Better to Give than to Receive? Impact of Adding a Donation Scheme to Reward-based Crowdfunding Campaigns

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Abstract

Motivated by the adoption of donation schemes at some leading reward-based crowdfunding platforms and a lack of understanding of the role of funding schemes, we examine the effect of adding a donation scheme to reward-based crowdfunding and explore its underlying mechanisms. Leveraging an unannounced site change at a leading crowdfunding platform, we estimated the impact of introducing the donation scheme using a novel triple matching-DID technique. We found that the introduction of the donation scheme, which resulted in two contribution channels (i.e., donation and reward), increased the success rate of reward campaigns by 19%. The increased success occurred mainly to reward campaigns with prosocial causes. Further analyses of underlying mechanisms revealed that increased campaign success came mainly from campaigns that received donations. The added donation channel not only had a primary effect, as evidenced by a third of campaigns attracting donations, and a secondary "crowd-in" effect on the reward channel, as evidenced by a positive impact of early donations on subsequent contributions through the reward channel, beyond the known effect of early contributions on subsequent ones. Our findings suggest that, for reward campaigns with prosocial causes, the addition of a donation channel not only provides a better fit for some backers of reward campaigns, but also inspires others more willing to contribute through the reward channel.

Keywords: crowdfunding, donation, reward, crowding-in effects, funding schemes

1. Introduction

Originally a fundraising tool for supporting artistes, crowdfunding has evolved to be a popular avenue for a broad set of individuals (i.e., entrepreneurs, journalists, philanthropists, activists, patients, and researchers) to raise funds online (Cholakova and Clarysse 2015; Hemer 2011). To cater to a diverse range of campaigns, the crowdfunding industry provides four different funding schemes, including a donation scheme that offers token rewards such as acknowledgments, mentions, and small gifts in return for a contribution, a reward scheme that provides tangible goods, a debt scheme that promises interests plus payback, and an equity scheme that offers shares of a startup. In practice, most crowdfunding platforms offer only one funding scheme. For instance, Indiegogo, GoFundMe, AngelList, and LendingClub offer the reward, donation, equity, and debt scheme, respectively, as their sole funding scheme on their crowdfunding platforms. Only a handful of exceptions exist: for example, Kickstarter and Zhongchou[1] have allowed backers to choose between donations and contributions in exchange for rewards (henceforth *reward contributions*) (See Table A1 for a sample of funding schemes used by leading reward crowdfunding platforms). Sellaband, a crowdfunding platform for the music community, allows backers to support bands and musicians through either donation or equity crowdfunding.

The scarcity of mixed funding schemes stands in contrast with research that showed backers of the same campaign have diverse motivations: some are motivated by tangible rewards while others have prosocial motives to help owners to reach their funding goals (Dai and Zhang 2019; Gerber and Hui 2013). The practice of utilizing a purist funding scheme to serve a pool of backers with varied backer motivations appears to be suboptimal. The lack of uptake of mixed funding scheme in practice raises an interesting question: would crowdfunding campaigns perform better by offering mixed funding schemes instead of a single funding scheme?

One may assume that by mixing two types of funding schemes, say the reward and donation schemes, a crowdfunding platform would be able to accommodate both reward-seeking backers and those

[1] "ZhongChou" translates to "crowdfunding" in Chinese. Zhongchou (www.zhongchou.com) is one of the largest Chinese crowdfunding platforms.

who are willing to help without rewards. However, prior literature on prosocial behavior suggests that tangible rewards can crowd out prosocial behaviors (Ariely et al. 2009) as mixed signals sent to potential backers can negatively affect their incentive to donate (Bénabou and Tirole 2006; Dubé et al. 2017). Therefore, it is unclear if a mixed scheme is truly advantageous. Even if so, we do not know what types of campaigns would benefit most from such a mixed scheme. Motivated by this gap in our understanding and by the lack of platforms that utilize a donation scheme alongside reward-based scheme, we study *whether and when adding a donation scheme to reward campaigns can improve the fundraising outcomes.*

With the added donation scheme, backers effectively face two contribution channels. The new donation channel can interact with the existing reward channel in complex ways. First, as we have mentioned earlier, the existing rewards could potentially crowd out the backers' incentives to donate, which, in its extreme form, can render the donation channel useless. Second, even if there are donations, they may impact reward contributions in uncertain ways. For example, they may inspire subsequent backers to also contribute via the donation channel, therefore serving as a substitute to reward-based contributions. Alternatively, they could highlight the intangible benefits of the campaign and makes reward backers more willing to contribute. Examining this interaction effect is fundamental to understanding why two funding schemes may (or may not) work together. It also lets campaign owners choose appropriate messaging and promotion strategies for potential backers (e.g., knowing early donations have a positive effect on subsequent reward contributions, campaign owners may use facts about early donations to motivate reward contributions). To gain insights into such interactions, we examine whether the added donation channel has a **primary effect** of inducing contributions through the donation channel, and whether the donations have a **secondary effect** on the subsequent contributions through the reward channel.

To answer the above questions, we leverage a quasi-experiment that took place on a leading crowdfunding platform in China, *Zhongchou.com*, which hosts both reward and charity campaigns. At first, reward campaigns only accept reward contributions and charity campaigns only accept donations. In August 2015, however, the site added a donation channel to reward campaigns, allowing them to accept both donations and reward contributions. We employ a novel triple matching process, initially proposed by

Keele et al. (2019), to form a pool of statistically identical reward and charity campaigns before and after the site change. We use the matched campaigns to estimate the impact of the new donation scheme on reward campaigns' success within a difference-in-differences (DID) framework. A battery of empirical checks is performed to ascertain that estimation assumptions are reasonable and that the matched sample is sufficiently robust against omitted variable bias.

The results indicate that the addition of the donation scheme increases the success rate of reward campaigns, especially campaigns with prosocial goals. This improvement in success rate comes through an increase in contribution frequency and dollar amounts. We further find that the introduction of the donation scheme increases campaign success in two ways. First, it induces a primary effect, as evidenced by non-trivial amounts of donations, especially among campaigns with prosocial objectives. Second, donations exert a positive secondary effect on the reward channel, as evidenced by a positive effect of early donations on subsequent amount of reward contributions, after controlling for the total amount of early contributions.

This work makes a few contributions. First, the study contributes to the literature on crowdfunding design (Agrawal et al. 2011; Kuppuswamy and Bayus 2013; Mollick 2014). Though the extant literature on crowdfunding has identified various success factors related to campaign features, there remains a striking shortage of research on the role of funding schemes, especially the simultaneous use of different funding schemes (Allison et al. 2015; Belleflamme et al. 2014). To the best of our knowledge, our work is the first systematic study that empirically examines whether one should mix the use of reward and donation schemes.

Second, our work contributes to the literature on the interplay between tangible rewards and prosocial motives on online platforms. While the existing literature has investigated the effect of offering tangible rewards in prosocial activities (Burtch et al. 2018; Khern-am-nuai et al. 2018), we examine the impact of offering a prosocial (i.e., donation) contribution channel in reward-based campaigns. The latter issue becomes increasingly relevant as more and more corporations and for-profit entities introduce prosocial goals along with monetary incentives (e.g., prosocial marketing and promoting employee volunteerism). Our unique setting provides an opportunity of examining how this would play out in the context of crowdfunding.

Finally, in estimating the effect of the added donation scheme, we had to use separate campaigns before and after the treatment for both the reward and charity groups. This prohibits us from using the traditional DID setup as repeated observations for the same unit both before and after the treatment is not available. To address this issue, we employ a novel triple-matching technique, initially proposed by Keele et al. (2019), to create statistically identical samples of both reward and charity campaigns, before carrying out the DID estimation. As the first empirical IS paper that applies the triple-matching technique, our work serves to introduce this estimation method to the IS research.

2. Related Literature

2.1 Crowdfunding Success

An extensive literature has focused on understanding the success factors and dynamics of crowdfunding campaigns. Early work on this topic shows that the amount and timing of contributions by other backers have a material impact on subsequent contribution behaviors (Burtch et al. 2013; Kuppuswamy and Bayus 2013; Zhang and Liu 2012). Another set of studies finds that the success rates of campaigns are related to the location in which campaigns are launched (Agrawal et al. 2011; Lin and Viswanathan 2016; Mollick 2014). Moreover, the social capital of campaign owners could also play a role in influencing crowdfunding success, especially in the early stage of fundraising (Colombo et al. 2015; Lin et al. 2013). Campaign characteristics (i.e., funding goal, duration, media usage, campaign updates, pitch quality, pitch narrative, and reward limit), along with the attributes of the campaign owner (i.e., number of campaigns backed, race, and gender) are also found to influence crowdfunding success (Allison et al. 2015; Cordova et al. 2015; Greenberg and Gerber 2014; Kunz et al. 2017; Mitra and Gilbert 2014; Mollick 2014; Pope and Sydnor 2011). Finally, the support patterns of backers also shed light on the funding decision and process of crowdfunding campaigns (Solomon et al. 2015). While these works provide a rich set of guidelines to campaign owners on how to set up crowdfunding projects, platform owners remain relatively uninformed on how to design incentive schemes, which represents a core aspect of crowdfunding platforms.

A small, emerging set of literature has attempted to fill this gap by shedding light on the design of funding schemes. For instance, Burtch et al. (2018) and Wash and Solomon (2014) have examined the impact of the return rule (i.e., whether to return all contributions to backers for unsuccessful campaigns) on the donation decisions of backers. Belleflamme et al. (2014) study the relative performance of two funding schemes, namely pre-ordering and profit-sharing, using theoretical modeling. Through the use of surveys, Cholakova and Clarysse (2015) investigate whether investors would contribute to or invest in a campaign that is simultaneously made available on reward- and equity-based crowdfunding platforms. Our work contributes to this understudied area of funding scheme design by empirically examining the value of adding a donation scheme to reward-based crowdfunding.

2.2 Backer Motivations

There are various motivations why backers would contribute to crowdfunding campaigns (Gerber and Hui 2013; Muller et al. 2013). Among these motivations, economic considerations of project quality and the likelihood of receiving the promised reward constitute as prominent motivations for backing decisions in a few studies (e.g., Bapna 2019; Freedman and Jin 2011; Li and Duan 2016; Lin et al. 2013; Zhang and Liu 2012). However, recent research found that prosocial motives may be an even more important determinant of backing decisions in reward crowdfunding, outweighing economic considerations (Dai and Zhang 2019). Recent surveys of reward-based crowdfunding backers suggest that while some backers are solely motivated by the rewards, a significant set of backers are motivated by rewards alongside altruistic and involvement motives (Cecere et al. 2017; Steigenberger 2017).

A deeper look at the literature on prosocial behavior reveals that such behaviors are driven by different levels of altruistic motives. Altruistic backers may derive utility from the knowledge that they have donated to the project serving certain moral causes (Andreoni 1990; Cecere et al. 2017). This is referred to as a "warm glow" effect (Crumpler and Grossman 2008; Ottoni-Wilhelm et al. 2017). Through magnetic resonance imaging, Moll et al. (2006) found that acts of charitable giving activate the subgenual area that is responsible for releasing oxytocin, providing a neurological explanation of why people engage in charitable giving can experience the warm glow effect. Such backers may spend their money to gain intangible benefits that allow them "feel good about themselves" (Dubé et al. 2017; Steigenberger 2017), gain shared identities (Muniz and O'Guinn 2001), and improve their social image *(Andreoni 1990; Lacetera* *and Macis 2010).* The literature on backer motivations informs our theoretical development on how the new donation channel interacts with the existing reward channel from the perspective of backers choosing between different channels to suit their motivations.

2.3 Contribution Dynamics

Our examination of the secondary effect is related to the literature on contribution dynamics. Extant research has shown that prior contributions impact subsequent contribution decisions differently depending on backers' interpretations of the prior contributions. First, prior contributions may create rational herding signals that allow subsequent backers to draw positive inferences about the campaign's quality, which increases their likelihood of contribution (Banerjee 1992; Bapna 2019; Zhang and Liu 2012). Second, for reward campaigns with an all-or-nothing funding rule, every additional contribution reduces the risk of campaign failure. This, in turn, reduces the opportunity costs in the monetary investment and time of subsequent backers, thereby increasing their contribution likelihood (Kuppuswamy and Bayus 2013; Li and Duan 2016). While these economic considerations predict a reinforcement effect of early contributions, Burtch et al. (2013) found evidence that early contributions can partially substitute subsequent contributions. They attribute this substitution effect to backers perceiving their contributions to have diminishing marginal utility to the campaign owner after many have contributed to the campaign. We note that all of the above studies focus on contribution dynamics in the same channel, whereas we examine the effect of contributions in one channel (i.e., the donation channel) on another (i.e., the reward channel).

3. Hypothesis Development

With the addition of the donation channel, backers can contribute to the same campaign in two ways – donation and reward contribution, analogous to consumers can choose between multiple channels (e.g., brick-and-mortar, catalog channel, Internet channel) to fulfill their shopping goals in multichannel shopping. We, therefore, draw on the multichannel shopping literature for terminologies and reference frameworks. The multichannel shopping literature holds that with multiple channels, there could be cross-channel interactive effects, jointly influencing consumers' shopping behaviors and overall sales (Huang et al. 2016). In multichannel shopping, consumers choose between channels by considering whether each channel's characteristics maximizes their utility (Balasubramanian et al. 2005) or meets their specific shopping goals (Balasubramanian et al. 2005). When a new channel is added, a *cannibalization* effect is likely to occur when the new channel provides more appealing features to a certain target audience (Avery et al. 2012). Meanwhile, there could also be complementarity between multiple channels. For example, multiple channels allow consumers to find a channel that better fits their shopping needs (called the "*goodness-of-fit effect*") (Huang et al. 2016).

