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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, we examine the effect of adding a donation scheme to reward-based crowdfunding and explore its underlying mechanisms. This work also helps to fill the knowledge gap on the role of funding schemes. Leveraging an unannounced site change at a leading crowdfunding platform, we estimated the impact of introducing the donation scheme by developing and applying a novel two-step matching and difference-in-differences technique for cohorted quasi-experimental settings. We find that the introduction of the donation scheme increased the success rate of reward campaigns by 19%. The increased success occurred mainly in reward campaigns with prosocial causes. Further analyses of underlying mechanisms reveal that the 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, but also a secondary "crowd-in" effect on the reward channel, as shown by a positive impact of early donations on subsequent contributions through the reward channel, beyond the known effects of early contributions. 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 to be more willing to contribute through the reward channel.

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1. Introduction

Originally a fundraising tool for supporting artists, 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 (Hemer 2011, Cholakova and Clarysse 2015). 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 interest plus payback; and an equity scheme that offers shares of a start-up. In practice, most crowdfunding platforms offer only one funding scheme. For instance, Indiegogo, GoFundMe, AngelList, and LendingClub offer the reward, donation, equity, and debt schemes, respectively, as the sole funding scheme on their crowdfunding platforms. Only a handful of exceptions exist. For example, Kickstarter and Zhongchou[1] allow backers to choose between donations and contributions in exchange for rewards (henceforth reward contributions) (See Online 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 crowdfunding industry's reliance on purist funding schemes stands in contrast with the evidence that campaign backers have diverse motivations: some are motivated by tangible rewards, whereas others are motivated by prosocial causes, such as advancing education, reducing poverty, and helping disadvantaged individuals or groups (Gerber and Hui 2013, Dai and Zhang 2019). The lack of mixed funding schemes to serve diverse backers raises an interesting question: would crowdfunding campaigns perform better by offering mixed funding schemes instead of a single funding scheme? More specifically, with major crowdfunding platforms, for example, Kickstarter and Zhongchou,

beginning to accept donations on their reward crowdfunding platforms, we are interested in knowing whether or when adding a donation scheme to reward campaigns can improve the fundraising outcomes.

With the addition of the donation scheme on a reward crowdfunding platform, backers are effectively offered two contribution channels: reward and donation. Offering mixed funding schemes is analogous to pursuing a multichannel strategy. The multichannel literature suggests that such strategies do not always lead to more customers or higher profitability (Rosenbloom 2007). One risk of multichannel strategies is that the additional channel may be composed largely of customers who originate from existing channels, resulting in "channel cannibalization" rather than attracting new customers (Rosenbloom 2007). This can be especially problematic if the newly added channel is less profitable than the existing ones (Moriarty and Moran 1990). There can be other conflicts between channels: poorly designed multichannels can confuse customers and lead to suboptimal experiences in each channel, driving customers to competitors (Rosenbloom 2007). Similar concerns exist for the mixed funding scheme in crowdfunding; for example, the added donation could cannibalize the existing reward channel and cause confusion in terms of the campaign's value proposition. It is, therefore, imperative to systematically study whether and how the adding of a donation scheme can affect the reward scheme and overall campaign performance.

More specifically, for the mixed donation–reward scheme to be successful, one hopes that (a) some backers contribute via the added donation channel and (b) the donations received stimulate further contributions through the reward channel. Neither effect should be taken for granted for the following reasons. First, there are known conflicts between tangible rewards and charitable contributions. Prior literature on prosocial behavior suggests that tangible rewards may crowd out the incentives to donate (Ariely et al. 2009). This raises the issue of whether a nontrivial fraction of backers would choose to receive the tangible rewards instead of making donations when both options are offered. Second, it is unclear how these two channels interact with each other. Would the added donations reduce the contribution through the reward channel (i.e., when backers simply switch from the reward channel to the donation channel), creating a cannibalization effect? Or would the donations increase the receipt of reward-based contributions, creating a "synergistic" effect? To address these uncertainties, we examine both the primary effect of adding a donation channel, that is, whether or when the added channel can lead to a nontrivial amount of donations, and the secondary effect, that is, how donations affect contributions through the reward channel. These effects are fundamental for understanding when and how the adding of a donation scheme can improve the overall funding performance.

