An Examination of Social Comparison Triggered by Higher Donation Visibility over Social Media Platforms

Completed Research Paper

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Abstract

With the recent development of social media, social networking sites have become an important channel for charitable fundraising. Some social networking sites, like Facebook and Weibo, initiate their own charitable campaigns by collaborating with nonprofit organizations. By changing donation visibility, social media platforms can alter the level of social comparison and affect users' donation patterns. Using individual-level data from a microblogging platform where a donation service is embedded, we investigate how individual donation decisions are influenced by the visibility of donation information. We find that despite the platform designer's desire to improve fundraising performance, higher visibility of donors' contributions may have a negative impact on fundraising. We also find that donations made by users' followees generally have a positive impact on users' propensity to donate. On the contrary, donations made by the crowd only positively affect a subset of users, while they have a negative impact on other users.

Keywords: Crowdfunding, fundraising, social media, social comparison

Introduction

In recent years, social networking sites started to participate in charitable fundraising efforts. On 25 April 2015, a deadly earthquake hit Gorkha, Nepal, killing more than 9,000 and injuring more than 23,000 (Wikipedia 2015). Promptly, Facebook launched a donation button at the top of the timeline to raise funds to assist in the relief of Gorkha earthquake victims (Berenson 2015). Donors were asked to share their donations on their timelines. By doing so, they encouraged their followers to donate. This Facebook campaign raised more than $15 million from 750,000 donors, amounting to nearly half of the donations raised by the American Red Cross overall. Similarly, the largest microblogging platform in China, Sina Weibo, raised over $15 million in 72 hours after the 2013 Ya'an earthquake (Sina 2015), through 37 crowdfunding projects in its affiliated crowdfunding platform, Weibo Philanthropy (gongyi.weibo.com). Weibo Philanthropy solicits donations for needy individuals as well as national scale grassroots initiatives, and has raised over ￥400 million from over 20 million individuals in three years since its inception (Li 2015).

Nonprofit organizations also actively leverage the social media channel to promote their fundraising campaigns. One keynote campaign is the Ice Bucket Challenge. It mobilized users with its unique design of challenge over the social network. The Ice Bucket Challenge requires participants to tag five friends to either upload a video clip showing themselves dumping icy water over their heads or to donate to Amyotrophic Lateral Sclerosis Association (ALSA). It raised over $114 million for ALSA from July to September 2014 (Wikipedia 2014). Another example is the annual movement of the hashtag #GivingTuesday. The hashtag #GivingTuesday promotes a new global day of giving on the first Tuesday of December in the United States. Its introduction in 2012 is regarded as a milestone in philanthropic history, and recognized by President Obama (Obama 2014). Every year, a large scale of nonprofits utilize Facebook and Twitter to encourage users to make donations on Giving Tuesday. In 2015, it produced 114 billion Twitter impressions, and raised $116.7 million for thousands of nonprofits (Herrling 2014).

Social media increase donation visibility, and allow charitable campaigns to reach a larger audience. At a very low transaction cost, donors can declare their acts of giving through user-generated posts, automated acknowledgements from crowdfunding platforms, or aggregate-level display of contributions in their social profiles (Smith 2010). The greater visibility of donations is usually believed to have a positive impact on fundraising performance (Andreoni and Petrie 2004). This is because with greater donation visibility, users receive a higher reputation gain as altruists (Satow 1975, Wiepking 2008). However, it was also found that higher visibility can demotivate those who contributed a lot because people avoid looking too altruistic (Jones and Linardi 2014). Given the opposing effects of donation visibility, a rigorous empirical examination is emergent to understand the phenomenon and shed light on social media incentive designs.

To understand the impact of donation visibility, we employ a dataset from a leading donation-based crowdfunding platform in China, Weibo Philanthropy. Weibo Philanthropy was developed by Weibo, the largest microblogging website in China. Users can post microblogs and follow other users on Weibo as on Twitter. Weibo has developed this crowdfunding marketplace as an integrated component of its major microblogging platform to bridge users formally with nonprofits. Nonprofits register causes on Weibo Philanthropy and solicit donations from microblogging users. When users make donations, the system publishes a microblog to the donor's timeline in the hope of raising awareness and engaging the donor's followers. Donation transactions are documented and published with donors' ID, which allows researchers to match donations with the donors' social network topology on the microblogging platform.

Conducting such an empirical study is challenging for three reasons. First, donation visibility is usually fixed. Without an exogenous shock, it is difficult to infer the causality of higher visibility. To handle this challenge, we employ a unique website change on Weibo Philanthropy. At the end of 2013, the microblogging platform added a donation history widget to users' social profiles to display their past donations made through Weibo Philanthropy. The introduction of this widget imposes an exogenous shock to donation visibility because donors' past donation counts are now publicly consumable to all users. This design change provides us with an identification source to understand the role of donation visibility which is difficult to examine otherwise.

Second, user-level heterogeneity needs to be accounted for (Toubia and Stephen 2013). People's donation decisions are affected by various factors, and their underlying donation preference will determine how they respond to changes in donation visibility. We employ the Finite Mixture Model to capture unobserved

individual heterogeneity. The Finite Mixture Model employs users' observed decisions together with a set of covariates to infer their unobserved donor types. From our data, we identify three types of donors that exhibit different donation patterns. The first segment becomes more likely to donate after the introduction of this widget, the other two segments become less likely to donate after the introduction of this widget. Segmenting prospective donors significantly improves our model's predictive power by 14.57%.

Third, to fully grasp the implications of higher visibility, we need to understand users' long-term value on fundraisings. We consider two interesting measurements of users' long-term value. The first measure is a user's solicitation performance. The availability of users' charitable profiles on Weibo Philanthropy allows us to explicitly evaluate donors' solicitation outcomes. The second measure is users' influence in funds distribution among all the charitable projects. In crowdfunding platforms, the rich-get-richer problem is more serious than in traditional fundraising (Meer 2011). Users are attracted to popular projects, and those receiving little attention become less likely to be funded (Jaworski 2012). In our study, we find that while most users tend to follow others in selecting projects to donate, a group of users will crowd out from popular projects and crowd in to support the less popular ones. This group of users can alleviate the rich-get-richer problem, and their responses to higher donation visibility is of our particular interest.

We have a rich set of findings. First, we find that the introduction of the donation history widget triggered social comparison with higher donation visibility. Donors with low past donations tended to increase donation probabilities, and donors with medium and high past donations tended to decrease donation probabilities after the donation history widget was implemented. Second, other than past donation counts, other attributes also contribute to users' differing responses to the introduction of the widget. Specifically, users that have the highest number of followers and who usually donate at early phases of fundraising are demotivated by the widget. Third, by examining users' solicitation outcomes, we find that these users who donated at early phases are the most active in solicitation. We also find that users who have the highest counts of past donations have rich friends who are willing to contribute to charitable causes. Last, while prior donations made by the crowd may have positive or negative impacts on subsequent donations, prior donations made by users' followees generally have a positive impact on subsequent donations.