Using multichannel shopping as an analogy, we argue that backers will also choose between donation and reward channels to maximize their utility and suit their specific needs, and there could also be cross-channel effects. Therefore, to understand the effect of adding a new donation channel, we must consider both its *primary effect*, i.e., the contributions through the new donation channel, and the *secondary effect*, i.e., the change in the contributions through the reward channel as the result of the contributions through the donation channel. Drawing on the literature on crowdfunding motivations, we discuss the primary and secondary effects, in turn, followed by the overall effects of the new donation channel.

3.1 The Primary Effect

We first consider the primary effect of the new donation channel. Here we focus on whether the new donation channel can attract a nontrivial amount of contribution. Prior research has shown that backers can be motivated to support a campaign that offers no tangible rewards (Dai and Zhang 2019; Gerber and Hui 2013). Such backers are likely motivated by *impure altruism*, wherein people develop a sense of "warm glow" and "feel good about themselves" from the act of contributing to some prosocial causes (Andreoni 1990). According to Mijovic-Prelec and Prelec (2010), impure altruists use their actions to draw inferences about their self-image, and when they make personal sacrifices to support prosocial causes, they can boost their self-image and "feel good about themselves" (Dubé et al. 2017).

With the reward channel already in place, however, simply harboring altruistic motives may not be inadequate to motivate people to donate. Like multichannel consumers, backers facing both donation and reward channels must face the trades-off in expected utility of the two channels. When an impure altruist contributes through the reward channel, they can derive utility from the reward, but the utility from warm glow would be much lower. This is because prior research has shown that receiving rewards for donation contributions can send mixed signals about one's true motivation, thus diminishing the image value of such contribution (Bénabou and Tirole 2006; Dubé et al. 2017). This implies that only when backers' altruistic motive is strong enough such that the utility of warm glow from donation strongly outweigh the utility of rewards, they would choose the donation channel over the reward one.

The above analyses suggest that the new donation channel could attract altruistic backers who weigh a feeling of warm glow more heavily than the rewards promised by the campaign. Such backers seem to exist because prior research shows that not only do prosocial motives exist on reward crowdfunding platforms (Cecere et al. 2017; Steigenberger 2017), but also for some backers, prosocial motives outweigh economic considerations (Dai and Zhang 2019). Therefore, we hypothesize:

H1 *(The Primary Effect): The addition of the donation channel to reward campaigns results in a nontrivial amount of contribution through the donation channel.*

We note that not all reward campaigns can invoke altruistic motives. Prior research on donation contributions suggests that individuals are selective in making their donations. Specifically, donations are mainly made to non-profit organizations that share their values in serving certain moral causes (Bhattacharya and Elsbach 2002; van Dijk et al. 2019). In our context, some reward campaigns feature not only for-profit goals but also prosocial causes, such as advancing education, reducing poverty, advancing arts, and helping disadvantaged individuals or groups. For example, a campaign initiated by a fruit retailer from a poor village is not seeking economic returns for the fruit retailer, but also helps reduce poverty for fruit farmers in his village as well. Such reward campaigns more likely appeal to altruistic backers who identify with the prosocial causes of the campaigns and are more willing to donate. Therefore, we hypothesize:

H2: *After the addition of the donation channel, reward campaigns with prosocial causes are more likely to attract donations than those without.*

3.2 The Secondary Effect

Next, we consider the secondary effect of the donation channel on the reward channel. Different from the multichannel shopping literature, in the crowdfunding context, backers can observe the contributions made through both channels, which allows them to draw inferences about the campaign (e.g., its quality or likelihood of success). As a result, early contributions can naturally impact subsequent contribution behaviors (Burtch et al. 2013; Zhang and Liu 2012). For example, research has found that prior contributions may create rational herding signals that increase subsequent backers' likelihood of contribution (Bapna 2019; Zhang and Liu 2012). Such contribution dynamics can lead to cross-channel effects, but these are not specific to the donation channel. To focus on the unique effect of the donation channel, the secondary effect can be examined through *the effect of early donations,* ***when holding the total amount of early contributions constant****, on subsequent contributions through the reward channel*. We focus on the effect of early donations to avoid some of the endogeneity concerns.

When holding the total amount of early contributions constant, the existence of early donations can send an additional signal about the campaign's prosocial causes. As we have argued earlier, backers who donate to the campaign tend to have a strong altruistic motive to help campaign owners and strongly identify with the campaign's prosocial causes. Just like one individual's prosocial behavior can prompt other individuals to adopt similar prosocial behaviors (Dimant 2019; Tsvetkova and Macy 2015), early donations can strengthen subsequent backers' altruistic motives toward the same prosocial causes. This allows subsequent backers to see the additional effect of helping the campaign owner and his/her prosocial causes and develop a sense of warm glow. For some backers whose altruistic motives are strong enough, this may result in a switch to the donation channel (and thus become part of the primary effect). For backers whose altruistic motives are strengthened but not strong enough to enable a channel switch, they may expect higher utility from a reward contribution due to an enhanced sense of warm glow, and thus are more willing to contribute. Therefore, we hypothesize a positive secondary effect:

H3 *(The Secondary Effect): Holding the total amount of early contributions constant, reward campaigns with early donations would attract more subsequent contributions through the reward channel.*

3.3 The Overall Effect

The overall effect of adding a donation channel depends crucially on the size of the primary and secondary effects. The added donation channel may imply that some backers may switch from the reward channel to the donation channel, and thus a cannibalization effect may exist (Avery et al. 2012). On the other hand, the added donation channel may enable backers who have strong altruistic motives to choose a channel to better fit their needs, and thus a positive "goodness-of-fit" effect may exist (Huang et al. 2016). A strong goodness-of-fit effect can lead to an overall increase in total contribution, despite the cannibalization across channels. The strength of the "goodness-of-fit" effect is tied to the strength of the primary effect because the more backers choose the donation channel, the greater the realized benefits of fit.

Meanwhile, a significant secondary effect can also help offset the potential cannibalization and lead to an overall increase in the total contribution. If the primary effect is trivial (i.e., a lack of actual donations) or the secondary effect is too weak to offset the cannibalization effect, then the overall effect of the new donation channel may not be significant. Both the strength of the primary effect and that of the secondary effect depend on enough backers harboring altruistic motives towards the reward campaigns, which seems to be the case per prior research on backer motivation on reward crowdfunding platforms (Cecere et al. 2017; Steigenberger 2017). We, therefore, hypothesize a positive effect of the new donation channel:

H4 *(The Overall Effect): The addition of the donation channel to reward campaigns increases their likelihood of success.*

Similar to **H2**, we also hypothesize that the overall effect of the donation channel is more salient among reward campaigns that feature prosocial causes.

H5: *The addition of the donation channel has a greater impact on reward campaigns' likelihood of success when these campaigns feature prosocial causes than when they do not.*

4. Empirical Methodology

4.1 Study Context

We base our study on one of the largest crowdfunding platforms in China, *Zhongchou.com*, by which we have access to its proprietary data. Like most other reward-based crowdfunding sites, Zhongchou.com follows the all-or-nothing rule, wherein the monetary contributions are only released to the campaign owners in cases where the campaign's target goal is met. Since its inception in 2013, the crowdfunding platform has raised over 200 million RMB and has hosted over 13,500 campaigns, with a funding success rate of 30.7 percent. The site caters to a variety of crowdfunding categories, including science, agriculture, arts, education, entertainment, product, and others (see Table 1A for a breakdown of campaign type proportion). Across all crowdfunding categories, 690 new campaigns are posted on the site each month on average. The average amount solicited by each campaign is 53,776 RMB, and the amount raised by each campaign ranges from 0 to 6,211,933 RMB, with a mean of 12,430 RMB. The average duration of campaigns is about 6 weeks, which is comparable to campaign durations from other crowdfunding sites.[2] Across all campaigns, we observe that the average total amount raised accounts for 23% of the total target goal. Among the successfully funded campaigns, the average amount raised is 38,200 RMB and 1,058 RMB is raised each day for these campaigns on average.

--Insert Table 1A--

Zhongchou.com supports both reward and charity campaigns on its platform. Similar to other crowdfunding sites, reward campaigns on the site provide tangible rewards in exchange for monetary contributions, while charity campaigns do not offer rewards of tangible value to donors. Instead, the charity campaigns provide token gifts such as thank-you cards, mugs, t-shirts, and recognition souvenirs, as an appreciation for the donations received. Given the monetary value of these items are quite small, we broadly categorize the contributions to charity campaigns as donations.[3] On August 27, 2015, the platform introduced a donation scheme to its reward campaign. Effectively, all post-shock reward campaigns have a donation channel in addition to the reward channel. The donation scheme for these post-shock reward campaigns is similar to those used in charity campaigns. Backers are to specify the dollar amount they wish to donate. The site change resembles a quasi-experiment setup allowing for the assessment of the impact of the donation scheme on crowdfunding outcomes by contrasting the outcomes of different campaign types in the pre- and post-shock periods.

[2] Average duration for other sites is available at https://www.fundable.com/crowdfunding101/crowdfunding-statistics.

[3] While some reward campaigns also offer tokens of appreciation as rewards for the lowest tier of contribution, the incidence of such campaigns is not common. Less than 6.5% of the reward campaigns in the study offer such rewards.

We focus our main analyses on campaigns that were listed between April 23, 2015, and January 14, 2016, such that we have campaigns from both the pre- and post-shock periods. We made an intentional decision of leaving out the period between August 12, 2015, and September 24, 2015, as we were aware that the site was testing and redeploying the donation scheme in the weeks before and after the launch date.[4] Our resultant dataset has 16 weeks of campaigns in each of the pre- and post-shock periods. In our dataset, we have the following campaign-level information: the target amount solicited, the start and end dates, the amount raised, the number of backers, the campaign category, the campaign content (via textual, pictorial, and video descriptions), the available contribution tiers, and the location of the campaign. Campaign owners typically create multiple contribution tiers with the different required amounts of contribution. We rely on the difference between required amounts for the highest and lowest contribution tiers as a proxy for various financial brackets available for contribution. We classify the locations of the campaigns into eight categories: eastern, southern, central, northern, northwestern, southwestern, northeastern, and undisclosed, to account for potential geographical differences in contribution behaviors (Lin and Viswanathan 2016). In addition to the campaign characteristics, we also observe information related to the campaign owners, such as whether they list their social media account (e.g., Weibo, WeChat, or blog), their citizenship ID, and/or business licenses, their level of educational attainment, and the date when they joined the platform. Given that backers may use such information to infer the legitimacy and the likelihood of success of the campaign, we constructed a set of covariates based on such information to account for inter-campaign differences.

Just like higher-quality ads can signal a marketer's confidence in a product's quality and potential success (Moorthy and Hawkins 2005; Nelson 1974), the quality of the pictures used in promoting the crowdfunding campaigns can signal the quality of the campaigns to backers, which can, in turn, influence their backing decisions. To control this aspect, we relied on an image processing model to assess the quality of the images posted on campaigns.[5] The quality score for each image in each campaign is computed and

[4] This precautionary step allows the sample of pre-treatment campaigns not to have exposure to the donation scheme, and the sample of post-shock campaigns would only be experiencing a stabilized consistent version of the feature, which gets us to a cleaner estimation of the donation scheme.

[5] The image processing model, BRISQUE, is used to compute the image quality scores for the images. Please see online

the average score is taken to be the picture quality for the campaign.

Our main dependent variable, $Success_i$, tracks whether the target amount is successfully raised at the end of the fundraising period. This dependent variable equals '1' when the campaign is successfully funded and '0' otherwise. A detailed description of our dataset is shown in Table 1B. Finer breakdowns of summary statistics by campaign type and study period are provided in Appendix A. Figure 1A shows the number of campaigns hosted by the platform across the pre- and post-shock periods, by which we see that the average number of campaigns posted weekly increased by about 47 percent in the later period. In Figure 1B, we see that the crowdfunding outcomes (campaign success, number of backers, number of contributions, and amount raised) are slightly worse in the post-shock period, though not significantly different from that in the pre-shock period. However, with a net increase in the number of campaigns initiated on the site (776 more campaigns) in the post-shock period, along with a lower average number of backers, contribution frequency, and amount raised, there is likely greater competition among the campaigns, which is why we see a drop in the average campaign success.[6] We bear this critical information in mind as we interpret our results in the subsequent sections.

--Insert Table 1B, Figure 1A and 1B here--

4.2 Estimation of the main effect

The introduction of the donation scheme in reward campaigns on Zhongchou.com provides us with the opportunity to assess its impact on campaign success while addressing the aforementioned endogeneity concerns. A major benefit of this setting is the unannounced timing of introducing the donation scheme. As such, the introduction of this feature is likely exogenous to the decisions of both the campaign owners and backers, reducing the chance of users timing their behaviors in anticipation of a donation scheme in the future. With the donation scheme affecting only the reward campaigns and not the charity campaigns after the site change, a double-differencing technique based on the principles of the difference-in-differences

Appendix D for more details about this image quality measure.

[6] The CIO of the site further validated this insight.

(DID) framework is used to account for endogeneity concerns stemming from the effects of campaign type and temporal trends.

The DID framework is commonly used to quantify the changes in outcomes in the treatment group after a shock or policy change (e.g., Card and Krueger 1995; Chan and Ghose 2014; Xu et al. 2017). By contrasting the difference in outcomes of the treatment group before and after the shock, with the same difference from the control group, the DID framework provides insights into the average treatment effect. Specifically, the first difference conducted across pre- and post-shock periods within each group plays the role of removing inter-group differences across the units, thereby alleviating endogeneity issues stemming from differences across reward and charity campaigns. The second difference of applying the first difference of the control units on the first difference of the treated units has the effect of removing changes in outcomes due to temporal effects, which accounts for the differences in success rates across the pre- and post-shock periods.

In our context, the charity campaigns may serve as control units to be contrasted with the reward campaigns, such that potential temporal effects that were present on the site may be removed via a differencing method. However, the traditional DID is applied in contexts where outcomes of the treated and control units are observed in both the pre- and post-shock periods. Given that each crowdfunding campaign only has one instance of campaign outcome (i.e., success or failure) in either the pre- or post-shock period, it would not be possible to apply a traditional DID estimation directly in our setting.