To gain insights on these issues, 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 could only accept reward contributions and charity campaigns could only accept donations. In August 2015, the site added a donation option to reward campaigns, allowing them to accept both donations and reward contributions. We develop and employ a novel two-step matching process to form a pool of statistically identical reward and charity campaigns before and after the site change. We then use the matched campaigns to estimate the impact of the new donation scheme on reward campaigns' success under a difference-in-differences (DID) framework. A battery of empirical checks is performed to ascertain that estimation assumptions are reasonable and 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 with campaigns having prosocial goals being the primary beneficiaries. 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 nontrivial amounts of donations received, 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 the 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 identifies 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 (Belleflamme et al. 2014, Allison et al. 2015). To the best of our knowledge, our work is the first systematic study that empirically examines the impact of simultaneously using reward and donation schemes.

Second, our work contributes to the literature on the interplay between tangible rewards and prosocial motives on online platforms. Whereas the existing literature investigates 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 elements along with monetary incentives in their corporate events (e.g., prosocial

marketing and promoting employee volunteerism). Our unique setting provides an opportunity for examining the effect of combining rewards and prosocial motives in the context of crowdfunding.

Finally, we make a methodological contribution in this work. In estimating the effect of the added donation scheme, we had to work with 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 before and after the treatment are not available. To address this issue, we develop a novel two-step matching technique to create statistically identical samples of both reward and charity campaigns before carrying out the DID estimation.[2] We offer a theoretical proof of the proposed approach's unbiasedness and asymptotic consistency and demonstrate how it can be applied in practical settings along with a set of checks to ascertain the soundness of the approach. As the first empirical information systems (IS) paper that develops and applies the two-step matching technique for cohorted treatment, our work serves to formally introduce this estimation method to the IS research.

2. Related Literature

2.1. Crowdfunding Success

An extensive literature focuses 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 (Zhang and Liu 2012, Burtch et al. 2013, Kuppuswamy and Bayus 2013). 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, Mollick 2014, Lin and Viswanathan 2016). Moreover, the social capital of campaign owners can also play a role in influencing crowdfunding success, especially in the early stage of fundraising (Lin et al. 2013, Colombo et al. 2015). 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 (Pope and Sydnor 2011, Greenberg and Gerber 2014, Mitra and Gilbert 2014, Mollick 2014, Allison et al. 2015, Cordova et al. 2015, Kunz et al. 2017). Finally, the support patterns of backers also shed light on the funding decision and process of crowdfunding campaigns (Solomon et al. 2015). Whereas 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 attempts to fill this gap by shedding light on the design of funding schemes. For instance, Burtch et al. (2018) and Wash and Solomon (2014) examine 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, preordering and profit-sharing, using theoretical modeling. Through the use of surveys, Cholakova and Clarysse (2015) investigate whether investors 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. Multichannel Management

The mixing of donation and reward funding schemes is analogous to multichannel strategies studied in retailing (Barlow et al. 2004, Van Bruggen et al. 2010, Krafft et al. 2015), for example, offering both e-commerce and brick-and-mortar channels (Gundlach et al. 2006, Kozlenkova et al. 2015) to both supply chain and financial services contexts (Easingwood and Storey 1996, Coelho and Easingwood 2003). Whereas the multichannel literature often points to its benefits of serving the needs of multiple customer segments and expanding access to a company's offerings, it also highlights a few downsides of multichannel strategies, for example, bearing the risk of confusing consumers by exposing them to conflicting product offerings in different channels (Easingwood and Storey 1996). As a result, a multichannel strategy may not always outperform a single-channel strategy. For example, Coelho et al. (2003) find that the use of multiple channels can sometimes lower profitability and produce less reliable service. According to sales data from a major U.S. retailer, some segments of customers of a single channel have a higher level of channel loyalty and/or stickiness than those of multichannel offerings (Thomas and Sullivan 2005).

Furthermore, the multichannel literature also cites channel conflict and cannibalization as frequent problems. For example, in the retail context, cannibalization of customers and sales results if a new channel too closely mimics the entrenched channels (Deleersnyder et al. 2002) or offers far superior capabilities (Alba et al. 1997). In a related study, Webb and Hogan (2002) find that the frequency of conflict can negatively affect channel performance. Overall, the multichannel literature finds that a multichannel strategy is not necessarily better than a single-channel one. A successful multichannel strategy is ultimately dependent on whether an optimal channel mix or portfolio can be achieved (Coelho et al. 2003, Rosenbloom 2007). Poorly designed multichannel efforts can result in suboptimal and problematic outcomes

(e.g., increase consumers' dissatisfaction) that can drive customers toward competitors (Rosenbloom 2007).