Our paper makes several contributions to the literatures of psychology, crowdfunding, and economics of charitable giving. To begin, we are the first to discover social comparison triggered by higher donation visibility in social media fundraising. Leveraging a unique design change, we discover evidence of automaticity in social comparison. It shows that social comparison does not have to be triggered explicitly by ranks or whether a user is above or below the medium. The unconscious and spontaneous nature of social comparisons on social media platforms is critical to the incentive designs of these platforms. Second, the social network topology within the microblogging platform allows us to track the flow of influence among donors, and separate the impact of donations made by followees from donations made by the crowd. To the best of our knowledge, this is the first work that separates these two effects. Third, we employ the Finite Mixture Model to analyze different donation patterns. This method enables us to understand how donation visibility, donations made by followees and the crowd impact donors' decisions jointly. More importantly, we identify a segment of donors that crowd out from attention-getting projects. The existence of these donors provides a potential direction to alleviate the rich get richer problem. Last but not least, we leverage user-level solicitation outcome data to comprehensively understand users' values to the platform. This allows us to better evaluate the higher donation visibility that triggered social comparison.

The remaining part of this manuscript is organized as follows: We first review related literature in section 2, and then describe our research context in section 3. We introduce our data in section 4, and provide model-free evidence in section 6. We present our results, segment characteristics analysis, and robustness checks in section 7. In section 8, we discuss our managerial implications, followed by a concluding remark.

Literature Review

Psychology

Social comparison was first proposed by social psychologist Leon Festinger (Festinger 1954). Related to our work, Festinger proposed that "an increase in the relevance of an ability will increase pressure toward reducing discrepancies concerning that ability". In our context, increasing donation visibility explicitly increased the relevance of charitable image, and should reduce the discrepancy of giving.

Following Festinger (1954), a series of laboratory experiments were conducted to examine social comparison. Most of these studies present social comparison information in a supraliminal way, explicitly showing the comparison between participants and others. For example, Gilbert et al. (1995) showed a user's ability score relative to the full scale "you scored 10 out of 18" (Gilbert et al. 1995). Other studies present participants with their relative rank or the mode score of the group (Frey and Meier 2004, Harper et al. 2010). Some works just list the names of comparisons, but the participants are aware of the comparison dimension (Stapel and Koomen 2000). Stapel and Blanton (2004) provided the first evidence that subliminal exposure to comparison information also induces the self-evaluation effects (Stapel and Blanton 2004). Their work supported the existence of spontaneous and unconscious comparisons. That is to say, even when people are not aware of the presence of comparison information and do not intend to evaluate themselves, social comparison takes place automatically. Their finding serves as a foundation of our work because the more visible donation information induces social comparison in an implicit way.

Other than laboratory experiments, field experiments have been conducted to examine social comparison in the provision of public goods (Frey and Meier 2004, Harper et al. 2010, Schultz et al. 2007, Shang and Croson 2006). Related to our work, Jones and Linardi (2014) conducted an experiment to show that people are averse to both positive and negative reputations for altruism, and prefer to behave like an "average altruistic" person.

Crowdfunding

Crowdfunding is an emerging phenomenon that has received much attention from academia in recent years. Kuppuswamy and Bayus (2014) divide crowdfunding projects into four categories: reward-based, equity-based, lending-based, and donation-based crowdfunding platforms (Kuppuswamy and Bayus 2014). Studies in donation-based crowdfunding platforms mainly focus on project-level determinants of successful projects (Meer 2014) and the impact of prior donations on subsequent donations (Bøg et al. 2012, Burtch et al. 2013, Koning and Model 2013). They find that prior donations, especially the initial donations, are vital to the success of crowdfunding projects because they signal the quality of the project. This is consistent with theoretical analysis that discusses the announcement of early donations (Andreoni 2006, Vesterlund 2003). In the field of online journalism, however, evidence of crowding out was found, which is consistent with traditional economic theory (Andreoni 1989, Andreoni 1990, Burtch et al. 2013). Saxton and Wang (2013) found that in the social media environment, the number of followers each nonprofit has will positively impact fundraising performance because of network effects (Saxton and Wang 2013).

Research on individual-level decisions on crowdfunding platforms is relatively limited because individual contribution data is not commonly collectable on such platforms. Burtch et al. (2015) conducted a randomized field experiment and showed that delaying donation information reduces the contribution amount, but increases the donors' propensity to give (Burtch et al. 2015). Smith et al. (2015) found evidence of peer effects on the amount of donations in the context of online fundraising for the London marathon. Castillo et al. (2014) found that public peer-to-peer solicitation is more effective than private peer-to-peer solicitation (Castillo et al. 2014). We believe that this paper is the first work that investigates the impact of reputation, peer effect and popularity effect on individual donation decisions jointly on charity-based crowdfunding platforms.

Philanthropy

Our work is related to a large body of literature that investigates the role of donation visibility. Visibility of donation information has been shown to be a strong determinant of donation decisions because it affects the dominating factor of reputation (Bekkers and Wiepking 2010). Silverman et al. (1984) found that the announcement of donors' names can improve donors' reputation status, thus drive more donations (Silverman et al. 1984). Andreoni and Petrie (2004) demonstrated that donors prefer to reveal their identities for their donations to enhance their reputation; contributions in higher amounts can be collected in such settings.

In our work, we also controlled for the impact from prior donations made by the crowd and by donors' peers. Social information about donations made by the crowd has been studied recently for ways to encourage donations and resolve the free-rider problem in charitable fundraising. Some researchers find positive impact from prior donations made by the crowd (Gu et al. 2009, Shang and Croson 2009, Sugden 1984, Xia et al. 2012). This could be because individuals derive negative utility if they do not conform to social norms according to which giving is valued (Shang and Croson 2009). An alternative explanation to

this enforcement phenomenon is that previous donations can be perceived as a signal of the charity's quality (Vesterlund 2003). Negative impact from prior donations on subsequent donations is also documented in the previous literature (Adar and Huberman 2000, Burtch et al. 2013). This is mainly due to crowding out when the causes are taken care of by others. In terms of the impact of donations made by peers, positive effects are found from literature (Carman 2003, Meer 2011, Smith et al. 2015). Meer (2011) examined the impact of solicitation from a person the prospective donor knows on his donation decisions. Carman (2003) provided evidence of positive peer influence for charitable donations in the context of workplace teams. The most closely related work to our study in terms of peer effect is Smith et al. (2015) which examined the impact of peer influence on donation amount in the context of fundraising for the London Marathon. However, they mainly examined the impact of previous donations on follow-up donations rather than measuring the peer effect based on the social network structure.

Characteristics of the recipient, the nonprofit organization, and the solicitor also influence donation decisions. First, evidence was found that the urgency of need is positively correlated to the possibility of donations (Schwartz 1974). Second, nonprofits with high efficacy and trust from society perform better in fundraising (Bowman 2004). These nonprofits are usually better connected to mass media, and can benefit from preferential attachment effect (Barabási and Albert 1999). What is more, the solicitor plays an important role in fundraising. When solicited by family and friends, or by people with high social status, potential donors are more likely to give (Bekkers 2004, Schervish and Havens 1997). Further, donors are more likely to donate when they have a larger peer group size (Einolf et al. 2013). Last, donors have heterogeneous preferences in charity type (Bekkers and Wiepking 2010).