To accommodate situations where before and after subjects for the same group are different, we adopt Keele et al. (2019)'s DID framework, which uses a combination of a "*triple matching process*" and DID. They show that a DID estimator based on tripe-matched samples can produce unbiased estimates of the treatment effect for such situations. Following their framework, we implement a tripe-matching + DID estimation framework described as follows.

We first perform propensity score matching, using one-to-one closest neighbor caliper matching, on the set of charity campaigns posted before and after the site change, based on defining characteristics of crowdfunding campaigns (i.e., description length, no. of pictures, picture quality, no. contribution tiers, the monetary difference in highest and lowest tiers, target amount, and project duration). Effectively, this matching removes post-shock charity campaigns that cannot be reasonably matched to a pre-shock charity campaign.

In the second step, we conduct another round of matching where the reward campaigns (i.e., treated campaigns) are matched to the charity campaigns (i.e., control campaigns) in the respective pre- and post-shock periods. That is, reward campaigns in the pre-shock period are matched to charity campaigns of the same period, while another matching is further performed for campaigns in the post-shock period.[7] The second round of matching conducted between campaign types not only ensures that the treated and control campaigns are statistically comparable but would also allow the treated campaigns posted in the two periods to be statistically comparable. Thus, with two rounds of matching, we arrive at a sample of reward and charity campaigns that are statistically identical across periods. Results of the statistical comparison of the covariates of the campaign types are shown in Table 2B. Under the standard 5% significance level, t-tests reveal that all covariates are statistically similar between the reward and charity campaigns. The overall quality of the triple matching process is shown in Figure 2, where there is a good amount of overlap in the distribution of the propensity scores of the treated and control units, indicating that the overall matching has good common support.

--Insert Table 2A here--

--Insert Table 2B and Figure 2 here--

4.3 Estimation Specification

We next describe how we apply the DID technique to matched samples to achieve our estimation goals. This empirical strategy is used to directly assess H4, but can be easily modified to test out H3 and H5. To assess the impact of the donation channel on reward campaigns, we estimate the following model:

$$CampaignSuccess_i = \alpha \cdot Reward_i + \beta \cdot Post_i + \gamma \cdot (Reward_i \times Post_i) + \theta \cdot X_i + \epsilon_i, \qquad (1)$$

[7] In the first step where we match charity-based campaigns across pre and post periods, 270 out of 398 charity campaigns in the pre-period were matched. In the second step of the matching, 270 out of 1246 reward campaigns in the pre period were matched, and 268 out of 2152 reward campaigns in the post period were matched.

where i indexes the campaign. Our main campaign outcome variable is $CampaignSuccess_i$, which denotes whether campaign i was successfully funded.[8] The variable, $Reward_i$, denotes if the posted campaign is of the reward type. This binary variable controls for the impact of time-invariant group differences between campaign types, accounting for the first source of endogeneity mentioned earlier. The binary variable, $Post_i$, an indicator for whether campaign i was posted after the site change, is used to capture common temporal effects. By accounting for the differences in success rate across the two study periods, this term controls for the second source of endogeneity. The interaction term, γ, is the main estimator of interest. It captures the impact of adding a donation channel on the success rate of reward campaigns. Finally, given that campaigns within each campaign type can still vary from one another in terms of characteristics, we include a vector of covariates X_i to control for the third source of endogeneity stemming from effects from various campaign-related attributes.

5. Pre-analyses Checks

5.1 Check the Quality of Matched Samples

After this matching is conducted, we assess if covariates of the charity campaigns posted before and after the site change are statistically comparable. Based on the results of the t-tests, we see that attributes of charity campaigns in the pre-shock period are statistically indistinguishable from that of charity campaigns posted in the post-shock period (Table 2A). Through these results, the charity campaigns across the two periods are deemed to bear statistically similar properties.

5.2 Checking the Validity of the Control Group

For the matched charity campaigns to be valid control, we need to ensure that they are not affected by the treatment. One potential threat is a potential "displacement" effect – the addition of the donation channel to reward campaigns may cause some "would-be" charity backers to switch to reward campaigns. We argue that this is not a significant concern because, for "would-be" charity backers, reward campaigns with a donation scheme may not be a close substitute for charity campaigns: the former's primary objectives tend

[8] The use of differencing techniques on a binary outcome variable has also been performed in the past (e.g., Blundell et al. 2004).

to be profit-oriented (instead of charity-focused objectives of charity campaigns) and their rewards tend to be tangible products (instead of token appreciation). Still, we take the following steps to check for any signs of displacement effects.

5.2.1 Statistical Tests on Charity Campaigns

Our first series of tests focus on contribution patterns to charity campaign before and after the treatment. If there is a displacement effect, we would expect some changes in contribution patterns. We conducted t-tests on the number of backers, number of contributions, and amount raised before and after the treatment and found no significant difference. It might also be possible that the number of charity campaigns has reduced after the treatment, which can potentially cause backers to devote more attention to the reward campaigns leading to greater funding likelihood for the treated campaigns. We used a t-test to verify this possibility and found that the weekly number of charity campaigns did not differ significantly across these two periods. These four tests jointly suggest that there were no signs of change to charity campaigns.[9]

5.2.2 Check for the Displacement Effect via a User-Decision Analysis

To address the concern that backers may systematically shift to reward projects after the shock, we conduct a user-decision analysis among recurring backers, i.e., backers who backed campaigns both before and after the treatment. Following the approach of Liu et al. (2015), we consider a backer's choice between a group of active campaigns at each decision time (i.e., the time of the backer's actual contribution), and estimate a conditional logit model for the backer's backing decision:

$$logit(I_{ijt}) = \alpha_{it} + \beta_1 \cdot Post_t + \beta_2 \cdot Reward_j + \beta_3 \cdot Post_t \times Reward_j + \varepsilon_{ijt}$$

The dependent variable I_{ijt} is a binary variable indicating whether a backer i backs a campaign j at the decision time t. $Post_t$ indicates whether the decision time t is post shock. $Reward_j$ indicates whether the campaign j is a reward type. α_{it} is the user-decision fixed effect and ε_{ijt} is the error term. We are

[9] There is no significant difference between the average number of backers for charity campaigns in the pre-shock period (M=54.27, SD=90.87), and that in the post-shock period (M=42.78, SD=74.19); t(536)=1.61, p =0.11. There is no significant difference in the average number of contributions per charity campaign during pre-shock period (M=92.29, SD=214.61) and that in post-shock period (M=71.28, SD=114.09); t(536)=1.42, p =0.18. There is no significant difference between the average amount raised during pre-shock period (M=13,521.44, SD=64415.77) and that in post-shock period (M=8,484.81, SD=25048.45); t(536)=1.19, p =0.23.

mainly interested in the interaction term $Post_t \times Reward_j$. If the coefficient of the term is positive and significant, we can then infer that the backers were more likely to contribute to a reward campaign after the treatment. The results of the analysis, shown in Table A9, indicate that backers are slightly less likely to contribute to reward campaigns after the treatment. Therefore, they did not systematically shift to reward projects after the treatment.

5.2.3 A Further Check via A Randomized Online Experiment

Though the previous analyses show that there were no significant shifts in the charity campaign's contribution patterns, availability, or backer preference between the two types of campaigns, it is likely that absence of the treatment, charity campaigns would have been preferred more, attracted more contributors, and been more available. To rule out such a possibility, we designed and executed a randomized online experiment to observe how individuals' backing decisions might change after the reward campaigns gain a donation option. We recruited 161 participants from a crowdsourcing platform to review four closely matched pairs of charity and reward campaigns from our sample. Each participant was asked to select a campaign to contribute to. After they reviewed the eight campaigns and made their decision, we informed them that they have a chance to revisit their earlier decision. We randomly assigned them to treatment and control groups, with the only difference being that the treatment group was presented with a new donation option for all the reward campaigns. We find that 7.5% of treated users switched from charity to reward campaigns and 6.25% switched from reward to charity campaigns. Within the control group, 3.7% of the users switched from charity to reward campaigns and 4.9% switched from reward to charity campaigns. We find that the rate of switching (to reward campaigns) among treated users who picked a charity campaign initially (M=0.10, SD=0.04) was not significantly different from that of control users (M=0.05, SD=0.03; p=0.27). This randomized experiment, combined with earlier analyses, consistently shows that the introduction of the donation channel was unlikely to have systematically caused backers to switch to reward campaigns.

5.3 Parallel Trends Assumption

Before we can use the DID framework, we need to assess if the assumptions behind the differencing technique are met. Specifically, we use a leads-lags analysis to check if the parallel trends assumption is held. In this test, we substituted the *Post* variable with week dummies and interacted these dummies with the *Reward* variable. Effectively, each interaction coefficient captures the difference between the campaign success rates of reward and charity campaigns in that week. The results of this analysis are reported in Figure 3, with the first week of treatment (W+1) being the baseline week.[10] We observe that the success rate of reward campaigns is not statistically different from that of charity campaigns before the introduction of the donation scheme.[11] This supports the parallel trend assumption. We further note that the success rate of reward campaigns displays an upward trend in the post-shock period. In particular, we see that W+8, W+11, and W+12 produce positive and significant coefficients (Coeff=0.29, SD=0.15, $p<0.10$; Coeff=0.37, SD=0.15, $p<0.05$; Coeff=0.33, SD=0.15, $p<0.05$, respectively), while other weeks do not. Thus, this improvement in success rate was not uniformly observed across the post-periods. An empirical check reveals that the weeks that experience a positive and significant effect are also ones that had the largest count and proportion of reward campaigns that received donations.[12] This trend suggests that the positive impact of the donation scheme would only materialize when the treated campaigns receive actual donations. We explore why this relationship arises in a subsequent test.

--Insert Figure 3 here--

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[10] There were no W+2 campaigns because this week coincided with a week-long National Day holiday in China, during which the site's office was closed such that no one was able to manually vet or approve new campaigns. All campaigns need to be manually vetted before they can go live.

[11] The pre-treatment weeks close to the treatment shock have fewer campaigns to begin with, as there are not as many campaigns with crowdfunding durations lasting 2 weeks or less. After the matching process, we did not get any campaigns in W-2 and W-1. To be able to derive estimates for these two weeks, we included the unmatched campaigns in these weeks in our regression. Regression results that only consider the matched campaigns also produced similar results.

[12] T-tests indicate that W+8, W+11, and W+12 had a greater raw count *(M=8.33, SD= 1.15)* and proportion *(M=0.44, SD= 0.10)* of reward campaigns that received donations than the raw count *(M=5.55, SD=3.83; p =0.05)* and proportion of reward campaigns *(M=0.28, SD=0.13; p=0.09)* in other post-shock weeks.

6. Results

6.1 Overall Effect

Since Equation 1 is our main specification from which most of the other empirical tests are derived, we would first report the analysis results for the overall effect (i.e., H4), followed by those for hypotheses regarding the primary and secondary effects (i.e., H1, H2, and H3). Our campaign-level analysis relies on a linear probability model (LPM) and we report its results in Table 3. For comparison, we first show the results on the full sample before any matching (Model 1). We find the coefficient of the interaction term to be positive and significant, suggesting that the addition of the donation scheme to reward campaigns leads to a 13% increase in the success rate. Similar results are shown for the sample of statistically comparable campaigns derived by the triple matching. Specifically, in Model 2, the interaction term indicates that the donation scheme increased the success rate of the reward campaigns by 20%. In a stricter specification that includes campaign-category fixed effects (Model 3), the coefficient remains positively significant. In sum, the results of the main analysis indicate that the donation scheme exerted a net positive impact (19%) on the success of reward campaigns, **supporting H4.**

We also find the $Reward_i$ variable to have a significant negative coefficient, suggesting that the success rate of reward campaigns is lower than that of charity campaigns, on average. This finding is consistent with past findings (Belleflamme et al. 2013). We further find the $Post_i$ coefficient to be negative and significant, implying that campaigns launched after the site change experienced a lower success rate, on average. This is consistent with our earlier observation that greater competition among campaigns in the post-shock period led to a decline in the overall success rate. Given that reward campaigns performed worse than charity ones on average, a smaller decrease in their success (relative to that of charity campaigns) in the post-shock period indicates that the success rate of reward campaigns improved in the post-shock period. Based on this finding, we expect the donation scheme to produce sizable positive effects on the success rate if competition effects were absent. The heightened campaign success in reward campaigns was unlikely caused by changes in the charity campaigns, as the success rate and number of charity campaigns did not change significantly across the periods (see Section 5.1 for details), We also observe other interesting relationships across the three regressions. The number of pictures posted, the provision of citizenship ID, and the provision of business licenses have a positive impact on funding success. These results can be intuitively understood as a consequence of information signaling: they are positive cues of credibility and legitimacy. The number of contribution tiers has a positive influence on the success rate. This is reasonable, given that more contribution tiers allow for a larger variety of backers to contribute. The target amount and project duration hold a negative relationship with funding success, which is consistent with the past findings (Mollick 2014). We further see that posting owners' social media accounts hurts funding outcomes. Further analysis suggests that the negative effect is attributed solely to posting WeChat accounts.[13] Finally, geographical indicators have a significant impact on funding success (omitted due to space limitation), which aligns with past results (Agrawal et al. 2011; Lin and Viswanathan 2016).

--Insert Table 3 here--

We further test a logit specification for the main analysis, given the binary nature of our dependent variable (Table 4). The odds ratios of the interaction term are consistently larger than one, implying a positive effect of the donation scheme on reward campaigns. Since the magnitude of interaction terms in non-linear models cannot be directly interpreted (Ai and Norton 2003), we followed Karaca-Mandic et al. (2012) to obtain the marginal effects of the donation scheme for reward campaigns (the "Reward – Charity" row). All models produce qualitatively similar conclusions. Under the strictest specification (Model 3), the donation scheme had a net positive impact of 16 percent for reward campaigns, which is more conservative than the LPM estimates. Overall, the findings of the logit model are largely similar to those from the LPM. Considering the greater ease in interpreting LPM results, we adopt the LPM as our main specification going forward.