Funding schemes as channels are not merely different ways of contributing to a campaign, but also offer distinct types of benefits to backers. This, combined with the complex interaction between motivations for reward- and donation-based contributions, distinguishes the focal study of mixed funding schemes from the existing multichannel literature.

2.3. Backer Motivations

There are various motivations why backers 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 prominent motivations for backing decisions in a few studies (e.g., Freedman and Jin 2011, Zhang and Liu 2012, Lin et al. 2013, Bapna 2019, Li et al. 2020). However, recent research finds 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, whereas 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) find 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 to 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.

2.4. Contribution Dynamics

Our examination of the secondary effect is related to the literature on contribution dynamics. Extant research shows 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, Zhang and Liu 2012, Bapna 2019). 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 et al. 2020). Whereas these economic considerations predict a reinforcement effect of early contributions, Burtch et al. (2013) find 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 these 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 choosing between multiple channels (e.g., brick-and-mortar, catalog, internet) 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 can 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 maximize their utility (Balasubramanian et al. 2005) or meet 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 than the existing channel (Avery et al. 2012). Meanwhile, there can also be complementarity between multiple channels. For example, multiple channels allow consumers to be served by a channel that better fits their shopping needs, resulting in a goodness-of-fit effect (Huang et al. 2016).

Using multichannel shopping as an analogy, we argue that backers 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, that is, the contributions through the new donation channel, and the secondary effect, that is, 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 shows that backers can be motivated to support a campaign that offers no tangible rewards (Gerber and Hui 2013, Dai and Zhang 2019). 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 adequate to motivate people to donate. As with multichannel consumers, backers facing both donation and reward channels must face the trade-off in the expected utility of the two channels. When impure altruists contribute through the reward channel, they can derive utility from the reward, but the utility from a warm glow would be much lower. This is because prior research shows 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 the warm glow from donation strongly outweighs the utility of rewards, would they choose the donation channel over the reward one.

These analyses suggest that the new donation channel could attract altruistic backers who weigh the feeling of a 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).

Hypothesis 1 (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 nonprofit 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 not only seeks economic returns for the fruit retailer, but also helps reduce poverty for fruit farmers in the village as well. Such reward campaigns are more likely to appeal to altruistic backers who identify with the prosocial causes of the campaigns and are more willing to donate.

Hypothesis 2. *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 (Zhang and Liu 2012, Burtch et al. 2013). For example, research finds that prior contributions may create rational herding signals that increase subsequent backers' likelihood of contribution (Zhang and Liu 2012, Bapna 2019). 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 argue 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 as one individual's prosocial behavior can prompt other individuals to adopt similar prosocial behaviors (Tsvetkova and Macy 2015, Dimant 2019), 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 the owner's 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 because of an enhanced sense of warm glow and, thus, are more willing to contribute. Therefore, we hypothesize a positive secondary effect.

Hypothesis 3 (The Secondary Effect). *Holding the total amount of early contributions constant, reward campaigns with early donations 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 toward 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.

Hypothesis 4 (The Overall Effect). *The addition of the donation channel to reward campaigns increases their likelihood of success.*

Similar to Hypothesis 2, we also hypothesize that the overall effect of the donation channel is more salient among reward campaigns that feature prosocial causes.

Hypothesis 5. *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. Similar to 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 in which the campaign's target goal is met. Since its inception in 2013, the crowdfunding platform has raised more than 200 million renminbi (RMB) and has hosted more than 13,500 campaigns with a funding success rate of 30.7%. The site caters to a variety of crowdfunding categories, including science, agriculture, arts, education, entertainment, product, and others (see Table 1 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 six weeks, which is comparable to campaign durations from other crowdfunding sites.[3] 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.

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, whereas 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 is quite small, we broadly categorize the contributions to charity campaigns as donations.[4] On August 27, 2015, the platform introduced a donation scheme to its reward campaign. Effectively, all postshock reward campaigns have a donation channel in addition to the reward channel. The donation scheme for these postshock reward campaigns is similar to those used in charity campaigns. Backers are

Table 1. Proportion of Campaigns by Type

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

to specify the dollar amount they wish to donate. The site change resembles a quasi-experimental 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 preshock and postshock periods.