Research Context

Background

Our research context is Weibo Philanthropy (http://gongyi.weibo.com/). Weibo Philanthropy was founded in 2012, and is the largest social-media crowdfunding marketplace in China. By 2015, more than $60 million in donations towards various charitable causes was raised through Weibo Philanthropy from 20 million individuals. Similarly to other crowdfunding marketplaces like Kickstarter, nonprofit organizations or qualified individuals register projects by setting up a webpage on Weibo Philanthropy (Figure 1(A)). On the webpage, descriptions of causes, fundraising durations, and locations of victims are listed. Project owners are responsible for delivering funds and updating the status of the recipient. Microbloggers visit the cause webpages and make donations electronically. Each charitable campaign has a pledging goal, and the money remaining to reach the goal is displayed next to it. The transaction-level donation history is publicly accessible from the donation list at the bottom of the cause webpage. Weibo Philanthropy applies the "Keep-It-All" (KIA) model, such that the amount raised will be delivered to the beneficiaries regardless of whether the goal is reached or not, or surpassed.

Weibo Philanthropy is an integrated component of the largest microblogging website in China, Weibo.com (NASDAQ: WB). Users are required to log in to their Weibo accounts before they can donate to Micro-Charity. This allows us to uniquely identify donors with their microblogging IDs, and access their social network information on the microblogging platform (Figure 1(C)). One key feature of the integration is the system-generated acknowledgements of donations. After a user makes a donation on Micro-Charity, the system will automatically post (with the donor's permission) a microblog on the donor's timeline announcing her acts of giving. For instance, when a donor made a donation for the charity in Figure 1(A), a microblog was generated on her timeline to show her donation to this charity cause (Figure 1(B)). As a result, her followers on Weibo will receive this information when they browse through their news feeds. This system enables propagation of charitable cause information over donors' peer network, and consequently provides researchers with opportunities to measure the impact of peer influence.

Weibo Philanthropy creates a donation profile for each user (Figure 2). This donation profile explicitly shows the user's solicitation efforts and outcomes. The statistics documented in the donation profile are calculated by Weibo Philanthropy. The solicitation attempt is the number of times a user shared charitable campaigns facilitated in Weibo Philanthropy. Weibo Philanthropy tracks the microblogs containing the links of the charitable campaigns. The number of solicitation impressions measures the size of audience reached by these soliciting microblogs, and the number of influenced donors is the number of people who made a donation decision after clicking into the link in the microblogs. The monetary contribution made by the influenced donors are summed up to reflect a user's solicitation outcome. The information about the

individual's solicitation outcome is very difficult to obtain in traditional fundraising, and becomes accessible in the online environment. It allows us to measure users' long-term value to the platform.

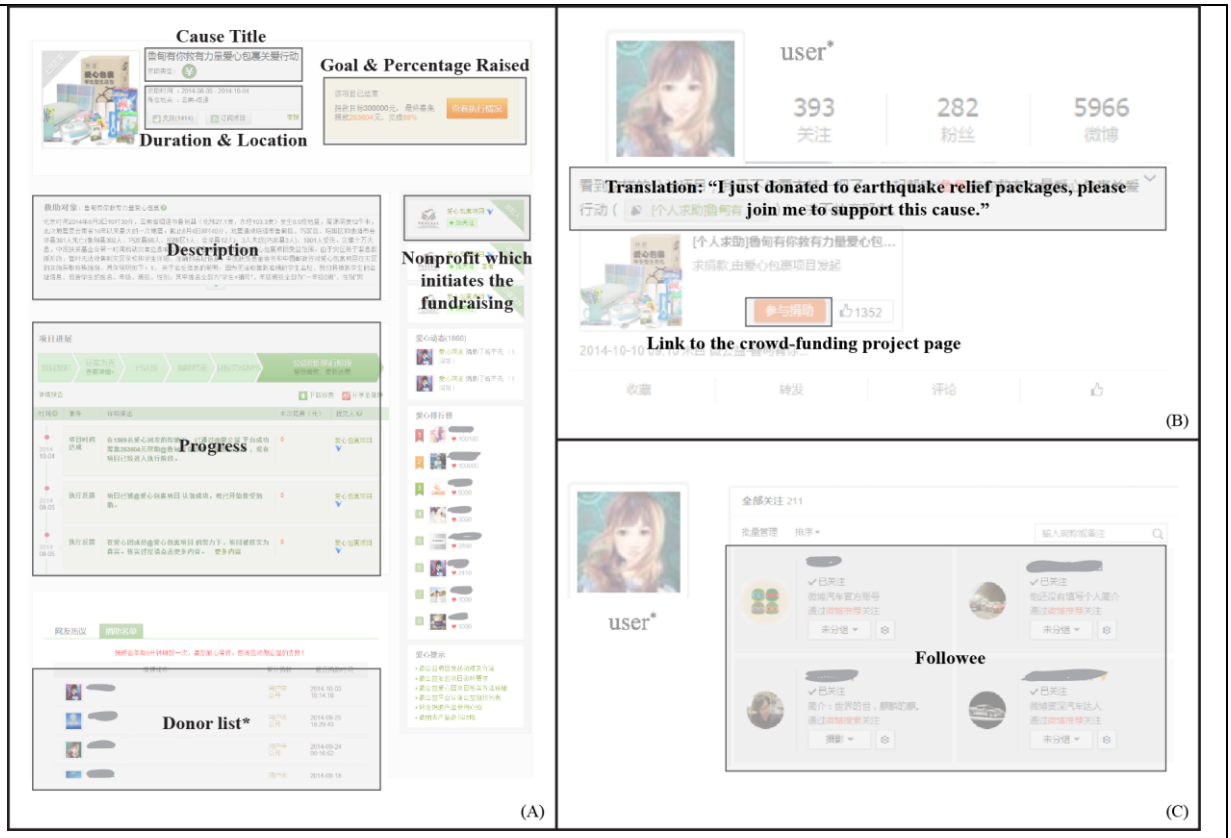

Figure 1. Donation-based Crowdfunded Market

Note: (A) donation-based crowdfunding page; (B) microblog acknowledging donation; (C) Followee List

* We anonymize donor's identities.

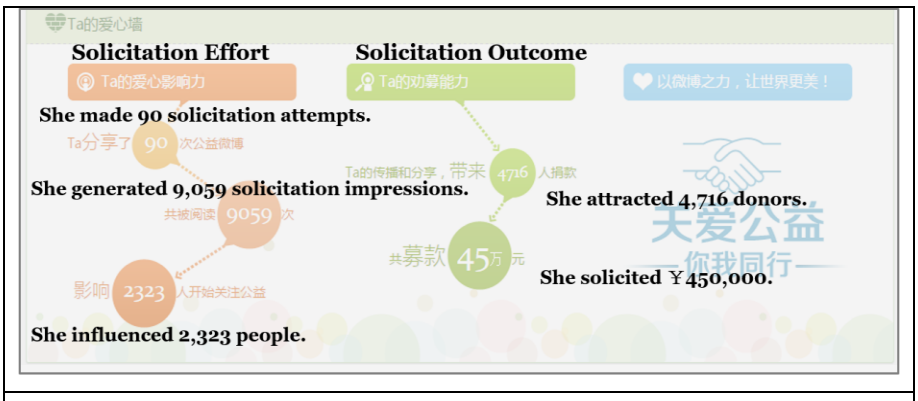

Figure 2. Donation Profile

Exogenous Shock

At the end of 2013, the website introduced a charity history widget to each user's profile (Figure 3). This widget publicly displays the charitable projects supported by each individual. The total counts of past

donations are highlighted at the top, and thumbnails of the projects are shown underneath. Since the widget is displayed on users' social profiles, it is publicly consumable for all users on the microblogging platform.