[13] WeChat is a private messaging platform and backers must become campaign owners' WeChat friends to chat with them and gain access to their WeChat postings. However, campaign owners have little way of knowing whether a friend request is coming from a potential backer, and thus may ignore such friend requests. The non-response may cause these backers to lose confidence in these owners, resulting in a reduced propensity to contribute to their campaigns.

6.2. Potential Mechanisms

Thus far, our main analyses have uncovered a positive impact of the donation scheme on crowdfunding success, and the effect is robust against a series of tests (See also Section 7). We next examine the possible mechanisms behind this positive relationship. Our theoretical development process indicates that the donation scheme may enhance campaign success if the campaign attracts donations, and it impacts campaign outcomes either through a primary or secondary effect. We examine these possibilities in turn.

6.2.1 The Role of Donations

We begin by empirically verifying whether the heightened success came from the subset of reward campaigns that received donations. To check this, we create an indicator, *With Donation*, to denote post-shock reward campaigns that received funds via the donation channel.[14] Table 6 shows that post-shock reward campaigns with donations experienced a positive and significant improvement in campaign success (Models 1 and 2). Similarly, these campaigns also saw an increased contribution count and dollar amount (Models 3 and 4). Interestingly, the original interaction term (Reward × Post) is no longer significant. These results indicate that having the donation scheme alone is not enough to increase campaign success, but the actual receipt of donations is necessary for the positive impact of the donation scheme to manifest. This is in line with the trend we saw earlier in the leads-lags model, wherein a significant positive effect was observed only in weeks where there were a significant number of reward campaigns with donations.

--Insert Table 6 here--

6.2.2 The Primary Effect

With the above understanding, we next examine the primary effect of the donation channel. We assess the impact of the primary effect of the donation channel along two dimensions, namely the scope and intensity. We operationalize scope as the proportion of treated campaigns with donations. We found that the scope of the primary effect is practically sizable, with 39% of all post-shock reward campaigns receiving donations from the new channel. We operationalize intensity as the ratio of the donation amount to the campaign goal.

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[14] It should be noted that the coding of this indicator is in the same spirit as the *Reward* × *Post* interaction term, which means that it is based on double-differencing.

Among campaigns that did receive donations, we find that the intensity of the primary effect constituted a sizable 12% of the campaign goal. Therefore, our findings **support H1 -** the addition of the donation channel resulted in a significant proportion of donations received.

6.2.3 The Secondary Effect

We next examine the secondary effect of the donation channel on subsequent reward contributions. As argued in our theoretical section, we focus on early donations. A post-hoc analysis showed that 75% of the donations came in the first half of the campaigns' duration, which further underscores the importance of early donations. Specifically, we regress the monetary amount received from the reward channel in the second half of each campaign, $\textit{Reward Amount}_{i,\ second}$, on the presence of donations in the first half of the same campaign, $\textit{With Donation}_{i,\ first}$. To better see the incremental impact of the dollar amount from donations, we varied thresholds of donation amounts from at least 0% (no threshold), to 2% and 4% of the campaign target. Given our interest in assessing the premium effect of early donations on top of the known effect of early contributions, we controlled for the contribution amount in the first half of each campaign, denoted by $\textit{Total Amount}_{i,\ first}$. The resultant regression specification is shown below.

$$\delta \cdot Donation_{i,first} + \vartheta \cdot Total\ Amount_{i,first} + \theta \cdot X_i + \ \epsilon_i, \tag{4}$$

Table 7's Model 1 shows that donations received in the early phase of a crowdfunding campaign positively influenced the receipt of reward contributions in the second phase but the effect was not statistically significant. As the donation amount increases to at least 2% and 4% of the campaign goal (Models 2 and 3), its positive impact becomes statistically significant, increasing the reward contribution amount in the second half of the campaign by 28% and 39%, respectively. These results indicate that the early donations exerted a positive secondary effect that crowded in reward contribution, **supporting H3**.

Having tested the primary and secondary effects, it is useful to know the relative size of these effects. Within reward campaigns that did receive donations, we find that the primary effect is responsible for 40% to 48% of the overall effect, while the secondary effect is responsible for 52% to 60% of the overall effect.[15]

--Insert Table 7 here--

6.2.4 Heterogeneous Effects and Underlying Motives

We further investigate which set of campaigns are more likely to benefit from the donation channel. We hypothesized that reward campaigns with prosocial causes are more likely to receive donations (H2) and benefit from the added donation channel (H5). We test these theoretical conjectures by regressing the presence of donations and a campaign's success on the campaign's prosocial causes. We hired a research assistant to code a post-shock reward campaign to be prosocial if it has any of the prosocial causes listed by an official national classification,[16] .

We first regress the binary indicator of whether a campaign received donations on the prosocial variable for reward campaigns in the post period. The results of this regression are shown in Table 8. After conditioning for the various characteristics of the campaigns, we find that reward campaigns with prosocial objectives are more likely to receive donations, **supporting H2**. To further understand if the prosocial reward campaign would also translate to a greater likelihood of funding success in the post-period, we further include the prosocial variable and its interaction with the DID term in our main model. As reported in Table 9 below, we see that the three-way interaction is significant, which shows that the main beneficiaries of the added donation channel are prosocial reward campaigns. Hence, **H5 is also supported**.

--Insert Table 8 here--

[15] The average target amount of post-period reward campaigns that received any donation is $39000.96, to which the primary effect constituted 12% of this amount. The attribution of the secondary effect can be broken down in two groups, a) campaigns with first half donation amounts making up at least 2% of the campaign target, and b) campaigns with first half donation amounts making up at least 4% of the campaign target, as our regressions have these the effect size of these two types of campaigns. The average reward amount raised in the second half for reward campaigns that received any donation is $18024.69. For the first type of campaign, the donation-induced reward amount raised in second half is 0.28*18024.69= $5047, which represents (5047/39000.96)*100 = 13% of the target goal of the focal campaigns. For the second set of campaigns, donation-induced reward amount raised in second half is 0.39*18024.69= $7029, which represents (7029/39000.96)*100 = 18% of the target goal of focal campaigns. Contrasting these percentages to the primary effect (12%), we can further derive the proportion of the primary to the overall donation effect as ranging from 40% (12/30) to 48% (12/25), and that the size of secondary effect increases with the early donation amount received, i.e., 52% to 60%.

[16] According to Charities Act 2011 of UK (https://www.legislation.gov.uk/ukpga/2011/25/section/3), prosocial acts can include activities that (1) prevent or relieve poverty, (2) advance educational goals, (3) preserve health or save lives, (4) advance arts, culture, heritage or science, and (5) help needy population groups (e.g., children, seniors, sick, disabled, individuals suffering from financial hardship or other disadvantages).

-- Insert Table 9 here--

To further understand the nature of the motives of the backers who contributed to the post-reward campaigns, we adopt the empirical strategy of Dai and Zhang (2019) to contrast the speed of contributions arriving in the 95%-100% phase with that in the 100%-105% phase. As theorized by Dai and Zhang (2019), backers motivated by tangible rewards should prefer to contribute to projects that have reached their goals because it eliminates the risk of campaign failure. In contrast, backers whose altruistic motives are strong enough would be more willing to contribute before the campaign goal is reached because their marginal impact on campaign success would be the greatest (Karlan and List 2007). Finally, backers whose altruistic motives are not strong enough are equally likely to contribute before and after a campaign goal is reached, because they derive the utility of feeling good about themselves from the act of giving (Andreoni 1990; Lacetera and Macis 2010).

We tabulated the time taken in hours for each post reward campaign to go from 95% to 100%, and from 100% to 105%. We then statistically contrast the pre-goal funding speed with the post-goal speed using a t-test. Results show that there is no significant difference between these two funding speeds, which indicates that backers whose altruistic motives are strengthened but not strong enough to enable a channel switch are more willing to contribute – leading to a positive secondary effect from the donation channel to the reward channel.

--Insert Table 4 here--

7 Robustness Checks

7.1 Sensitivity to Matching Parameters and Algorithms

We first assess the sensitivity of the matching process to alternative matching parameters and algorithms. First, we use stricter caliper sizes to see if results change. Second, we also utilize coarsened exact matching (CEM) to examine the sensitivity to matching algorithms. Table A7 shows that the main results remain qualitatively similar across various matching parameters and algorithms.

7.2 Sensitivity to Omitted Variables During Matching

A common criticism of matching is that it is unable to account for the effects of unobservables, which weakens its ability to derive truly similar samples. Though we have used many variables of importance for matching, there could still be omitted factors. We, therefore, ran two tests to check the sensitivity of our findings to omitted variables.

We first perform a Rosenbaum bounds sensitivity analysis to assess how strong the effect of unobservables needs to be for the validity of matching to be undermined (Rosenbaum 2002). Results of the Rosenbaum sensitivity analysis (Table A6) indicate that the unobserved variable bias needs to increase the odds of being treated by at least 2.6-fold and be a strong predictor of campaign success for the current results to be affected by it. This threshold is higher than the typical levels reported in social science research (Keele 2010). This suggests that our matching is robust against omitted variables.

Next, we run post-estimation tests to assess if our results remain robust with the inclusion of additional covariates that capture "unobservable" campaign characteristics. Specifically, we manually coded project innovativeness, project feasibility, owner ability/competence, and owner commitment based on project descriptions, and included them as covariates in matching and regressions. Such measures, which we chose based on a literature search, are arguably important but "unobservable" aspects of campaigns unless coded by human coders. The campaign labeling procedure and the results are described in online Appendix B. Should the matching on observables fail to capture the effects of such important unobservable factors, the inclusion of these new covariates would qualitatively alter the results (See Table B2 in Appendix B).

7.3 Alternative Specification using Traditional DID and Active Campaigns at the Time of Shock

We further evaluate the robustness of the results using a traditional DID test on a select sample of campaigns that experienced the site change during their fundraising period. In this test, we seek to understand if the daily contribution count of the reward campaigns experiences a change after the donation scheme is introduced, while differencing out any temporal effect using the change in contribution count of matched charity campaigns in the same period. In effect, the model specification here is similar to our main model, but the dependent variable becomes the number of daily contributions and the analysis is conducted at a campaign-day level instead (Equation 2). If the triple matching is invalid, then the sign and significance of its estimates would not be aligned with those derived under this DID specification.[17]

$$Contribution\ Count_{it} = \alpha \cdot Reward_i + \beta \cdot Post_{it} + \gamma \cdot (Reward_i \times Post_{it}) + \epsilon_i, \qquad (2)$$

To address concerns of incomparability between charity and reward campaigns, we run a DID analysis in which we use reward campaigns in the pre-shock period as control units. We matched the reward campaigns that were active during the site change with pre-shock reward campaigns, using the same covariates as before. Because the control campaigns did not experience a shock, they were assigned the same shock time as their matched treated campaign that they are matched with, so that the $Post_{it}$ variable and the interaction term can be estimated.[18]

After checking the validity of the differencing techniques (see Online Appendix D for details), we performed the traditional DID analysis at the day-contribution level, using reward and charity campaigns that experienced the shock live as treated and control groups (Equation 2). Campaign and day of the week fixed effects are added to the model. Model 1 of Table 5, we see that the interaction is positive and significant, indicating that the donation scheme increases the number of daily contributions received by the reward campaigns. Under this model, the introduction of the donation scheme to the campaigns increases the daily contribution frequency by 13.82, on average. It is also possible that charity campaigns have a different contribution pattern over their lifetime, making them inappropriate controls for reward campaigns. Thus, we utilize a set of matched reward campaigns from the pre-shock period as controls and adopt the same analysis framework in Model 2. The interaction coefficient remains positive and significant, indicating that the DID results are robust against the idiosyncrasies of campaign type. Specifically, under

[17] While this DID specification may seem like a better specification for this study, we argue that it is only good as a secondary reference to back up the results derived under the campaign level analysis. This is because contribution behaviors are known to be influenced by the prior contribution levels, and that reward campaigns can bear different dynamics in contribution patterns over time from charity campaigns. Furthermore, the DID analysis does not allow us to make inference on campaign success, which is arguably a more important outcome compared to contribution frequency, as campaigns are governed by an all-or-nothing rule.

[18] Because these campaigns are matched by duration, matched campaigns will have the same pre-treatment duration and post-shock duration.

Model 2, we see that the treated campaigns experienced about 15 more daily contributions, on average, in the period when the donation scheme was incorporated.

--Insert Table 5 here—

7.4 Falsification Test

An alternative explanation to the observed improvement in funding success in the reward campaigns is that the observed effects might occur spuriously due to a seasonal trend each year. To rule out this explanation, we repeat the main analysis using data from a year before the intervention (i.e., 2014), with August 2014 being the placebo treatment month. The results of this check are shown in Table A8. The interaction term is statistically insignificant in all the models tested, indicating that the observed effects did not arise because of seasonal contribution patterns.

8. Summary and Discussion

Motivated by the recent addition of a donation scheme at some leading reward crowdfunding platforms and the underexplored role of funding schemes, we examine the effect of adding a donation scheme to reward crowdfunding and explore its underlying mechanisms. Leveraging an unannounced site change at a leading crowdfunding platform that effectively affected only reward but not charity campaigns, we constructed matched samples of reward and charity campaigns before and after the site change, which we contrasted using a triple matching-DID technique. We found that the introduction of the donation scheme increased the success rate of reward campaigns by 19%. Several empirical checks validated the key assumptions of our estimation approach, and our findings remained stable to alternative specifications.