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 preshock and postshock periods. We made an intentional decision to leave 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.[5] Our resultant data set has 16 weeks of campaigns in each of the preshock and postshock periods. In our data set, 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 intercampaign differences.

Just as higher quality ads can signal a marketer's confidence in a product's quality and potential success (Nelson 1974, Moorthy and Hawkins 2005), 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.[6] The quality score for each image in each campaign is computed and 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 one when the campaign is successfully funded and zero otherwise. A detailed description of our data set is shown in Table 2. Finer breakdowns of summary statistics by campaign type and study period are provided in Online Appendix A. Figure 1 shows the number of campaigns hosted by the platform across the preshock and postshock periods, by which we see that the average number of campaigns posted weekly increased by about 47% in the later period. In Figure 2, we see that the crowdfunding outcomes (campaign success, number of backers, number of contributions, and amount raised) are slightly worse in the postshock period though not significantly different from that in the preshock period. However, with a net increase in the number of campaigns initiated on the site (776 more campaigns) in the postshock 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.[7] We bear this critical information in mind as we interpret our results in the subsequent sections.

4.2. Estimation of the Main Effect Using Two-Step Matching

The introduction of the donation scheme in reward campaigns on Zhongchou.com provides us with the opportunity to assess its impact on campaign success and address 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 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 preshock and postshock periods within each group plays the role of removing intergroup 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 resulting from temporal effects, which accounts for the differences in success rates across the preshock and postshock periods.

Table 2. Summary Statistics

Variable	Mean	Standard deviation	Minimum	Maximum	Median
DVs and IVs					
Success	0.29	0.46	0	1	0
Amount raised	10,241.94	58,428.87	0	2,052,718	464.50
Log amount raised	5.61	3.43	0	14.53	6.14
Number of contributions	62.92	305.24	0	8,944	9
Log number of contributions	2.48	1.77	0	9.10	2.30
Number of backers	41.58	267.91	0	8069	6
Log number of backers	2.15	1.59	0	9.00	1.95
Covariates					
Target amount solicited	39,166.81	195,416.10	500	6,000,000	10,000
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	3,378.69	2,714.52	49	34,309	2,610.50
Log length of project description	7.82	0.82	3.91	10.44	7.87
Number of pictures posted	11.45	8.36	1	152	9
Log number 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
Number of videos posted	0.10	0.37	0	6	0
Log number of videos posted	0.07	0.22	0	1.95	0
Number of contribution tiers	5.03	2.10	1	36	5
Difference bet. the highest and lowest tiers (in RMB)	9,154.33	54,457.04	1	2,200,000	880
Log difference 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

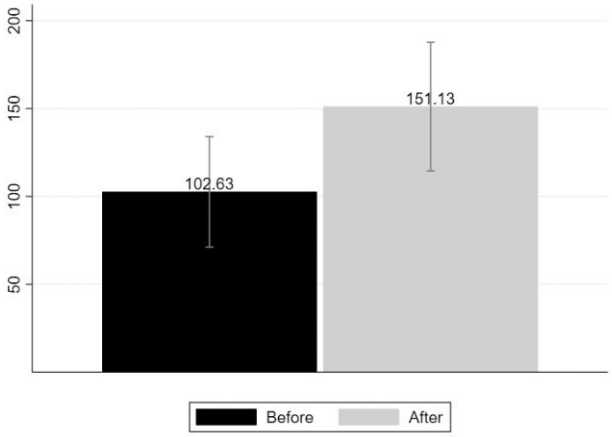
Notes. Observations = 4,060. We assign a number to each of the days in our study period (with an increasing number for each passing day). The owner's tenure is the day number by which the owner joins the site.

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 in which outcomes of the treated and control units are observed in both the preshock and postshock periods. Our context represents a cohorted treatment: the treatment only affected reward campaigns that were either active or would be launched but not the reward campaigns that had ended. Consequently, the preshock reward campaigns are not the same campaigns as the postshock ones, making a traditional DID estimation unsuitable.

To accommodate the cohorted-treatment situation, we propose a two-step matching procedure that first matches preshock and postshock units from the control group. Then, in the second round of matching, it matches preshock treatment units with preshock control units and postshock treatment units with postshock control units. The two-step matching ensures that not only are the treated and control units statistically comparable in both pretreatment and posttreatment periods, but also the preshock and postshock units in the same group are statistically comparable. This enables us to conduct a DID estimation on the two-step matched samples. In Online Appendix E, we provide formal proof of the unbiasedness and consistency of the two-step matching DID estimator. We note that the two-step matching DID procedure we develop here is generally applicable to cohorted-treatment settings.