Figure 3. Individual Donation History Widget

In contrast to microblog-level visibility from the system-generated microblogs (Figure 1(B)), this widget (Figure 3) greatly improves the visibility of users' contributions. First, this widget provides a single view that emphasizes the aggregate level of past donations. This makes it easy for visitors to view an accurate picture of the focal user's contribution level. Second, system-generated posts to acknowledge users' contributions are only broadcast to donors' followers. However, this widget makes this information available to any registered user of this platform. Third, system-generated microblogs will be superseded by new microblogs quickly, while this widget is deployed in a stable manner. The introduction of this widget provides exogenous shock to people's reputation status while keeping other factors unchanged. It enables us to identify donors' responses to the higher visibility of their contributions.

Data

We used the donation transactions four weeks before and four weeks after the introduction of the widget to conduct our study from December, 2013 to January, 2014. In our two-months of data, we had 10,637 donations made to 549 charitable projects by 5,112 individuals. We aggregated donations at the weekly level and ended up with eight periods. In each period, all ongoing projects were included in each individual's choice set unless the individual had donated to the same project before. We randomly selected 75% of donors in our data as the estimation sample, and the remaining 25% of donors in our data as the holdout sample to validate the performance of our model calibrated by the estimation sample.

At the individual level, we included users who donated to at least two projects in their entire donation history from 2/6/2012 to 7/21/2014 to avoid purely impulse-driven donors. We also excluded users who have fewer than 10 followers or are following fewer than 10 users to avoid zombie microbloggers. We removed those who participated in a charity lottery project with a monetary reward because they had potential monetary motivation which is not the focus of this paper. Further, we excluded donors who donated to an abnormally large number of projects. Finally, donors who made at least one donation during the two-month period of our study were included as active potential donors in our sample to examine the determinants of donation choice. At project level, we excluded extremely popular projects which received more than 1000 donations. For these attention-getting projects, other factors like media exposure or celebrity endorsement may have come into play.

We list the summary statistics with the original scales in Table 1. Because all measurements are skewed, we took the log of these variables when we estimated the model.

Table 1. Summary Statistics

	Covariates	Mean	S.D.	Min	Min
Individual Level (n=5112)	Followers	3546.09	36902.41	10.00	1250929.00
	Past Donations	9.00	13.70	1.00	99.00
Choice Level	Donated Followees	0.04	0.39	0.00	88.00

(n=7655721)	Donated Nonfollowees	60.97	72.76	0.00	397.00
	Goal (Left)	34920.32	24559.09	-1721.00	119900.00
	Treatment	0.51	0.50	0.00	1.00
Project Level (n=549)	Nonprofit Follower	37422.04	151952.7	0	2120734
	Goal (Static)	35585.55	24669.37	500	120000

Table 1. Summary Statistics

The goals of these projects ranged from ¥500 to ¥120,000. Since the fundraising is not capped, the amount remaining to reach the goal can be negative when the raised amount exceeds the goal. To accurately account for the urgency of need, we truncate the left *goal* at zero in our estimation. We plotted the static goal of each project together with their final pledged amount in Figure 4. From this plot, we see strong evidence of under-contribution, indicating free riding. Many projects, especially those with high goals, didn't raise enough funds to meet the need. What is more, the pledged amount at each goal level seems to follow a power law distribution. This indicates that fundraising over social media is a preferential attachment process where the rich get richer.

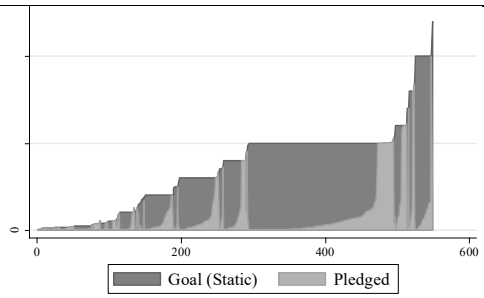

Figure 4. Project Funding Status

Model-free Evidence

In this section, we provide model-free evidence to compare users' responses to the introduction of the donation history widget, which we refer to as the treatment. We explicitly examine the dimensions of 1) past donation counts, and 2) number of followers.

Past Donations

We choose past donation counts as a dimension for three reasons. First, past donation count is an important part of the donation history widget. When users have a higher count of past donations, they receive higher reputation gain at the introduction of the widget. Second, literature has documented the moderating role of past contributions on social comparisons (Frey and Meier 2004). Third, past donation is a criterion that can be easily adopted by nonprofit organizations for donor targeting.

We calculate the median of past donation counts at the beginning of the observation period (week one), and use it as cutoff values to divide all users into two subgroups. The donation counts for each group before and after the treatment are summarized in Table 2. As can be seen, users whose past donation counts were below the median radically increased their donation counts after the introduction of the widget by 31.68%. On the other hand, those whose contributions were above median reduced their donation counts by 15.52%. This table shows the clear pattern that users adjust their donations to get closer to the average level.

Table 2. Social Comparison with Respect to Past Donations

	Before Treatment	After Treatment	Difference= After-Before

Below Median	1815	2390	575
Above Median	2771	2341	-430

Table 2. Social Comparison with Respect to Past Donations

Followers

We choose follower as a dimension to examine the impact of donation visibility because it is commonly used as a proxy for users' reputation status. Prior literature has shown that people are more likely to give when they are aware that their giving behavior is observed by others (Satow 1975). Users with more followers are watched by a larger audience, and likely to be more sensitive to changes in donation visibility.

Table 3. Social Comparison with Respect to Follower			
	Before Treatment	After Treatment	Difference= After-Before
Below Median	2265	2259	-6
Above Median	2321	2472	151

Table 3. Social Comparison with Respect to Follower

From Table 3, we discover that users whose numbers of followers are below the median are not much affected by the introduction of the widget. However, those whose numbers of followers are above the median see a donation count increase at 6.5%. This confirms that the number of followers can be regarded as a proxy for reputation level, and people with higher reputation status are more likely to respond positively to the introduction of the widget.

Despite the interesting findings from the model-free analysis, a rigorous econometric model accounting for potential confounders needs to be developed to understand the actual effect of the treatment. We also notice that multiple factors may attribute to users' responses to the introduction of the widget simultaneously. For example, while a user whose past donation is above the median may decrease her donation probability after treatment due to social comparison, she may also increase her donation propensity if she has lots of followers. We will develop a model that takes into account individual heterogeneity comprehensively affected by all features of individuals.

Model

In this section, we discuss how we examine social comparison in our context. We first introduce our baseline individual-level choice model. We then formally present the Finite Mixture Model, which extends the baseline model to allow users to have heterogeneous donation patterns.