Our analyses suggest that the added donation scheme helped reward campaigns without reducing contributions to charity campaigns on the same platform. The increased campaign success came mainly from campaigns that received donations. We further found that the donation channel exerted both a primary and secondary effect. A nontrivial number of campaigns enjoyed the primary effect (i.e., received contributions from the donation channel), and those that did have a sizable proportion of their campaign goal met by the funds from the new channel. This finding lends support to the existence of backers who have strong altruistic motives that they would refuse to take tangible rewards to uphold their prosocial ideals. Interestingly, the donations produced a complementary secondary effect that increased the subsequent contributions through the reward channel. The positive secondary effect suggests that reward-seeking backers are likely to harbor altruistic motives not strong enough that would be activated and heightened by prosocial signals such as existing donations to campaigns. Our tests of heterogeneous effects show that the added donation channel primarily benefited reward campaigns with prosocial objectives.

Regarding the potential selection bias problem, as far as we know, campaign owners work with a listing agent to choose the payment scheme to list their campaigns under, there is no detail on how they arrive at the decision. However, for most cases, there is a natural fitting scheme (charity or reward) for each campaign. Some campaigns are only suitable for the reward scheme (e.g., a campaign involving a for-profit product). Likewise, some campaigns are only suitable for the donation scheme (e.g., a campaign that helps a poor child to go to school does not have tangible rewards to offer and thus may not be listed as a reward campaign). Overall, we expect that only a small portion of campaigns may not have a clear choice between the two schemes. Further, by matching reward campaigns before and after the shock, we ensure that reward campaigns before and after the shock are systematically similar, which helps mitigate selection-related issues.

8.1 Implications for Research

Our findings bear several implications for the existing literature. First, our findings have direct implications for the crowdfunding literature, particularly regarding the choice of funding schemes, which has received limited attention thus far (Allison et al. 2015; Ellman and Hurkens 2014). Apart from finding a positive overall effect of offering a donation channel along with a reward channel, we also gain insights on when and how the addition of a donation channel can help a reward campaign succeed. Specifically, the donation channel helped reward campaigns only if these campaigns can attract donations. Critically, reward campaigns with prosocial causes are the primary beneficiaries of the donation channel. This insight suggests that mixing reward and donation schemes is not always be beneficial and would only produce positive outcomes when the campaign objectives are aligned with altruistic motives. Further, our quantification of the relative contribution of the primary and secondary effects toward funding goals shows that the secondary effect of received donations is no less important than the primary effect. We further found that the added donation scheme enhanced the success rate of reward campaigns without reducing contributions to charity campaigns on the platform, suggesting that the positive effect of the added donation scheme should apply to cases where the platform only hosts reward campaigns.

Second, our findings speak to the literature on the interplay between tangible rewards and prosocial motives. While there are studies on how offering tangible rewards may crowd out (or, in some cases, crowd in) prosocial behavior (Burtch, Hong, Bapna, et al. 2018; Khern-am-nuai et al. 2018), the effect of offering a prosocial contribution channel alongside a reward channel has not been examined previously. Interestingly, the simultaneous offering of the two channels in our context did not result in a crowding out of prosocial behaviors. Instead, prosocial contributions spurred altruistic reward-seeking individuals to contribute to these campaigns. This finding is interesting because the literature has mainly focused on the one-way crowding effect from rewards to prosocial motives while we show the reverse can also happen. In the latter case, prosocial acts serve as information signals that align with the (weakly) altruistic motives of reward-seeking individuals, leading them to make more subsequent contributions. Future work may wish to extend this line of work by investigating other contextual factors that amplify this positive complementary secondary effect.

8.2 Implications for Practice

The study results provide a few key practical implications for crowdfunding sites and campaign owners. First, our results show that the funding scheme is an important design dimension, and platforms should not assume that the crowdfunding process can only be facilitated uniquely by only one funding scheme. In particular, we show that the addition of a donation scheme can heighten the success rate of reward campaigns substantially. Despite this positive outlook, campaign owners should note this positive effect works only on campaigns that have prosocial goals. To make the donation scheme more effective, crowdfunding sites should aim to enhance the desire to donate to campaigns hosted on the platforms. Second, given altruistic motives underlying contribution decisions are not very strong, campaign owners should take steps to highlight the prosocial aspects of their crowdfunding campaign. In particular, it is helpful to make clear the beneficiaries of the campaign, their needs, and also how the funds are used to address their needs. Third, our findings of a subsequent crowding-in effect of donations received meant that campaign owners could play a more active role in encouraging early donations to their campaign. Early contributions from the owner's direct social network tend to be fundamental for gaining the necessary momentum toward the campaign goal (Kuppuswamy and Bayus 2013). Our study found that early contributions in the form of donations are especially potent for inducing subsequent contributions, to which campaign owners should pay more attention.

8.3 Limitations and Future Research

This study is not without limitations. First, charity campaigns are not a perfect control group, despite our best effort to ensure the comparability between control and treatment groups. Furthermore, though we find no evidence of the charity campaigns being affected by the site change, we cannot completely rule out such a possibility. Future research may remedy such concerns through an experiment where a random sample of reward campaigns could be used as controls. Second, the match process itself is imperfect as it cannot match observable factors. While our sensitivity analyses show that this is not a significant concern, it remains a limitation of our study. Third, our results are based on one reward crowdfunding site. Future research could explore if the same results hold in other reward or equity crowdfunding sites. Finally, our initial analysis of mechanisms provided interesting cross-channel effects, but our explanations are still preliminary. Future research should further examine such interesting interactions between different funding schemes.

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Tables

Table 1A: Proportion of Campaigns by Type

Campaign Type	*Proportion*	*Category*	*Proportion*
		Science	1.03%
		Agriculture	14.09%
Reward	83.60%	Arts	6.72%
		Education	19.68%
		Entertainment	5.97%
		Product	12.59%
Charity	16.40%	Publishing	6.06%
		Others	33.86%

Table 1B: Summary Statistics

Variable	*Mean*	*Std. dev*	*Min*	*Max*	*Median*
DVs and IVs					
Success	0.29	0.46	0	1	0
Amount raised	10241.94	58428.87	0	2052718	464.50
Log amount Raised	5.61	3.43	0	14.53	6.14
No. of contributions	62.92	305.24	0	8944	9
Log no. of contributions	2.48	1.77	0	9.10	2.30
No. of backers	41.58	267.91	0	8069	6
Log no. of backers	2.15	1.59	0	9.00	1.95
Covariates					
Target amount solicited	39166.81	195416.10	500	6000000	10000
Log target amount solicited	9.24	1.50	6.22	15.61	9.21
Project duration (in days)	33.75	16.38	0	92	30
Log project duration	3.44	0.49	0	4.53	3.43
Length of project description	3378.69	2714.52	49	34309	2610.50
Log length of project description	7.82	0.82	3.91	10.44	7.87
No. of pictures posted	11.45	8.36	1	152	9
Log no. of pictures posted	2.32	0.67	0.69	5.03	2.30
Picture Quality	0.43	0.18	-0.03	1.62	0.42
No. of videos posted	0.10	0.37	0	6	0
Log no. of videos posted	0.07	0.22	0	1.95	0
No. of contribution tiers	5.03	2.10	1	36	5
Diff. bet. the highest and lowest tiers (in RMB)	9154.33	54457.04	1	2200000	880
Log diff. bet. the highest and lowest tiers	6.92	1.92	0.69	14.60	6.78
Owner's tenure (in days)	103.14	114.89	0	798	87
Log owner's tenure	4.10	1.21	0	6.68	4.48
Social media account listed	0.75	0.44	0	1	1
Education attainment listed	0.04	0.20	0	1	0
Citizenship ID listed	0.58	0.49	0	1	1
Business license listed	0.63	0.48	0	1	1
Location					
Eastern	0.31	0.46	0	1	0
Southern	0.16	0.37	0	1	0
Central	0.09	0.29	0	1	0
Northern	0.19	0.39	0	1	0
Northwestern	0.07	0.26	0	1	0
Southwestern	0.14	0.34	0	1	0
Northeastern	0.04	0.20	0	1	0
Not Disclosed	0.00	0.04	0	1	0

Note. Observations = 4060. We assign a number to each of the days in our study period (with an increasing number for each passing day). The Owner's tenure is the day number by which the owner joins the site.

Table 2A: Balance check for key covariates of charity campaigns matched across periods

Variable	Unmatched (U)	Mean		t-test		%bias	%reduction in |bias|
	Matched (M)	Before	After	t	p>|t|		
Length of the project description	U	8.53	8.35	4.31	0.00	33.7	69.0
	M	8.40	8.35	1.21	0.23	10.5	
No. of pictures posted	U	2.12	2.15	-0.87	0.38	-6.8	4.3
	M	2.13	2.08	-0.77	0.44	8.2	
Picture Quality	U	0.45	0.40	3.67	0.00	29.7	97.9
	M	0.40	0.40	-0.08	0.94	-0.6	
No. of contribution tiers	U	5.27	4.37	6.46	0.00	50.7	75.3
	M	4.59	4.37	1.64	0.10	12.5	
Diff. bet. highest and lowest tier	U	6.61	6.23	2.89	0.00	22.7	36.1
	M	6.47	6.23	1.65	0.10	14.5	
Target amount solicited	U	8.81	8.94	-1.22	0.22	-9.5	97.1
	M	8.93	8.94	-0.03	0.97	-0.3	
Project duration	U	3.42	3.28	3.47	0.00	27.2	56.4
	M	3.34	3.28	1.38	0.17	11.8	

Table 2B: Balance check for key covariates after the triple matching process

Variable	Unmatched	Mean		t-test		%bias	%reduction in |bias|
	Matched	Charity	Reward	t	p>|t|		
Length of the project description	U	8.44	7.75	24.87	0.00	102.3	97.6
	M	8.39	8.37	0.61	0.54	2.4	
No. of pictures posted	U	2.13	2.34	-8.87	0.00	-35.6	77.0
	M	2.13	2.08	1.68	0.09	8.2	
Picture Quality	U	0.42	0.43	-1.17	0.24	-4.2	7.1
	M	0.40	0.39	0.85	0.40	3.9	
No. of contribution tiers	U	4.82	5	-2.46	0.01	-9.6	76.5
	M	4.52	4.48	0.49	0.62	2.2	
Diff. bet. highest and lowest tier	U	6.46	6.96	-7.14	0.00	-27	96.7
	M	6.39	6.37	0.19	0.85	0.9	
Target amount solicited	U	8.88	9.29	-7.53	0.00	-28.9	92.4
	M	8.93	8.96	-0.44	0.66	-2.2	
Project duration	U	3.36	3.44	-4.34	0.00	-15.7	96.1
	M	3.33	3.32	0.11	0.91	0.6	

Table 3: LPM Regression of Success Probability

	Unmatched sample	Sample under triple matching	
	(1)	(2)	(3)
Reward project (Reward)	-0.31***	-0.34***	-0.37***
	(0.03)	(0.04)	(0.05)
Post site change (Post)	-0.15***	-0.20***	-0.17***
	(0.04)	(0.06)	(0.06)
Interaction (Reward × Post)	0.13***	0.20***	0.19***
	(0.04)	(0.06)	(0.06)
Log (Project description length)	0.03***	0.01	-0.02
	(0.01)	(0.03)	(0.03)
Log (No. of pictures posted)	0.04***	0.08***	0.09***
	(0.01)	(0.02)	(0.02)
Pictures quality	0.13***	0.02	-0.08
	(0.04)	(0.08)	(0.08)
Log (No. of videos posted)	0.06**	-0.02	-0.05
	(0.03)	(0.06)	(0.06)
No. of contribution tiers	0.02***	0.01	0.01
	(0.00)	(0.01)	(0.01)
Log (Diff. highest & lowest tier)	0.02***	0.03***	0.03**
	(0.00)	(0.01)	(0.01)
Log (Target amount)	-0.06***	-0.06***	-0.06***
	(0.01)	(0.01)	(0.01)
Log (Project duration)	-0.08***	-0.08***	-0.09***
	(0.01)	(0.03)	(0.03)
Log (Owner’s tenure)	0.01**	-0.00	-0.00
	(0.01)	(0.01)	(0.01)
Social media account listed	-0.35***	-0.42***	-0.41***
	(0.02)	(0.04)	(0.04)
Education attainment listed	0.02	0.08	0.05
	(0.03)	(0.07)	(0.07)
Citizenship ID listed	0.11***	0.10**	0.12***
	(0.02)	(0.04)	(0.04)
Business license listed	0.09***	0.11**	0.10**
	(0.02)	(0.04)	(0.04)
Location fixed effect added	√	√	√
Campaign category fixed effect added			√
R-squared	0.21	0.22	0.24
Observations	4060	1072	1072

*Note. The dependent variable is a binary variable that indicates whether a campaign has successfully reached its target goal. * p<0.10, ** p<0.05, *** p<0.01.*

Table 4: Logistic Regression of Campaign Success

	Unmatched sample	Sample under triple matching	
	(1)	(2)	(3)
Reward project (Reward)	0.23***	0.21***	0.16***
	(0.03)	(0.04)	(0.04)
Post site change (Post)	0.48***	0.39***	0.46**
	(0.10)	(0.11)	(0.14)
Interaction (Reward × Post)	1.60**	2.26***	2.18**
	(0.33)	(0.67)	(0.66)
Margins			
Charity, Pre-shock	0.60	0.62	0.61
Charity, Post-shock	0.45	0.43	0.45
Reward, Pre-shock	0.28	0.27	0.26
Reward, Post-shock	0.23	0.25	0.26
Δ in the probability of success post-shock			
Charity (Post-Pre)	-0.15	-0.19	-0.16
Reward (Post-Pre)	-0.04	-0.02	0.00
Reward - Charity	0.11	0.17	0.16
Location fixed effect added	√	√	√
Category fixed effect added			√
Log-likelihood	-1988.46	-592.61	-574.95
Adjusted R-squared	0.19	0.18	0.20
Observations	4060	1072	1072