Applying the two-step matching to our specific research setting, 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, number of pictures,

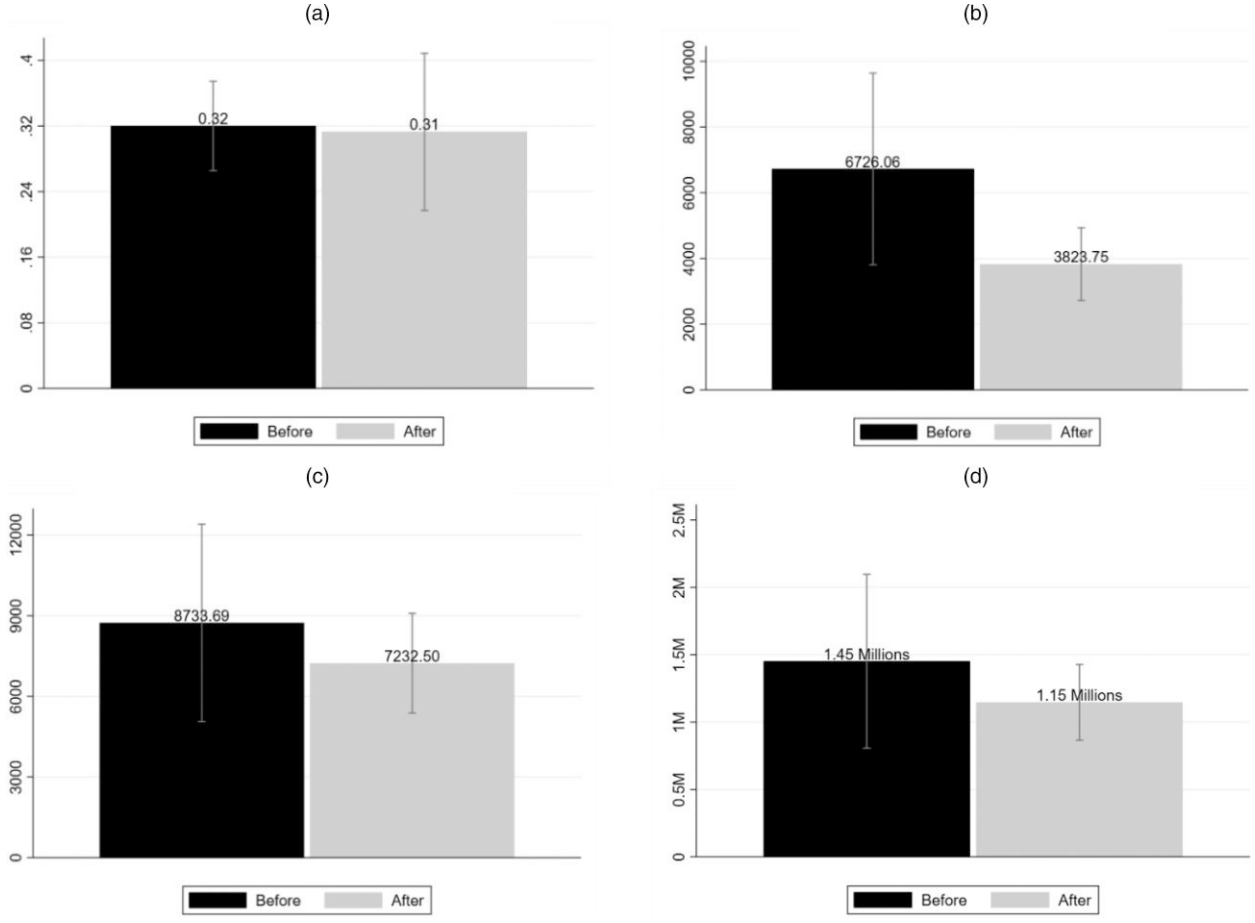
Figure 1. Average Weekly Number of Campaigns Across Study Periods



picture quality, number of contribution tiers, the monetary difference in the highest and lowest tiers, target amount, and project duration). Effectively, this matching removes postshock charity campaigns that cannot be reasonably matched to a preshock charity campaign.