Baseline Model

We construct a Logit model capturing individual donation choice. We use d_{ijt} to denote individual i's donation decision on charity project j at period t. $d_{ijt}=1$ if the donation is made at period t, and 0 otherwise. The donation probability for individual i over project j at period t can be written as: $\Pr(d_{ijt}=1)=\exp(V_{ijt})/(1+\exp(V_{ijt}))$. Here, V_{ijt} is further written below:

$$\begin{aligned} V_{ijt} &= \beta_1 Treatment + \beta_2 Donated\_Followees_{ijt} + \beta_3 Donated\_Nonfollowees_{ijt} \\ &+ \beta_4 Past\_Donations_{it} + \beta_5 Followers_i + \beta_6 User\_Type_i \\ &+ \beta_7 Project\_Type_j + \beta_8 Nonprofit\_Followers_j + \beta_9 Goal_{jt} \end{aligned} \quad (1)$$

The major independent variable of our interest is $Treatment$, which takes the value of zero when it is before the introduction of the donation history widget, and takes the value of one when it is after. Since the new widget applies to every user instead of just a subset of users like in a natural field experiment, we need to account for both observed and unobserved potential confounders to establish a causal relationship between the introduction of the widget and users' donation pattern changes.

At individual level, we account for a user's number of followers (*Followers*$_i$), and her user type (*User_Type*$_i$). On the microblogging site, users are categorized into four types: verified user, badge user, ordinary user, and corporate user. Verified users are people whose occupations are verified by their organizations. Badge users are those who actively engage on the microblogging platform. We exclude corporate users because we observe too few of them. We also dynamically calculate a user's past donation counts (*Past_donations*$_{it}$) at each point in time. At project level, we control for the type of project (*Project_Type*$_j$), as well as the amount remaining to reach the goal of the project (*Goal*$_{jt}$). Since the initiator of each project also has a Weibo account, we use his number of followers (*Nonprofit_Followers*$_j$) as a proxy of the initiator's influence.

Most importantly, we include a set of social information controls that vary at individual level, project level, and time level. First, we calculate the number of each user *i*'s followees that donate to project *j* before individual *i* at time *t* (*Donated_Followees*$_{ijt}$). This measure also allows us to assess peer influence. Second, we calculate the number of the crowd net of individual *i*'s followees that donate to project *j* before individual *i* at time *t* (*Donated_Nonfollowees*$_{ijt}$). This measure allows us to investigate the impact from prior donations on subsequent donations. It is worth mentioning that measuring peer influence is challenging because of the reflection problem, homophily, and correlated unobservables (Manski 1993). The timestamps of each transaction allows us to avoid the reflection problem, and we handle the other two problems in our robustness checks. It turns out that our results stay robust after controlling for both concerns.

Unobserved factors rise at individual, time, and project levels. First, to account for project-level unobserved heterogeneity, we cluster our data at project level to allow correlations within each project. We also conducted a fixed-effect estimation which yields results similar to our current results. Second, we accounted for time effects by including all time dummies in one of our robustness checks. It will turn out that there is no significant time trend in our period of study. Last, we account for individual level unobservable factors with the Finite Mixture Model that will be introduced in the next section.

Finite Mixture Model

For equation (1), we assume a simple scenario where the impacts of variables are the same across individuals. In this section, we relax this assumption and allow donors to be heterogeneous in their preferences. We employ the Finite Mixture Model where each donor is categorized to a certain segment with some probability. Individuals within the same segment are assumed to have homogeneous taste, while the ones in different segments have different preferences over a set of covariates (Dempster et al. 1977, Haaijer et al. 2000). By employing the Finite Mixture Model, we control better for unobserved heterogeneity among donors, and significantly improve the predictive power (Bapna et al. 2011). In addition, this method offers deeper managerial insights to better guide decision making of the platform.

In the Finite Mixture Model, we assume that there are S segments of donors. Accordingly, there are S distinct sets of preference parameters, $\boldsymbol{\beta} = (\boldsymbol{\beta}^1, \boldsymbol{\beta}^2, ..., \boldsymbol{\beta}^S)$. We use $\boldsymbol{\beta}^s$ to represent the coefficient for segment $s \in \{1, 2, ...S\}$. The unconditional probability for an individual to belong to segment *s* is π_s. Thus the probability of observing a sequence of choices for individual *i* in segment *s* is:

$$L_{i|s} = \prod_{t=1}^{T}\prod_{j=1}^{J}\left(\frac{\exp(\boldsymbol{\beta}^s\mathbf{x})}{1+\exp(\boldsymbol{\beta}^s\mathbf{x})}\right)^{d_{ijt}}\left(\frac{1}{1+\exp(\boldsymbol{\beta}^s\mathbf{x})}\right)^{1-d_{ijt}} \tag{2}$$

As researchers, we don't observe which segment individual *i* actually belongs to. Thus, we can only infer the individual probability of belonging to a segment based on the observed donation decisions. Therefore, we specify the unconditional likelihood of donors' sequence of choices with the weighted average of equation (2) over all segments.

$$L = \prod_{i=1}^{n}\sum_{s=1}^{S}\eta_{si}L_{i|s} \tag{3}$$

where η_{si} is the conditional probability that individual *i* belongs to segment *s*.

Directly maximizing the log of equation (3) is difficult because of numerical issues, thus we maximize the following equivalent expression (Dempster et al. 1977):

$$\ln L = \sum_{i=1}^{n} \sum_{s=1}^{S} \eta_{si} \ln L_{i|s} \tag{4}$$

It was proven that using an Expectation-Maximization approach, the maximization of equation (4) will always converge because the likelihood is non-decreasing (Dempster et al. 1977).

Results

Segmentations

A critical question for the Finite Mixture Model is to decide the value of segments S. In this research, we use likelihood-based information criteria including AIC and BIC both for our estimation sample and holdout sample to determine the optimal number of segments for the model. Other than the information criteria, interpretability and parsimony are important factors. To draw conclusions that are easy to understand by the crowdfunding platforms and nonprofits, we do not consider a model with more than four segmentations. We report the fit statistics for both the estimation sample and the holdout sample in Table 4. Overall, the model with 3 segments outperforms the other models. In the holdout sample, the 2-segment model is most preferred according to BIC, which is likely to result in a small model. The AIC for 3-segment model is slightly higher than that for the 4-segment model, but the increment is relatively marginal considering the interpretability and parsimony (Kamakura and Russell 1989). In the estimation sample, 3-segment model strictly outperforms the other models in terms of BIC, while the 4-segment model is the winner in terms of AIC. Considering all factors, we choose the 3-segment model as our main model. It is worth mentioning that even in the 4-segment model, our results stay stable.

Table 4. Social Comparison with Respect to Follower

		Estimation Sample (75%)	Holdout Sample (25%)
Number of observations		5684962	1970759
1-segment model	AIC	104711.13	36453.992
	BIC	104914.43	36728.859
2-segment model	AIC	101429.62	34927.218
	BIC	102297.03	**35726.829**
3-segment model	AIC	99581.753	34158.99
	BIC	**101533.43**	35958.115
4-segment model	AIC	**98689.582**	**33880.802**
	BIC	102159.24	37079.248

Table 4. Social Comparison with Respect to Follower

Finally, we calculated the prediction accuracy for the holdout sample. The 3-segment Finite Mixture Model has improved the prediction accuracy by around 14.57% from the 1-segment model. Specifically, the classification accuracy of the 1-segment model is 56.87%, and the classification accuracy of the 3-segment model is 65.16%, with the accuracy for each segment being 59.06%, 75.26%, and 67.56%.

