available data from online platforms, is the use of multiple research methodologies, and in particular the combination of observational and experimental data. Empirical strategies that combine the richness and detail of historical data with the potential for clean identification of experiments will, it is hoped, be employed in future studies to enhance our understanding of the phenomena described here and related ones. For example, Angrist (2014) stresses the importance of complementing observational evidence with randomized trials to assess the causal impact of peer and social spillover effects. Our exercise is in this spirit and, in fact, is consistent with Angrist's conclusion: we find very little, if any, causal evidence of genuine online social contagion in charitable giving.

Notes

1 "While the London event has almost 3,000 'likes' and 1,300 people say they will attend in Reading, Birmingham has mustered the support of just 35 people, with a mere 14 in Norwich" (http://www.theguardian.com/world/blog/2012/apr/20/kony-2012-cover-the-night).

2 There is a large body of literature that shows evidence of homophily in friendship patterns (e.g., Mouw and Entwisle 2006). See also McPherson, Smith-Lovin, and Cook (2001) for a review. Evidence of homophily in Facebook has been shown by Lewis et al. (2012); Leider et al. (2009) showed that altruistic individuals tend to have altruistic friends too. See also McPherson et al. (2001) for a review.

3 The power of a direct ask has indeed been found to be effective in other giving contexts (Meer 2011; Meer and Rosen 2011; Castillo et al. 2014; Sanders and Smith 2014; Yörük 2009).

4 Payments are handled by an external company, FirstGiving. HA does not store any financial or credit card information from the users.

5 See http://www.we-care.com/blog/2013/prhelpattack. HA's original web page was https://www.helpattack.com.

6 The website of HA contains 7,373 charities, 343 of which received at least one pledge.

7 Some charities almost entirely rely on Facebook for their HA donations (e.g., Homes for Our Troops Inc., Autism Society of America), whereas others have a higher number of pledges from Twitter (e.g., Mobile, Loaves and Fishes, NTEN). These details are not shown in the tables to save space but can be provided upon request.

8 Of pledges, 1.4 percent were inactive (i.e., the user did not have any activity for several weeks), and 6.2 percent were still active (i.e., they did not reach the end of the pledge period). We removed active and inactive pledges in our analyses.

9 No payment is due until the pledge period is over. The user can delete the pledge at any time before the end of the period. However, she may partially fulfill the pledge or pay in full before the end of the pledge period.

10 For the analyses using whether a pledge was deleted as the outcome variable, we used linear models instead of nonlinear, binary-outcome specifications, because we could conveniently include charity and user fixed effects without running into incidental-parameter problems (Angrist and Pischke 2009).

11 Almost 15 percent of users donate to more than one charity. The activity of these users corresponds to approximately 38 percent of all the pledges. The average charity has 3.31 users, and 37 percent of the charities have pledges from at least two users.

12 The raw network effects were 16 percent for pledges made through Twitter Proxy (i.e., pledges to donate through the Twitter updates of another person), and 30 percent for those through Twitter Tags (i.e., pledges to donate through a specific "hashtag"). However, only 204 pledges were made through these channels. Therefore we do not focus on them in this article.

13 The application allows a general broadcast, to all Facebook friends, or a selected broadcast, where the users may indicate some of his friends as recipients of the initial broadcast and the follow-up messages during the pledge.

14 Heifer provides domesticated animals and training to families, to improve their nutrition and generate income in a sustainable way. The family that receives the gift agrees to donate the offspring of the animal to another family in need. The animals are a source of both food and income. Milk from cows and goats, eggs from chickens, and honey from bees can be shared in the community or sold in the marketplace. The additional income and the training promote new opportunities for the creation of entrepreneurial activities, co-ops, or community savings groups.

15 Testing whether the identity and the mission of the charity influence the initial recruitment and the viral diffusion of the donations is, of course, also an interesting research question. However, this test would require a more sophisticated design to enable the researchers to control for the charity quality and user base. We plan to explore these issues in future research.

16 Some profiles are not entirely public, because users do not make their profile information publicly available, and the application can legally collect data from public profiles only. For some users, we have hometown, location, and several other controls.

17 Hypothetical questions, especially on topics for which respondents may be concerned about social desirability, might not be a good proxy for actual behavior. Researchers have been particularly aware of this issue in areas such as discrimination (Ayres and Siegelman 1995; Bertrand and Mullainathan 2004; Milkman, Akinola, and Chugh 2012), sexual orientation (Chandra et al. 2011; Coffman et al. 2013), and, more directly related to our topic, altruistic behavior (Lacetera, Macis, and Slonim 2013).
A further condition for assuring that single answers cannot be identified and attributed to a respondent is that the listed items are such that not everybody believes that they apply or do not apply to her. This is achieved, for example, by choosing items that are somewhat "negatively correlated" among each other, such that if a respondent believes that one or two of them apply to her, then it is likely that the others do not. This is the case in our survey, where very few respondents had a count of 0 or 4 (in the control) or 5 (in the treatment conditions).

18 Tucker (2011), for example, shows that the virality and persuasiveness of an online video may be negatively correlated.

19 Respondents in the "charity of choice" condition were not asked actually to indicate one specific recipient but could just think of the donation going to their hypothetical choices.

20 Within each condition, a subject was randomly assigned to two different orderings of the four or five items to mitigate any effect that the position of a particular item, and especially the one of our interest, might have on responses.

21 Of the 2,244 responses, 219 were incomplete and thus discarded. Moreover, 250 individuals took the survey twice, and we excluded these cases too.

22 In column 2 (as well as in columns 4, 6, and 8), the reported estimates come from a model that includes the full set of control variables (entered as categorical dummies) as derived from the survey. Because these variables were balanced across conditions thanks to the randomization and the relatively large sample size per condition, the inclusion of these variables in the regressions never affects the main estimates of interest.

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