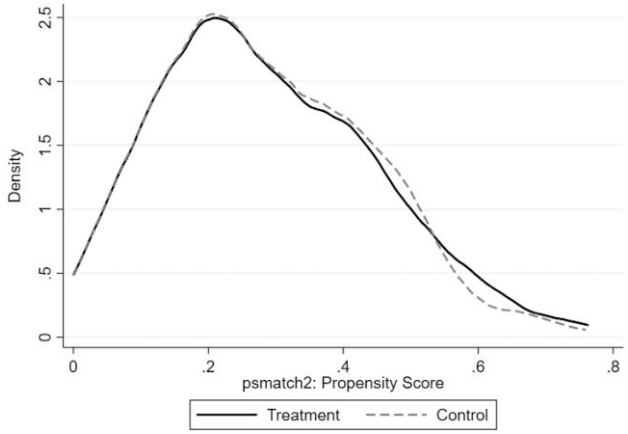
In the second step, we conduct another round of matching in which the reward campaigns (i.e., treated campaigns) are matched to the charity campaigns (i.e., control campaigns) in the respective preshock and postshock periods. That is, reward campaigns in the preshock period are matched to charity campaigns of the same period, whereas another matching is further performed for campaigns in the postshock period.[8] With two rounds of matching, we arrive at a sample of reward and charity campaigns that are statistically comparable across periods. Results of the statistical comparison of the covariates of the campaign types are shown in Table 3. Under the standard 5% significance level, *t*-tests reveal that all covariates are statistically similar between the reward and charity

Figure 2. Crowdfunding Outcomes and Patterns Across Study Periods



Notes. (a) Average campaign success rate per week. (b) Average number of backers per week. (c) Average number of contribution per week. (d) Average dollar amount raised per week.

Figure 3. Distribution of *p*-Scores of Treated and Control Units



campaigns. The overall quality of the two-step matching process is shown in Figure 3, in which 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.

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 Hypothesis 4 and can be easily modified to test out Hypotheses 3 and 5. To assess the impact of the donation channel on reward campaigns, we estimate the following model:

$$CampaignSuccess_i = \alpha \cdot Reward_i + \beta \cdot Post_i + \gamma \cdot (Reward_i \times Post_i) + \theta \cdot \boldsymbol{X_i} + \epsilon_i, \quad (1)$$

where i indexes the campaign. Our main campaign outcome variable is $CampaignSuccess_i$, which denotes whether campaign i was successfully funded.[9] 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. Preanalyses 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 preshock period are statistically indistinguishable from that of charity campaigns posted in the postshock period (Table 4). 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 controls, we need to ensure that they are not affected by the treatment. One potential threat is a potential "displacement"

Table 3. Balance Check for Key Covariates After the Two-Step Matching Process

		Mean		*t*-test			
Variable	Unmatched (U) / Matched (M)	Charity	Reward	*T*	$p > \|t\|$	%bias	%reduction in |bias|
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	
Number 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	
Number 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	
Difference between 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 4. Balance Check for Key Covariates of Charity Campaigns Matched Across Periods

	Unmatched (U)	Mean		*t*-test			
Variable	Matched (M)	Before	After	*T*	$p > \|t\|$	%bias	%reduction in |bias|
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	
Number 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	
Number 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	
Difference between 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	

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 to be profit-oriented (instead of charity-focused objectives of charity campaigns), and their rewards tend to be tangible products (instead of owner 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 focuses on contribution patterns to charity campaigns before and after the treatment. If there is a displacement effect, we 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 is 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.[10]

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, that is, 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. The variable $Post_t$ indicates whether the decision time t is postshock. The variable $Reward_j$ indicates whether the campaign j is a reward type. The term α_{it} is the user-decision fixed effect, and ε_{ijt} is the error term. We are 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 Online 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.

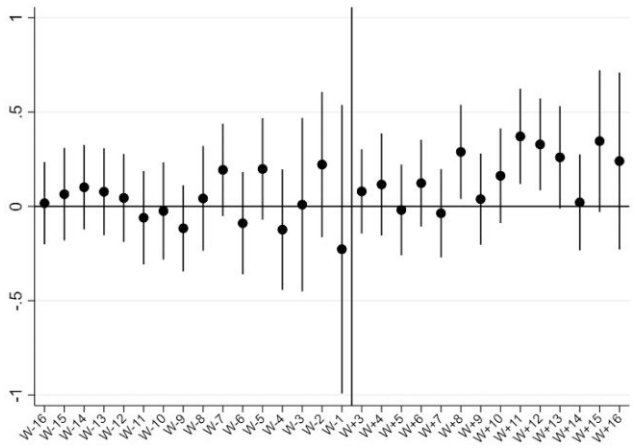
5.2.3. A Further Check via a Randomized Online Experiment. Though the previous analyses show that there were no significant shifts in the charity campaign's contribution patterns, availability, or backer preference between the two types of campaigns, it is plausible that, absent the treatment, charity 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 that are randomly selected from our sample. Each participant was asked to select a campaign to which to contribute. 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 is 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 lead–lag 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 4 with the first week of treatment ($W + 1$) being the baseline week.[11] 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.[12] This supports the parallel trends assumption. We further note that the success rate of reward campaigns displays an upward trend