Segment Characteristics

In this section, we compare the attributes across different segments. We took a snapshot of *past donation* counts right before the introduction of the widget as *past donation*^{t4}. We introduced *donation order* to reflect the extent of leadership for each donor. Donation order varies from 0 to 1, and a smaller value implies earlier donations. It is calculated using relative donation order at each project. For example, if a project has 5 donations in total, the relative donation order for the first donor is 1/5, and that for the last donor is 5/5. We calculated the donation order for each individual *i* by averaging this relative donation order across all her donations. The summary statistics are presented in Table 5 and illustrated in Figure 5.

Table 5. Descriptive Statistics of Three-Segment Finite Mixture Model

	Low-contribution		Medium-contribution		High-contribution	
Donation Order	0.501	(0.146)	0.455	(0.158)	0.498	(0.130)
Followers	5.881	(1.583)	6.061	(1.588)	5.850	(1.440)
Tenure	146.844	(181.9)	140.481	(175.45)	147.811	(168.078)
Past Donation^{t4}	1.012	(1.198)	1.164	(1.226)	1.449	(1.281)
Donated Followees	0.014	(0.108)	0.014	(0.104)	0.030	(0.184)
Donated NonFollowees	1.466	(0.2818)	1.466	(0.2820)	1.466	(0.2818)
Donate	0.001	(0.033)	0.001	(0.036)	0.001	(0.037)

Standard deviations in parentheses, log scales are used in this statistical summary for *Followers*, *Past Donations^{t4}*, *Donated_Followees*, and *Donated NonFollowees* to be consistent with our estimation.

Table 5. Descriptive Statistics of Three-Segment Finite Mixture Model

One key variable that highlights the difference between different groups is past donation counts. First, the low-contribution segment has the lowest average count of past donations. This segment constitutes about 40% donors of our sample, and the average past donation count in the original scale before the introduction of the widget is 6.75. Second, the medium-contribution group users have the highest number of followers, the most active involvement in engaging others to contribute, and are more likely to be early contributors. In a word, they exhibit leadership characteristics. These donors' average past donation count is 8.54 in the original scale, and they constitute about 20% of our sample. Third, the high-contribution segment has the highest count of past donations, and their contribution exceeds the average level of the whole community. Their average past donation count in the original scale is 11.86 before the introduction of the widget.

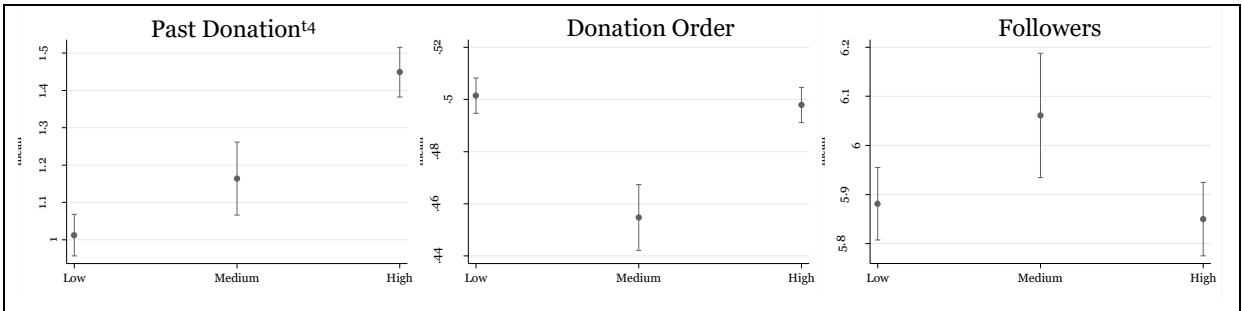

Figure 5. Measurements across Segments

We use the level of past donation counts to label different segmentations, referring the first segment as "low-contribution", the second segment as "medium-contribution", and the third segment as "high-contribution". This labeling is used for the ease of exposition and interpretation in the following sections.

It is also interesting that the medium-contribution group has the lowest donation order. This indicates that users from this group usually donates at early phases of fundraising durations. Since this group also has the highest number of followers, users in this group seem to exhibit leadership attributes. The discovery of this segment of users has great value because users in this segment can alleviate the rich-get-richer problem.

Parameter Estimations

We present the parameter estimates ($\boldsymbol{\beta}^s$) of the 3-segment Finite Mixture Model in Table 6. Note that this well-delineated segmentation is calibrated using all covariates with no constraints in how different factors affect the segmentation.

Table 6. Parameter Estimation of FMM Model

	Low-contribution		Medium-contribution		High-contribution	
Treatment	2.271***	(0.112)	-0.973***	(0.112)	-1.162***	(0.112)
Donated Followees	1.366***	(0.134)	2.689***	(0.122)	0.184+	(0.095)

Donated Nonfollowees	0.314***	(0.042)	-0.441***	(0.055)	0.404***	(0.047)
Past Donation	0.0160	(0.037)	0.0596*	(0.028)	0.226***	(0.030)
Goal	0.268***	(0.051)	0.191***	(0.039)	0.510***	(0.071)
Fans	0.00790	(0.014)	0.0257	(0.017)	0.00785	(0.011)
User.Expert	0.0732	(0.073)	-0.283*	(0.123)	-0.187**	(0.069)
User.VIP	-0.261*	(0.130)	-0.461*	(0.198)	-0.357**	(0.132)
Nonprofit Followers	-0.0648+	(0.039)	0.384***	(0.046)	-0.158***	(0.039)
Project.Health	-0.185	(0.220)	-0.818***	(0.167)	0.902***	(0.261)
Project.Natural Disaster	0.511+	(0.292)	0.688*	(0.329)	0.199	(0.498)
Project.Human Service	0.912*	(0.382)	0.446	(0.355)	0.366	(0.374)
Constant	-11.83***	(0.614)	-10.27***	(0.368)	-12.87***	(0.717)
Segment Share	40%		20%		40%	
R2	7.42%		7.68%		5.95%	
McFadden's Pseudo R2	6.88%					

Standard errors in parentheses, + p<0.10, * p<0.05, ** p<0.01, *** p<0.001

Table 6. Parameter Estimation of FMM Model

First of all, we find that the introduction of the widget (*treatment*) had significantly different impacts for donors in different segments. The coefficient of *treatment* is positive and significant for the low-contribution segment (β_1^1 =2.271, with p-value<0.001). Donors in this segment responded positively to this widget. The coefficients of *treatment* in the medium-contribution and high-contribution segments are negatively significant (β_1^2 =-0.973 and β_1^3 =-1.162, with both p-value<0.001). In these two segments, the users' probability of donating decreased after the introduction of the widget. In addition, the medium-contribution segment was less influenced by the introduction of the widget than the high-contribution segment. From the *segment share*, each of these three segments takes approximately 40%, 20% and 40% of the total sample respectively. Despite the platform owner's desire to improve fundraising, less than half of the donors responded positively to this new feature, while the majority of the donors had negative responses.

Combining this result with segment characteristics, we understand users' behavior better. First, by comparing the count of past donations right before the introduction of the widget, we find that social comparison seems to be a major reason for people's different responses to the widget. Those who contributed less are incentivized by the widget, and those who contributed more are demotivated. Second, we find that the donors in the medium-contribution segment are the most likely to be leaders in giving. They are early givers in the fundraising process, and they share charitable causes actively to engage their followers to contribute. They also have more followers on the microblogging platform. Finally, when we turn our spotlight on the preference of the high-contribution segment, we find that this segment of donors has relatively fewer followers. Although they contributed to many charitable causes, they did not engage their followers as actively as the medium-contribution segment. However, we shall see in later analysis that users in this high-contribution segment have the highest capability in soliciting amount contributions.