*Note. The dependent variable is a binary indicator, indicating whether a campaign has successfully reached its target goal. All controls in Table 3 are also added to the models in this table. * p<0.10, ** p<0.05, *** p<0.01.*

Table 5: Effect of Site Change on the Number of Daily Contributions: DID Estimation

	Matched with During-Shock Charity Campaigns	Matched with Pre-Shock Reward Campaigns
Reward project (Reward)	-27.40***	-0.76
	(3.40)	(13.44)
Post site change (Post)	-15.28***	-18.68***
	(3.46)	(4.92)
Interaction (Reward × Post)	13.82**	15.00**
	(5.49)	(7.16)
Controls added	√	√
R-squared	0.09	0.01
Observations	3278	10630

*Note. The dependent variable is the number of contributions received daily. The estimates here are for the post site change indicator. All controls in Table 3 are also added to the models in this table. * p<0.10, ** p<0.05, *** p<0.01.*

Table 6: Impact of Donation Received on Campaign Outcomes

	Matched Sample			
	(1)	(2)	(3)	(4)
	Success Rate	Success Rate	Contribution Count	Monetary Amount
Reward project (Reward)	-0.34***	-0.39***	-0.10***	-3.03
	(0.04)	(0.05)	(0.00)	(5.69)
Post site change (Post)	-0.18***	-0.15***	-0.06***	-145.46***
	(0.05)	(0.05)	(0.01)	(16.23)
Interaction (Reward × Post)	0.04	0.03	0.09***	27.01**
	(0.06)	(0.06)	(0.01)	(10.84)
With Donation	0.40***	0.39***	0.02**	285.02**
	(0.06)	(0.06)	(0.01)	(11.05)
Controls added	√	√	√	√
Locations fixed effect added	√	√	√	√
Category fixed effect added		√		
User fixed effect added			√	√
R-squared	0.25	0.19	0.003	0.002
Observations	1072	1072	2,067,846	2,067,846

*Note. The set of controls are similar to the ones used in Table 3. * p<0.10, ** p<0.05, *** p<0.01.*

Table 7: Secondary Effect of Donations Received on Reward Contributions

	(1)	(2)	(3)
	Second Half Reward Amount		
Reward project (Reward)	-0.19**	-0.20**	-0.19**
	(0.04)	(0.09)	(0.04)
Post site change (Post)	-0.03	-0.04	-0.03
	(0.10)	(0.10)	(0.10)
Interaction	0.00	0.02	0.02
(Reward × Post)	(0.10)	(0.10)	(0.10)
Donation from First Half	0.12	0.28*	0.39**
	(0.10)	(0.15)	(0.18)
Early Full Amount	0.07***	0.07***	0.07***
	(0.01)	(0.01)	(0.01)
Controls added	√	√	√
Locations fixed effect	√	√	√
Category fixed effect	√	√	√
Early Donation Threshold	0%	2%	4%
R-squared	0.11	0.12	0.12
Observations	1072	1072	1072

*Note. The set of controls are similar to the ones used in Table 3. * p<0.10, ** p<0.05, *** p<0.01. The coding of Donation from First Half is as follows: For column (1), if the received donation amount in the first half is greater than 0, Donation from First Half is coded as 1, otherwise 0. For column (2), if the received donation amount in the first half is greater than 2% of the campaign target, Donation from First Half is coded as 1, otherwise 0. For column (3), if the received donation amount in the first half is greater than 4% of the campaign target, Donation from First Half is coded as 1, otherwise 0.*

Table 8: Which Post-Period Reward Campaigns Are More Likely to Receive Donations

	(1)	(2)
Prosocial	0.26***	0.26***
	(0.07)	(0.07)
Log (Project description length)	-0.03	-0.03
	(0.05)	(0.06)
Log (No. of pictures posted)	0.08**	0.08*
	(0.04)	(0.04)
Picture quality	0.14	0.13
	(0.17)	(0.18)
Log (No. of videos posted)	0.76	0.85
	(0.68)	(0.69)
No. of contribution tiers	0.05***	0.05***
	(0.02)	(0.02)
Log (Diff. highest & lowest tier)	-0.01	-0.00
	(0.02)	(0.02)
Log (Target amount)	0.01	0.01
	(0.02)	(0.02)
Log (Project duration)	0.13**	0.14**
	(0.07)	(0.07)
Log (Owner's tenure)	0.04	0.02
	(0.05)	(0.05)
Social media account listed	-0.23***	-0.23***
	(0.07)	(0.07)
Education attainment listed	0.15	0.12
	(0.10)	(0.10)
Citizenship ID listed	0.10	0.09
	(0.07)	(0.07)
Business license listed	-0.04	-0.01
	(0.07)	(0.07)
Location fixed effect added	√	√
Survey covariates added		√
R-squared	0.23	0.25
Observations	266	266

*Note. The dependent variable is a binary variable that indicates whether a post-period reward campaign receives donations or not. * p<0.10, ** p<0.05, *** p<0.01.*

Table 9: Heterogeneity Effects of Prosocial Elements on Success Probability

	(1)	(2)
Reward project (Reward)	-0.24***	-0.31***
	(0.01)	(0.06)
Post site change (Post)	-0.11**	-0.09*
	(0.02)	(0.06)
Interaction (Reward × Post)	0.07	0.07
	(0.06)	(0.06)
Prosocial	-0.00	-0.04
	(0.05)	(0.06)
Prosocial × Reward × Post	0.18**	0.16**
	(0.08)	(0.08)
Controls added	√	√
Survey covariates added	√	√
Location fixed effect added		√
Category fixed effect added		√
R-squared	0.27	0.30
Observations	1072	1072

Note. The dependent variable is a binary variable that indicates whether a campaign has successfully reached its target goal.
** p<0.10, ** p<0.05, *** p<0.01.*

Figures

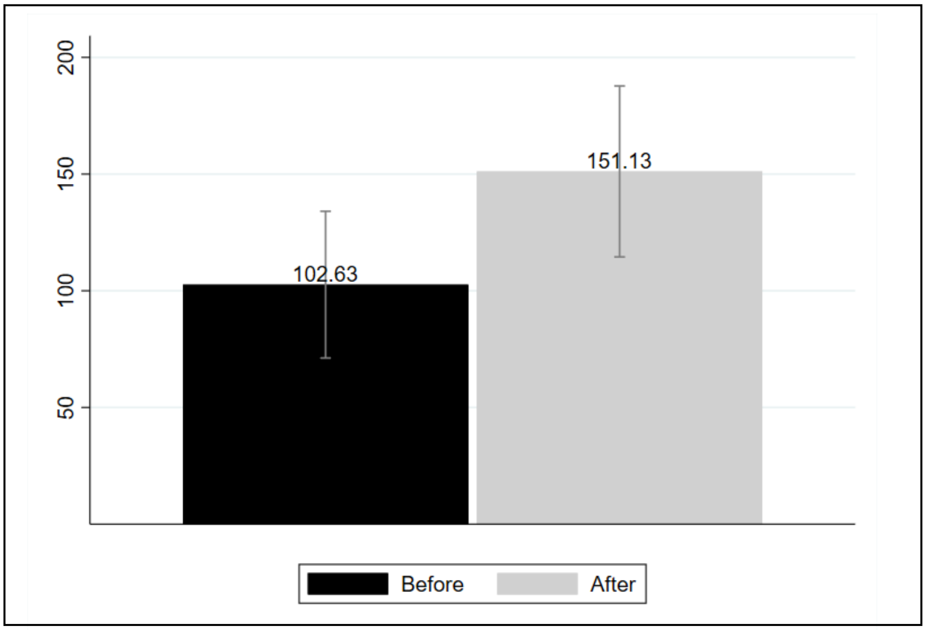


Figure 1A: Average weekly number of campaigns across study periods

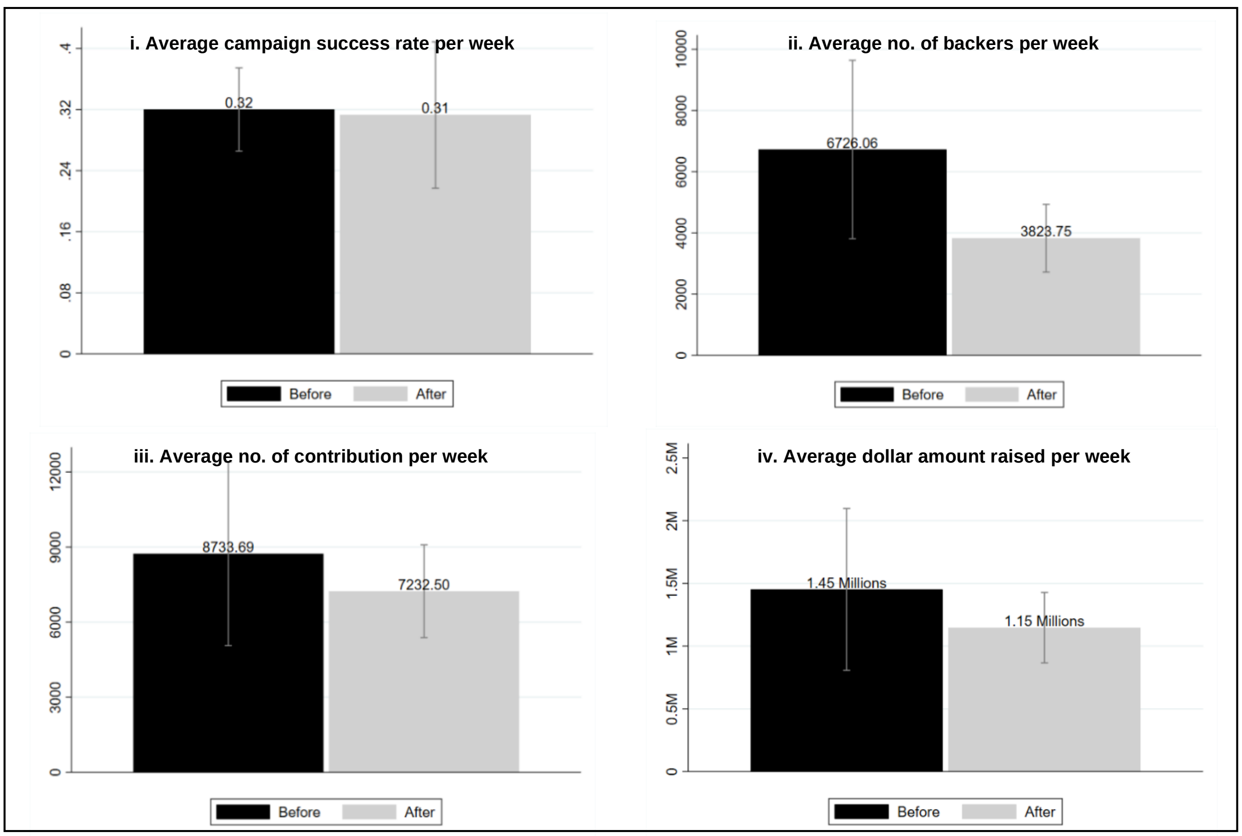


Figure 1B: Crowdfunding outcomes and patterns across study periods

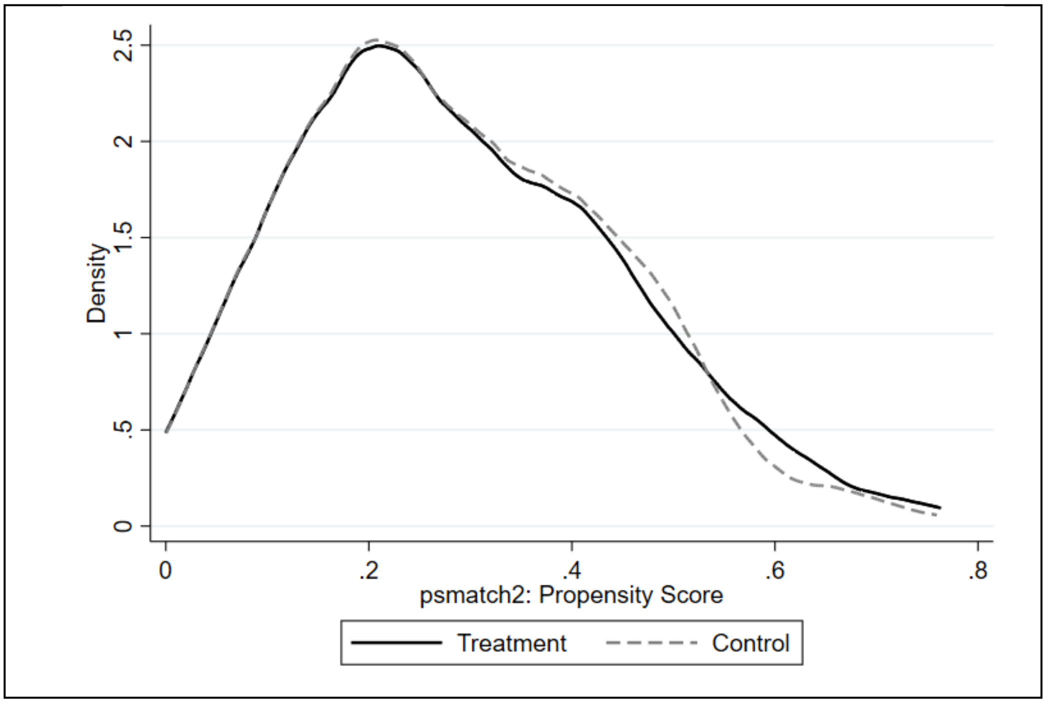
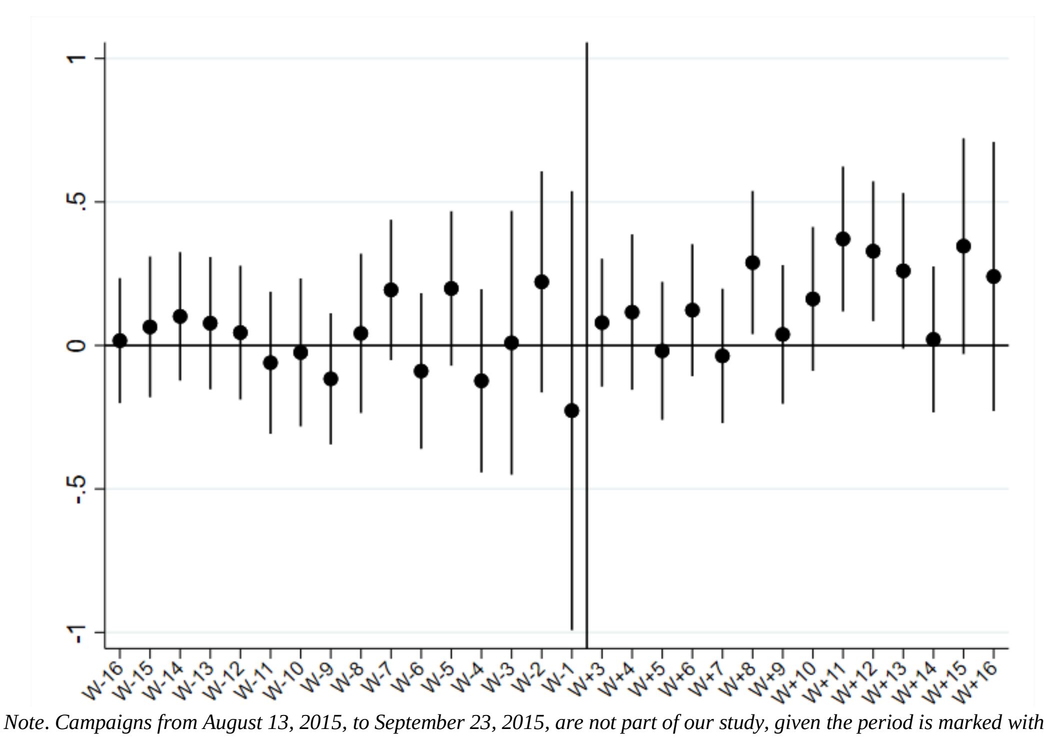