Figure 4. Lead–Lag Analysis of Treatment Effect on Campaign Success



Notes. 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 postshock period was omitted as the reference week.

in the postshock 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), whereas other weeks do not. Thus, this improvement in success rate was not uniformly observed across the postperiods. 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.[13] This trend suggests that the positive impact of the donation scheme only materializes when the treated campaigns receive actual donations. We explore why this relationship arises in a subsequent test.

6. Results

6.1. Overall Effect

Because Equation (1) is our main specification from which most of the other empirical tests are derived, we first report the analysis results for the overall effect (i.e., Hypothesis 4), followed by those for hypotheses regarding the primary and secondary effects (i.e., Hypotheses 1–3). Our campaign-level analysis relies on a linear probability model (LPM), and we report its results in Table 5. 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 two-step 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 Hypothesis 4.

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 postshock 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 postshock period indicates that the success rate of reward campaigns improved in

Table 5. LPM Regression of Success Probability

	Unmatched sample	Sample under the two-step matching PSM	
	(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 (Number 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 (Number of videos posted)	0.06**	−0.02	−0.05
	(0.03)	(0.06)	(0.06)
Number of contribution tiers	0.02***	0.01	0.01
	(0.00)	(0.01)	(0.01)
Log (Difference highest and 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^2	0.21	0.22	0.24
Observations	4,060	1,072	1,072

Note. The dependent variable is a binary variable that indicates whether a campaign has successfully reached its target goal.

*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

the postshock 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 to be 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 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.[14] Finally, geographical indicators have a significant impact on funding success (omitted because of space limitation), which aligns with past results (Agrawal et al. 2011, Lin and Viswanathan 2016).

We further test a logit specification for the main analysis given the binary nature of our dependent variable (Table 6). The odds ratios of the interaction term are consistently larger than one, implying a positive effect of the donation scheme on reward campaigns. Because the magnitude of interaction terms in nonlinear models cannot be directly interpreted (Ai and Norton 2003), we

Table 6. Logistic Regression of Campaign Success

	Unmatched sample	Sample under the two-step matching PSM	
	(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, Preshock	0.60	0.62	0.61
Charity, Postshock	0.45	0.43	0.45
Reward, Preshock	0.28	0.27	0.26
Reward, Postshock	0.23	0.25	0.26
Δ in the probability of success postshock			
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	−1,988.46	−592.61	−574.95
Adjusted R^2	0.19	0.18	0.20
Observations	4,060	1,072	1,072

Notes. The dependent variable is a binary indicator, indicating whether a campaign has successfully reached its target goal. All controls in Table 5 are also added to the models in this table.
*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

follow 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% 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.

6.2. Potential Mechanisms

Thus far, our main analyses uncover 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 postshock reward campaigns that received funds via the donation channel.[15] Table 8 shows that postshock reward campaigns with donations experienced a positive

Table 7. Effect of Site Change on the Number of Daily Contributions: DID Estimation

	Matched with during-shock charity campaigns	Matched with preshock 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^2	0.09	0.01
Observations	3,278	10,630

Notes. The dependent variable is the number of contributions received daily. The estimates here are for the post site change indicator. All controls in Table 5 are also added to the models in this table.
*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

Table 8. Impact of Donation Received on Campaign Outcomes

	Matched sample			
	(1) Success rate	(2) Success rate	(3) Contribution count	(4) 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^2	0.25	0.19	0.003	0.002
Observations	1,072	1,072	2,067,846	2,067,846

Note. The set of controls is similar to the ones used in Table 5.
*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

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 lead–lag model wherein a significant positive effect was observed only in weeks in which there were a significant number of reward campaigns with donations.