Next, we examine the impact from prior donations made by the crowd. The coefficients of *donated nonfollowees* for the low-contribution segment and the high-contribution segment are both positive and significant (β_3^1 =0.314 and β_3^3 =0.404, with p-value both less than 0.001). This suggests that donors in these two segments tend to donate to charitable causes that are well-liked by the public. One possible reason is that the donation count is a signal of quality, which is not as well understood by the non-leader segments. It is also possible that individuals in these two segments have a higher tendency to conform to the social norm of the community. To our surprise, the medium-contribution segment has a significantly negative coefficient for *donated nonfollowees* (β_3^2 =-0.441, with p-value less than 0.001*)*. This indicates that they will crowd out when projects are very popular. This crowding-out behavior signals their higher motivation

from altruism or "behaving altruistic", which is evidenced by their active solicitation efforts to engage others to contribute. The existence of this segment provides potential opportunities to resolve the rich get richer problem.

Finally, we interpret the impact from donations made by users' followees. The coefficients before number of *donated followees* are all positive for the three segments (β_2^1 =1.366, β_2^2 =2.689, with p-value both less than 0.001, β_2^3 =0.184, p-value=0.051). Peer influence are generally positive in social media fundraising environment. Discussions about the endogeneity problem of peer influence is in the robustness check.

Policy Analysis

The regression results present the direct outcome of the widget, and we evaluate other aspects of the policy in this section. We first look at solicitation attempts and solicitation outcomes with respect to the three groups. We then evaluate the changes in the distribution of funds.

Solicitation Performance

We extracted users' solicitation performance from their donation profiles (Figure 2) to understand users' indirect contribution from solicitation. We collected the donation profile data in July 2014 instead of upon the introduction of the widget at the end of 2013. As a consequence, these measures are potentially confounded with the policy change, and are not used in our major analysis. However, they still provide a picture of how differently users in each segment behave in solicitation. We plot the three key measures for each segment in Figure 6. The first measure is the number of past donations by July 2014 (Past Donation'), the second measure is users' solicitation attempts by that time. The third measure is the amount solicited by users. It is notable that this past donation is different from the one used in our main analysis which corresponds to different times. Since these measures are highly skewed, we take logs for each measure.

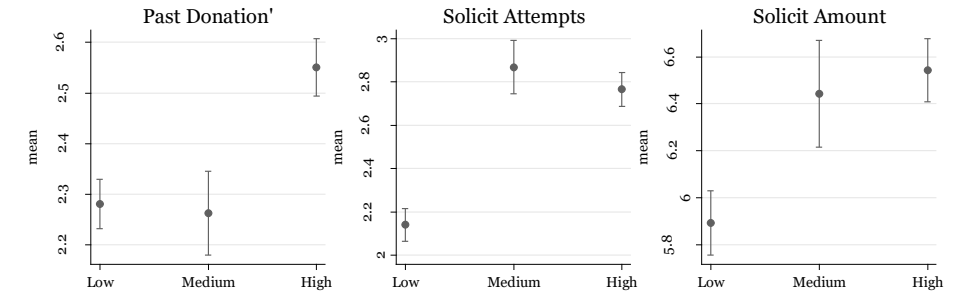

Figure 6. Measures from Donation Profiles

From Figure 6, we can see that overall, users in the first two segments donated to a similar number of projects by the end of July 2014, and the high-contribution segment donated to the highest number of projects. However, the medium-contribution segment significantly outperforms the other two segments in terms of solicit attempts. This shows that the medium-contribution segment is more active in solicitation, and plays an important role in propagating the charitable information. When we look at the solicit amount, we find that the high-contribution segment brings in slightly higher solicitation outcome despite the fact that users in the high-contribution segment make fewer solicitation attempts. This indicates that the high-contribution segment either have richer friends or their friends are more willing to give.

Such results imply that the introduction of the widget resulted in the loss of users who highly involve in solicitation and users who have rich friends. Although the platform gains new donations from the low-contribution segment, these new donations are not as valuable as the ones that are lost.

Fund Distribution

In crowdfunding, the rich-get-richer problem is commonly observed. As noted by an article from Nonprofit Quarterly, "attractive" projects may unfairly draw funds from projects that elicit less compassion (Jaworski 2012). From our findings, we observe that the medium-contribution segment will crowd out from popular projects and crowd in to the less popular ones. Given that users in this segment have the highest capability

in solicitation, they play a vital role in directing the funds to the needy. Fundraising efforts towards this group of users will improve the efficiency of funds allocation.

However, users in the medium-contribution group are demotivated from the introduction of the widget, leading to an undesired outcome. We further present the funds allocation before and after the treatment to show such an outcome. In Figure 7, we calculate the number of donations received by each project before and after the treatment. We further sort projects based on their donation counts, and display the donation count distributions before and after the treatment in Figure 7. Although the overall donation counts after the treatment (4,731) is greater than that before the treatment (4,586), funds are centered on a smaller range of projects after the treatment. This is a clear demonstration of inefficient funds allocation.

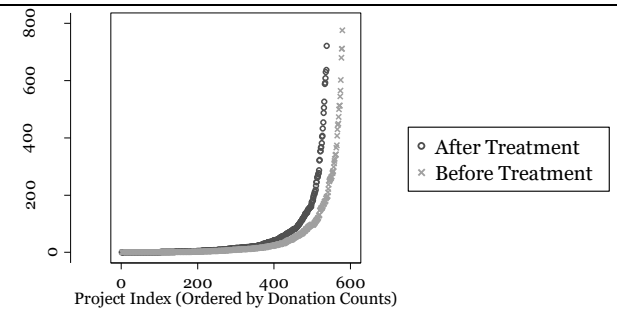

Figure 7. Fund Distribution Before and After Treatment

Robustness Check

We conducted a series of robustness checks to rule out alternative explanations, and show that the introduction of the donation history widget is likely the only reason triggering the social comparison.

Falsification Check

An alternative explanation of the donation pattern might be donors' phase in their donation lifecycle. During donors' lifecycle, they may put increasingly high efforts in the beginning phase, and drop out of the platform gradually as they approach the ending phases of their life cycle (Andreoni 1988). To rule out this explanation, we conducted two falsification tests where we used false times as treatment. In the pre-treatment falsification test, we changed the treatment time to two weeks before the actual treatment (12/17/2013), and used only the first four-week data when no website design change took place (12/3/2013-12/31/2013). In the post-treatment falsification test, we changed the treatment time to two weeks after the actual treatment (1/14/2014), and used the last four-week data (1/1/2014-1/28/2014), with the widget present at the beginning of this period. The results are presented in Table 7.