Figure 2: Distribution of p-scores of treated and control units



Note. *Campaigns from August 13, 2015, to September 23, 2015, are not part of our study, given the period is marked with site testing of the feature. The first week in the post-shock period were omitted as the reference weeks.*

Figure 3: Leads-lag analysis of treatment effect on campaign success

Appendix A

Table A1: Funding Schemes of Major Reward-based Crowdfunding Platforms (current as of Oct, 2021)

Crowdfunding Sites	URL	Geography	Funding Schemes
Pozible	*https://www.pozible.com/*	Australia	Reward+Donation
Kickante	*https://www.kickante.com.br/*	Brazil	Reward+Donation
Zhongchou	*http://www.zhongchou.cn/*	China	Reward+Donation
PolakPotrafi	*https://polakpotrafi.pl/*	Poland	Reward+Donation
Crowdfunder	*https://www.crowdfunder.co.uk/*	United Kingdom	Reward+Donation
Kickstarter	*https://www.kickstarter.com/*	United States	Reward+Donation
CROFUN	*https://www.crofun.be/nl/*	Belgium	Reward Only
JD Crowdfunding	*https://z.jd.com/*	China	Reward Only
Babeldoor	*https://www.babeldoor.com/fr*	France	Reward Only
Blue Bees	*https://bluebees.fr/en/*	France	Reward Only
KissKissBankBank	*https://www.kisskissbankbank.com/*	France	Reward Only
Ulule	*https://www.ulule.com/*	France	Reward Only
Mesenaatti	*https://mesenaatti.me/*	Finland	Reward Only
100 Fans	*https://100fans.de/*	Germany	Reward Only
Fund It	*https://fundit.ie/*	Ireland	Reward Only
PPL	*https://ppl.pt/*	Portugal	Reward Only
Apontoque	*http://www.apontoque.com/es/*	Spain	Reward Only
Wemakeit	*https://wemakeit.com/*	Switzerland	Reward Only
PledgeMusic	*https://www.pledgemusic.com/*	United Kingdom	Reward Only
ArtistShare	*http://www.artistshare.com/*	United States	Reward Only
Crowd Supply	*https://www.crowdsupply.com/*	United States	Reward Only
Fig	*https://www.fig.co/*	United States	Reward Only
Indiegogo	*https://www.indiegogo.com/*	United States	Reward Only
Patreon	*https://www.patreon.com/*	United States	Reward Only
Seed&Spark	*https://www.seedandspark.com/*	United States	Reward Only

Table A2: Summary Statistics of Reward Campaigns in the Pre-Treatment Period

Variable	*Mean*	*Std. dev*	*Min*	*Max*	*Median*
Success	0.26	0.44	0	1	0
Amount raised	15039.75	89144.02	0	2052718	459.50
Log amount Raised	5.69	3.47	0	14.53	6.13
No. of contributions	84.86	504.94	0	8944	8
Log no. of contributions	2.42	1.75	0	9.10	2.20
No. of backers	69.06	468.40	0	8069	6
Log no. of backers	2.18	1.65	0	8.99	1.95
Target amount solicited	36136.71	101920.40	500	1500000	10000
Log target amount solicited	9.29	1.49	6.22	14.22	9.21
Project duration (in days)	34.98	17.33	0	90	30
Log project duration	3.46	0.55	0	4.51	3.43
Length of project description	3397.31	2823.91	51	34309	2603.50
Log length of project description	7.85	0.77	3.95	10.44	7.86
No. of pictures posted	11.83	8.28	1	55	10
Log no. of pictures posted	2.34	0.68	0.69	4.03	2.40
Picture Quality	0.46	0.19	0.06	1.14	0.45
No. of videos posted	0.23	0.50	0	5	0
Log no. of videos posted	0.15	0.30	0	1.79	0
No. of contribution tiers	5.15	2.05	1	18	5
Diff. bet. highest and lowest tier (in RMB)	11864.65	74699.07	1	2200000	1000
Log diff. bet. highest and lowest tier	7.21	1.95	0.69	14.60	6.91
Owner's tenure (in days)	85.65	121.71	0	790	28
Log owner's tenure	3.45	1.53	0	6.67	3.37
Is social media account listed	0.99	0.12	0	1	1
Is education attainment listed	0.00	0.05	0	1	0
Is citizenship ID listed	0.97	0.17	0	1	1
Is business license listed	0.97	0.17	0	1	1
Location					
Eastern	0.32	0.47	0	1	0
Southern	0.17	0.38	0	1	0
Central	0.09	0.29	0	1	0
Northern	0.23	0.42	0	1	0
Northwestern	0.03	0.18	0	1	0
Southwestern	0.11	0.31	0	1	0
Northeastern	0.04	0.18	0	1	0
Not Disclosed	0.00	0.03	0	1	0

Note. Observations = 1244. We assign a number to each of the days in our study period (increasing number for each passing day). Owner's tenure refers to the number of days since by which the campaign owner has since joined the site.

Table A3: Summary Statistics of Charity Campaign in the Pre-Treatment Period

Variable	*Mean*	*Std. dev*	*Min*	*Max*	*Median*
Success	0.59	0.49	0	1	1
Amount raised	11359.61	54360.58	0	1000290	2643
Log amount Raised	7.34	2.54	0	13.82	7.88
No. of contributions	85.87	186.08	0	2803	36
Log no. of contributions	3.43	1.55	0	7.94	3.61
No. of backers	54.55	88.31	0	1049	25
Log no. of backers	3.07	1.50	0	6.96	3.24
Target amount solicited	16202.24	35748.60	500	500000	5000
Log target amount solicited	8.81	1.24	6.22	13.12	8.52
Project duration (in days)	33.54	16.73	5	90	30
Log project duration	3.42	0.50	1.79	4.51	3.43
Length of project description	5592.19	2580.69	213	21110	5148
Log length of project description	8.53	0.48	5.37	9.96	8.55
No. of pictures posted	8.25	4.70	1	35	7
Log no. of pictures posted	2.12	0.46	0.69	3.58	2.08
Picture Quality	0.45	0.21	-0.01	1.62	0.42
No. of videos posted	0.30	0.58	0	6	0
Log no. of videos posted	0.20	0.33	0	1.95	0
No. of contribution tiers	5.27	1.73	1	12	5
Diff. bet. highest and lowest tiers (in RMB)	4225.71	25992.51	1	500000	500
Log diff. bet. highest and lowest tiers	6.61	1.71	0.69	13.12	6.21
Owner’s tenure (in days)	47.68	81.59	0	423	13
Log owner’s tenure	2.93	1.34	0	6.05	2.63
Is social media account listed	0.98	0.12	0	1	1
Is education attainment listed	0.00	0.00	0	0	0
Is citizenship ID listed	0.98	0.12	0	1	1
Is business license listed	0.98	0.12	0	1	1
Location					
Eastern	0.13	0.34	0	1	0
Southern	0.08	0.28	0	1	0
Central	0.16	0.37	0	1	0
Northern	0.15	0.35	0	1	0
Northwestern	0.08	0.26	0	1	0
Southwestern	0.39	0.49	0	1	0
Northeastern	0.01	0.11	0	1	0
Not Disclosed	0	0	0	0	0

Note. Observations = 398.

Table A4: Summary Statistics of Reward Campaigns in the Post-Treatment Period

Variable	*Mean*	*Std. dev*	*Min*	*Max*	*Median*
Success	0.24	0.42	0	1	0
Amount raised	7478.03	34732.15	0	672499	237
Log amount Raised	5.11	3.47	0	13.42	5.47
No. of contributions	44.94	140.67	0	3604	7
Log no. of contributions	2.24	1.74	0	8.19	2.08
No. of backers	23.12	75.69	0	1576	4
Log no. of backers	1.89	1.49	0	7.36	1.61
Target amount solicited	47668.56	256001.60	500	6000000	10000
Log target amount solicited	9.33	1.55	6.22	15.61	9.21
Project duration (in days)	33.57	15.52	2	90	30
Log project duration	3.45	0.44	1.10	4.51	3.43
Length of project description	2776.60	2407.95	49	20378	1960
Log length of project description	7.61	0.82	3.91	9.92	7.58
No. of pictures posted	12.14	9.00	1	152	10
Log no. of pictures posted	2.36	0.69	0.69	5.03	2.40
Picture Quality	0.42	0.17	-0.03	1.31	0.40
No. of videos posted	0.01	0.12	0	5	0
Log no. of videos posted	0.00	0.05	0	1.79	0
No. of contribution tiers	5.00	2.20	1	36	5
Diff. bet. highest and lowest tier (in RMB)	9323.71	47231.24	1	999999	800
Log diff. bet. highest and lowest tier	6.90	1.93	0.69	13.82	6.69
Owner’s tenure (in days)	122.79	115.16	32	798	87
Log owner’s tenure	4.64	0.48	3.50	6.68	4.48
Is social media account listed	0.60	0.49	0	1	1
Is education attainment listed	0.07	0.26	0	1	0
Is citizenship ID listed	0.32	0.47	0	1	0
Is business license listed	0.40	0.49	0	1	0
Location					
Eastern	0.33	0.47	0	1	0
Southern	0.18	0.38	0	1	0
Central	0.08	0.27	0	1	0
Northern	0.18	0.39	0	1	0
Northwestern	0.09	0.28	0	1	0
Southwestern	0.09	0.29	0	1	0
Northeastern	0.05	0.22	0	1	0
Not Disclosed	0.00	0.03	0	1	0

Note. Observations = 2150.

Table A5: Summary Statistics of Charity Campaign in the Post-Treatment Period

Variable	*Mean*	*Std. dev*	*Min*	*Max*	*Median*
Success	0.48	0.50	0	1	0
Amount raised	8484.81	25048.45	0	291646	1334
Log amount Raised	6.70	2.85	0	12.58	7.20
No. of contributions	71.28	114.09	0	1025	29
Log no. of contributions	3.21	1.67	0	6.93	3.38
No. of backers	42.78	74.19	0	730	16
Log no. of backers	2.75	1.54	0	6.59	2.80
Target amount solicited	19131.74	31244.48	500	300000	7574
Log target amount solicited	8.93	1.42	6.22	12.61	8.93
Project duration (in days)	29.70	17.33	1	92	28
Log project duration	3.29	0.53	0.69	4.53	3.37
Length of project description	4835.30	2443.45	361	18680	4467
Log length of project description	8.36	0.53	5.89	9.84	8.40
No. of pictures posted	8.89	5.65	1	37	8
Log no. of pictures posted	2.15	0.53	0.69	3.64	2.20
Picture Quality	0.40	0.16	0.09	0.97	0.37
No. of videos posted	0.01	0.11	0	1	0
Log no. of videos posted	0.01	0.07	0	0.69	0
No. of contribution tiers	4.35	1.80	1	10	4
Diff. bet. highest and lowest tier (in RMB)	2534.19	6765.62	10	50000	500
Log diff. bet. highest and lowest tier	6.21	1.71	2.40	10.82	6.22
Owner’s tenure (in days)	109.01	76.87	59	620	87
Log owner’s tenure	4.59	0.38	4.09	6.43	4.48
Is social media account listed	0.43	0.50	0	1	0
Is education attainment listed	0.09	0.28	0	1	0
Is citizenship ID listed	0.26	0.44	0	1	0
Is business license listed	0.33	0.47	0	1	0
Location					
Eastern	0.35	0.48	0	1	0
Southern	0.08	0.28	0	1	0
Central	0.10	0.30	0	1	0
Northern	0.13	0.34	0	1	0
Northwestern	0.09	0.29	0	1	0
Southwestern	0.21	0.41	0	1	0
Northeastern	0.03	0.16	0	1	0
Not Disclosed	0.00	0.03	0	1	0

Note. Observations = 268.