Table 7. Robustness Check – Falsification Test

	Full Model		Pre-Treatment		Post-Treatment	
Treatment	0.562***	(0.130)	-0.0974	(0.147)	0.302+	(0.160)

Standard errors in parentheses, + p<0.10, * p<0.05, ** p<0.01, *** p<0.001

Table 7. Robustness Check – Falsification Test

The treatment effect for the pre-treatment model is insignificant. This indicates that the donation probability does not change without the introduction of the widget. Further, the treatment effect of the post-treatment model is significant at 0.1 level, with a smaller magnitude than that of the full model. This shows that the treatment effect lasts more than two weeks, and it decays in its effect over time. In sum, the results verify that the driver for users' behavior change at the end of 2013 is due to the introduction of the widget.

Split-Sample Analysis for Social Comparison

In this robustness check, we split our sample based on the size of past donation counts, and confirmed that social comparison is a major driver for our results. Specifically, we calculated the 40% and 60% quantiles

of past donation count, and used them as cutoff values to split the sample (they are 2 and 5, respectively). These percentages are determined using the segment share of our 3-segment Finite Mixture Model.

Table 8. Robustness Check – Split-Sample Analysis						
Past Donations	0-2		2-5		5+	
Treatment	0.824***	(0.116)	-0.460***	(0.117)	-0.307**	(0.105)
Segment Share	40%		20%		40%	

Standard errors in parentheses, + p<0.10, * p<0.05, ** p<0.01, *** p<0.001

Table 8. Robustness Check – Split-Sample Analysis

In this naïve split-sample analysis in Table 8, we find that donors with low past donation counts responded positively to the introduction of the widget, and donors with medium and high past donation counts responded negatively to the widget. These findings are consistent with the major explanation of social comparison from our Finite Mixture Model.

Homophily

In our context, individuals may follow their followees' choices either because they are influenced by their followees or because they are intrinsically similar to them. To test and control for homophily, we constructed another variable - followees' donation counts for the focal users' followees (*donated followees' followees*) - as an instrumental variable for *donated followees*. The rationale is that followees' followees will influence followees' donations, but not the focal users. This is the typical way to account for the endogeneity problem in peer influence literature. We used a standard IV estimation procedure for binary outcome variables, and checked the Wald test for exogeneity (Wooldridge 2010). It is shown that we cannot reject the null hypothesis of exogeneity (p-value = 0.7720), and a regular Logit model is a more proper specification.

Time Effect

To account for the time effect that may affect the whole community, prospective donors' followees, and the prospective donors at the same time, we include weekly time dummies that are homogeneous across groups into our model. From the parameter estimation result in Table 9, we learn that our major results stay robust. This corroborates our main model specification which does not control for time effect.

Table 9. Robustness Check – Time Effect						
	Low-contribution		Medium-contribution		High-contribution	
Treatment	2.337***	(0.181)	-0.916***	(0.181)	-1.094***	(0.173)
Donated Followees	1.378***	(0.128)	2.716***	(0.120)	0.194*	(0.088)
Donated Nonfollowees	0.316***	(0.040)	-0.427***	(0.055)	0.406***	(0.046)
Week 1	0.228	(0.159)	0.228	(0.159)	0.228	(0.159)
Week 2	-0.0176	(0.166)	-0.0176	(0.166)	-0.0176	(0.166)
Week 3	-0.00684	(0.117)	-0.00684	(0.117)	-0.00684	(0.117)
Week 5	-0.0728	(0.177)	-0.0728	(0.177)	-0.0728	(0.177)
Week 6	-0.0840	(0.159)	-0.0840	(0.159)	-0.0840	(0.159)
Week 7	0.00515	(0.139)	0.00515	(0.139)	0.00515	(0.139)

Standard errors in parentheses, controls omitted, + p<0.10, * p<0.05, ** p<0.01, *** p<0.001

Table 9. Robustness Check – Time Effect

Managerial Implication

This paper provides a rich set of implications for fundraisers and social media platform owners.

Donation Visibility

Donation visibility is controlled by social media platform owners and crowdfunding platform owners. For social media platform owners, it is common to display user attributes in their profiles. For example, Facebook displays the movies, books liked by a user, the reviews generated by a user, the groups she is in, and events she is going to join. However, the choice of whether to list the nonprofit organizations or campaigns users support is a sensitive decision. It not only concerns the user's privacy, but also likely changes the donation visibility to induce social comparison (de Vries and Kühne 2015). In Weibo, the introduction of the history donation widget demotivated those who are active in soliciting and have generous friends, directing funds to center more on the popular projects. Therefore, we suggest that social media sites not display this category of information in users' profiles. Actually, Weibo has removed this donation history widget. On the other hand, crowdfunding platforms also face the decision concerning donation visibility. While some crowdfunding platforms disable such information (gofundme.com), some choose to display users' past donations (razoo.com). Our results suggest that, when users' aggregate donation information is available, social comparisons are likely to be triggered automatically. This is in accordance with psychological evidence for subliminal exposure to comparison information (Stapel and Blanton 2004). Therefore, platform designers need to be careful with designs regarding donation visibility.

The Rich-get-richer Problem

Despite the great merits of crowdfunding, the rich-get-richer problem has become a serious issue faced by fundraisers. From our findings, identifying users who usually donate at early phases of fundraising is vital in directing funds to the more needy. For example, in our context, the medium-contribution segment should be the target group of users to alleviate the rich-get-richer problem. By putting more fundraising efforts on this group of users, funds can be allocated more efficiently.

For platform owners, it is worth figuring out incentive designs to motivate this "crowding-out" segment. In the donation history widget example on Weibo, an aggregate display of past donations turned out to demotivate this target group, leading to an undesired outcome. It is also notable that crowdfunding platforms like IndieGoGo.com offer personalized recommendations like "Top picks for you". By recommending the less popular projects to the crowding-out segment of users, a better funds allocation may be achieved. For fundraisers of the less popular projects, soliciting donations from this segment of users may have a higher conversion rate. These crowding-out users are also more likely to engage their friends to participate, further improving the fundraising performance.

Free-rider Problem

Under-provision of public goods has always been the central interest of economists. From the positive peer effect we discover and the large contribution from solicitation reported by Weibo Philanthropy, we confirm the significant role of peer influence. For platform owners, incentive designs can be employed to motivate users to share their donations. For example, GoFundMe shows a pop-up window showing that one share of a charitable cause on Facebook will bring in a $30 contribution. For fundraisers, a good campaign design that mobilizes users to share donations can greatly improve fundraising performance. For example, the Ice Bucket Challenge requires participants to tag five people who either take the challenge or donate to ALSA. Another interesting idea is corporate matching. For example, Macy's launched "Follow your heart and share the love" on the Valentine's Day of 2012. If users share their loves on Facebook and Twitter by tweeting #heart@Macys, Macy's will match each tweet with $2 up to $250,000 to the American Heart Association's Go Red For Women movement. Such novel designs have implications both for corporate philanthropy and advertising (Macy's 2012). It is an open domain for future study.

Conclusion

Given the great potential of social media fundraising, it is important to understand people's donation patterns and the effectiveness of incentive designs. Our result demonstrated the automaticity in social comparison, and provide a reminder that all incentive designs should take into consideration the consequence of social comparison. This is because users are affected by subliminal exposure to other people's information. In addition, the discovery of a crowding-out segment has great implications for platform owners and fundraisers. By putting more fundraising effort to engage this group of users, a more efficient allocation of funds can be achieved. Our study provides a starting point to understanding social media fundraising, and we look forward to more works of this domain.

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