Table A6: Rosenbaum Sensitivity Analysis for PSM

Gamma	Sig+	Sig-	t-hat+	t-hat-	CI+	CI-
1	0	0	0.5	0.5	2.6e-07	0.5
1.1	1.1e-16	0	0.5	0.5	-2.6e-07	0.5
1.2	3.2e-14	0	2.6e-07	0.5	-2.6e-07	0.5
1.3	2.9e-12	0	2.6e-07	0.5	-2.6e-07	0.5
1.4	1.3e-10	0	-2.6e-07	0.5	-2.6e-07	0.5
1.5	3.0e-09	0	-2.6e-07	0.5	-2.6e-07	0.5
1.6	4.6e-08	0	-2.6e-07	0.5	-2.6e-07	0.5
1.7	4.7e-07	0	-2.6e-07	0.5	-2.6e-07	0.5
1.8	3.5e-06	0	-2.6e-07	0.5	-2.6e-07	0.5
1.9	0.00002	0	-2.6e-07	0.5	-2.6e-07	0.5
2	0.000088	0	-2.6e-07	0.5	-2.6e-07	0.5
2.1	0.000327	0	-2.6e-07	0.5	-2.6e-07	0.5
2.2	0.001019	0	-2.6e-07	0.5	-2.6e-07	0.5
2.3	0.002743	0	-2.6e-07	0.5	-2.6e-07	0.5
2.4	0.006501	0	-2.6e-07	0.5	-2.6e-07	0.5
2.5	0.013782	0	-2.6e-07	0.5	-2.6e-07	0.5
2.6	0.026494	0	-2.6e-07	0.5	-2.6e-07	0.5
2.7	0.046728	0	-2.6e-07	0.5	-2.6e-07	0.5
2.8	0.076387	0	-2.6e-07	0.5	-2.6e-07	0.5
2.9	0.116769	0	-2.6e-07	0.5	-2.6e-07	0.5
3	0.168219	0	-2.6e-07	0.5	-2.6e-07	0.5

gamma - log odds of differential assignment due to unobserved factors
sig+ - upper bound significance level
sig- - lower bound significance level
t-hat+ - upper bound Hodges-Lehmann point estimate
t-hat- - lower bound Hodges-Lehmann point estimate
CI+ - upper bound confidence interval (a= .95)
CI- - lower bound confidence interval (a= .95)

Table A7: Robustness Check of the Matching Procedure

	No replacement matching with Stricter Caliper			
	Caliper	Caliper =0.05	Caliper =0.1	CEM
	(1)	(2)	(3)	(4)
Reward project (Reward)	-0.30***	-0.34***	-0.31***	-0.37***
	(0.05)	(0.04)	(0.04)	(0.06)
Post site change (Post)	-0.24***	-0.27***	-0.27***	-0.37***
	(0.07)	(0.06)	(0.06)	(0.09)
Interaction (Reward × Post)	0.17**	0.23***	0.21***	0.21***
	(0.07)	(0.06)	(0.06)	(0.08)
Controls added	√	√	√	√
R-squared	0.20	0.24	0.23	0.29
Observations	732	860	876	516

Table A8: Falsification Test on Success Probability for non-treatment year

	Unmatched sample	Sample under two-step
	(1)	(2)
Reward project (Reward)	-0.06	0.02
	(0.05)	(0.06)
Post site change (Post)	-0.03	-0.06
	(0.06)	(0.06)
Interaction (Reward × Post)	0.03	-0.05
	(0.06)	(0.09)
Controls added	√	√
R-squared	0.13	0.19
Observations	1764	456

*Note. The dependent variable is a binary indicator, indicating whether a campaign has successfully reached its target goal. All controls in Table 3 are also added to the models in this table. * p<0.10, ** p<0.05, *** p<0.01.*

Table A9: User-Decision Analysis for Previous Charity Backers

(DV:)	Contributing to a campaign or not
Reward project (Reward)	-0.0007**
	(0.0003)
Post site change (Post)	0.002
	(0.0021)
Interaction (Reward × Post)	-0.004***
	(0.0006)
User-time fixed effect added	√
Observations	325,696

*Note. * p<0.10, ** p<0.05, *** p<0.01.*

Appendix B

We run post-estimation tests to assess if our results remain robust with the inclusion of additional covariates that capture unobservable campaign characteristics. Essentially, we are contrasting the original estimation results with those derived from a regression which includes a set of previously unused variables (in matching and regression). This test is akin to the idea of using a holdout dataset in machine learning to assess if the results are robust toward unseen data points. Should the matching on observables fail to capture the effects of important unobservable factors, the inclusion of these new covariates would qualitatively alter the results. Specifically, we include the measures of project innovativeness, project feasibility, owner ability/competence, and owner commitment, which are arguably unobservable aspects of campaigns that are not readily captured by the observable covariates unless solicited via human coders. The survey items are given in Table C1.

Table B1: Survey Items

Campaign's innovativeness	
Uniqueness	This campaign is unique
Originality	This campaign is original
Novelty	This campaign is novel
Campaign's feasibility	
Market feasibility	This campaign is feasible from the perspective of market
Operation feasibility	The operation cost of this campaign is under a reasonable range
Campaign owner's ability	
Capability	The owner/team of this campaign has appropriate capabilities
Campaign owner's commitment	
Motivation	The owner/team of this campaign has a strong motivation to make this campaign successful
Passion	The owner/team of this campaign are passionate about the campaign
Campaign's category	What category does this campaign belong to?
Coder's familiarity	You are familiar with this kind of campaigns
Coder's interest	You are interested in this kind of campaigns

Note. All attitudinal items were measured on Likert scales anchored on "5=Strongly agree", "4=Agree","3=Neither agree nor disagree", "2=Disagree", and "1=Strongly disagree". The campaign's categories in multiple choice question include: agriculture, publishing, entertainment, science, arts, education, product, store, and others.

Campaign Labeling Procedure

Each campaign was read and labeled by two evaluators. Each evaluator was assigned to label about 350 campaigns to prevent effects of fatigue from affecting their labeling efforts. All evaluators were given sufficient time to perform the labeling (two weeks) so that they were not rushed. Evaluators did not know one another and performed the labeling independently. At the end of the labeling exercise, the evaluators were paid for their efforts using the standard RA payout rate at the authors' institute. The evaluators were aware of the payout rate prior to labeling the campaigns.

While the scores given by the independent evaluators are supposed to reflect personal, subjective assessment of the various attributes of the crowdfunding campaigns, we did notice that there was a large amount of agreement in the items across evaluators. Given that different users who saw the campaign on the crowdfunding site can have differing views of the campaign, we took the campaign score for each item based on each of the average scores received, to allow subjectivity in evaluation to be captured.

We further test the sensitivity of unobservables by including the list of new covariates on campaign innovativeness, campaign feasibility, owner competence, and motivations. Table C2 shows that the inclusion of these variables compresses the magnitude of the interaction term but does not change its direction or significance.

Table B2: Inclusion of Unused Perceptual Covariates to Main Regression Model

	Sample under two-step matching		Matched Sample under DID	
	(1)	(2)	(3)	(4)
Reward project (Reward)	-0.34***	-0.37***	-0.26***	-0.28***
	(0.04)	(0.05)	(0.04)	(0.05)
Post site change (Post)	-0.20***	-0.17***	-0.11**	-0.10*
	(0.06)	(0.06)	(0.06)	(0.06)
Interaction (Reward × Post)	0.20***	0.19***	0.12**	0.12**
	(0.06)	(0.06)	(0.05)	(0.05)
Log length of project description	0.01	-0.02	-0.02	-0.03
	(0.03)	(0.03)	(0.03)	(0.03)
Log no. of pictures posted	0.08***	0.09***	0.06**	0.07***
	(0.02)	(0.02)	(0.02)	(0.02)
Pictures quality	0.02	-0.08	-0.00	-0.07
	(0.08)	(0.08)	(0.08)	(0.08)
Log no. of videos posted	-0.02	-0.05	-0.02	-0.04
	(0.06)	(0.06)	(0.06)	(0.06)
No. of contribution tiers	0.01	0.01	0.02*	0.02*
	(0.01)	(0.01)	(0.01)	(0.01)
Log diff. bet. highest & lowest tier	0.03***	0.03**	0.02**	0.02**
	(0.01)	(0.01)	(0.01)	(0.01)
Log target amount solicited	-0.06***	-0.06***	-0.06***	-0.07***
	(0.01)	(0.01)	(0.01)	(0.01)
Log project duration	-0.08***	-0.09***	-0.07***	-0.07***
	(0.03)	(0.03)	(0.02)	(0.02)
Log owner's tenure	-0.00	-0.00	-0.00	0.00
	(0.01)	(0.01)	(0.01)	(0.01)
Is social media account listed	-0.42***	-0.41***	-0.42***	-0.41***
	(0.04)	(0.04)	(0.04)	(0.04)
Is education attainment listed	0.08	0.05	0.03	0.02
	(0.07)	(0.07)	(0.07)	(0.07)
Is citizenship ID listed	0.10**	0.12***	0.14***	0.15***
	(0.04)	(0.04)	(0.04)	(0.04)
Is business license listed	0.11**	0.10**	0.14***	0.14***
	(0.04)	(0.04)	(0.04)	(0.04)
Uniqueness			-0.03	-0.02
			(0.03)	(0.03)
Originality			0.01	0.01
			(0.02)	(0.02)
Novelty			0.11***	0.11***
			(0.03)	(0.03)
Market feasibility			-0.00	0.00
			(0.02)	(0.02)
Operation feasibility			-0.03	-0.04
			(0.03)	(0.03)

Owner's Capability			0.11***	0.09***
			(0.03)	(0.03)
Owner's Motivation			0.04	0.03
			(0.05)	(0.05)
Owner's Passion			0.06	0.07
			(0.05)	(0.05)
Locations fixed effect added	√	√	√	√
Category fixed effect added		√		√
Survey covariates added			√	√
R-squared	0.22	0.24	0.28	0.29
Observations	1072	1072	1072	1072

*Note. The dependent variable is a binary indicator, indicating whether a campaign has successfully reached its target goal. Detailed survey instruments are available in Appendix B. * p<0.10, ** p<0.05, *** p<0.01.*

Appendix C

<u>Image Quality Score</u>

BRISQUE is a no-reference image quality assessment model that uses scene statistics of locally normalized luminance coefficients to measure the "naturalness" in an image due to the presence of elements such as blur, noise, and watermarking (Mittal et al., 2012). In other words, the BRISQUE model measures deviations from natural images (i.e., those captured by an optical camera). Research shows that BRISQUE is highly competitive to other no-reference image-quality assessment approaches and can be efficiently computed (Mittal et al., 2012).

A low BRISQUE score indicates that a picture is likely unedited or unprocessed, while a high BRISQUE score indicates that a picture has likely been processed. Pictures that have undergone image processing are likely to be aesthetically more pleasing, given that their colors, hues, and tones are adjusted and enhanced to appeal to visual senses. For example in the figures below, the unprocessed/unedited image (a) has a lower BRISQUE score than a digitally processed/edited image (b).

The BRISQUE score for all images in each campaign is first computed. After which, we take the average of these scores for each campaign as the campaign's *picture quality*. A higher picture quality score indicates the use of a greater proportion of digitally enhanced photos, which are also visually more appealing.[1]

BRISQUE = 34.19 BRISQUE = 44.51

Angrist, J. D., & Pischke, J. S. (2008). *Mostly harmless econometrics: An empiricist's companion*. Princeton University Press.

Autor, D. H. (2003). Outsourcing at Will: The Contribution of Unjust Dismissal Doctrine to the Growth of Employment Outsourcing. *Journal of Labor Economics*, *21*(1), 1–42. https://doi.org/10.1086/344122

Mittal, A., Moorthy, A. K., & Bovik, A. C. (2012). No-Reference Image Quality Assessment in the Spatial Domain. *IEEE Transactions on Image Processing*, *21*(12), 4695–4708. https://doi.org/10.1109/TIP.2012.2214050

[1] In addition to BRISQUE, a holistic measure of image quality, we also calculated other specific metrics of images, including colorfulness, blurriness, hue, situation, and brightness that may have to do a campaign's appeal. However, none of these other metrics is correlated with campaign outcomes.

Appendix D

There is also a need to directly validate the differencing technique that was used to derive the estimates. To this end, we look towards the requirements in the standard DID literature for guidance. A core identification assumption in the DID framework is that the dependent variable needs to follow a similar pre-shock trend in the treatment and control group (Angrist & Pischke, 2008). We test the identification assumption using the regression framework established in the literature (Autor, 2003). Specifically, we test for the differences in the campaign success between the reward and charity campaigns under a flexible leads-lags specification with month dummies. The absence of a pre-shock trend, as exhibited by the lack of statistical difference in outcomes between the two groups in the pre-shock period, implies that the parallel trends assumption is satisfied. Finally, the results from the estimation framework above may simply arise spuriously. To rule out this possibility, we perform a falsification test where we re-run the main analysis in an earlier period when the donation scheme is not provided to the reward campaigns. Here, we place a placebo treatment indicator in the same month of an earlier year. If the placebo variable picks up a significant positive effect, it would mean that the results in the main analysis might simply be detecting a seasonal pattern that affects campaign success on the site.

Angrist, J. D., & Pischke, J. S. (2008). *Mostly harmless econometrics: An empiricist's companion*. Princeton University Press.

Autor, D. H. (2003). Outsourcing at Will: The Contribution of Unjust Dismissal Doctrine to the Growth of Employment Outsourcing. *Journal of Labor Economics*, *21*(1), 1–42. https://doi.org/10.1086/344122

Mittal, A., Moorthy, A. K., & Bovik, A. C. (2012). No-Reference Image Quality Assessment in the Spatial Domain. *IEEE Transactions on Image Processing*, *21*(12), 4695–4708. https://doi.org/10.1109/TIP.2012.2214050