Table 9. 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 (Reward × Post)	0.00	0.02	0.02
	(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 added	√	√	√
Category fixed effect added	√	√	√
Early donation threshold, %	0	2	4
R^2	0.11	0.12	0.12
Observations	1,072	1,072	1,072

Notes. The set of controls is similar to the ones used in Table 5. 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 zero, donation from first half is coded as one and otherwise zero. 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 one and otherwise zero. 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 one and otherwise zero.
*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

6.2.2. The Primary Effect. With this 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, scope and intensity. We operationalize scope as the proportion of treated campaigns with donations. We find that the scope of the primary effect is practically sizable with 39% of all postshock reward campaigns receiving donations from the new channel. We operationalize intensity as the ratio of the donation amount to the campaign goal. 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 Hypothesis 1: 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, $Reward\ Amount_{i,second}$, on the presence of donations in the first half of the same campaign, $With\ Donation_{i,first}$. 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 $Total\ Amount_{i,first}$. The resultant regression specification is shown in Equation (2).

$$\delta \cdot Donation_{i,\ first} + \vartheta \cdot Total\ Amount_{i,first} + \theta \cdot \boldsymbol{X_i} + \epsilon_i, \tag{2}$$

Table 9, 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 Hypothesis 3.

Table 10. Which Postperiod 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 (Number of pictures posted)	0.08**	0.08*
	(0.04)	(0.04)
Picture quality	0.14	0.13
	(0.17)	(0.18)
Log (Number of videos posted)	0.76	0.85
	(0.68)	(0.69)
Number of contribution tiers	0.05***	0.05***
	(0.02)	(0.02)
Log (Difference highest and 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^2	0.23	0.25
Observations	266	266

Note. The dependent variable is a binary variable that indicates whether a postperiod reward campaign receives donations or not.
*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

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%–48% of the overall effect, whereas the secondary effect is responsible for 52%–60% of the overall effect.[16]

6.2.4. Heterogeneous Effects and Underlying Motives.

We further investigate which set of campaigns is more likely to benefit from the donation channel. We hypothesized that reward campaigns with prosocial causes are more likely to receive donations (Hypothesis 2) and benefit from the added donation channel (Hypothesis 5). 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 postshock reward campaign to be prosocial if it has any of the prosocial causes listed by an official national classification.[17]

We first regress the binary indicator of whether a campaign received donations on the prosocial variable for reward campaigns in the postperiod. The results of this regression are shown in Table 10. After conditioning for the various characteristics of the campaigns, we find that reward campaigns with prosocial objectives are more likely to receive donations, supporting Hypothesis 2. To further understand if the prosocial reward campaign also translates to a greater likelihood of funding success in the postperiod, we further include the prosocial variable and its interaction with the DID term in our main model. As reported in Table 11, 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, Hypothesis 5 is also supported.

Table 11. 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^2	0.27	0.30
Observations	1,072	1,072

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

To further understand the nature of the motives of the backers who contributed to the postreward 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 are more willing to contribute before the campaign goal is reached because their marginal impact on campaign success is 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 postreward campaign to go from 95% to 100% and from 100% to 105%. We then statistically contrast the pregoal funding speed with the postgoal 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.

7. Robustness Checks

7.1. Sensitivity to Matching Parameters and Algorithms

We next assess the sensitivity of the matching process to alternative matching parameters and algorithms. First, we use stricter caliper sizes to see if the results change. Second, we also utilize coarsened exact matching to examine the sensitivity to matching algorithms. Online Table A6 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 use 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 (Online Table A7) 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 postestimation 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 Online Table B2).

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, 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 3). If the two-step matching is invalid, then the sign and significance of its estimates would not be aligned with those derived under this DID specification.[18]

$$Contribution\ Count_{it} = \alpha \cdot Reward_i + \beta \cdot Post_{it} + \gamma \cdot (Reward_i \times Post_{it}) + \epsilon_i, \tag{3}$$

To address concerns of incomparability between charity and reward campaigns, we run a DID analysis in which we use reward campaigns in the preshock period as control units. We matched the reward campaigns that were active during the site change with preshock 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 with which they are matched so that the $Post_{it}$ variable and the interaction term can be estimated.[19]

After checking the validity of the differencing technique (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 3). Campaign and day of the week fixed effects are added to the model. In Model 1 of Table 7, 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 preshock 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 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.

7.4. Falsification Test

An alternative explanation for the observed improvement in funding success in the reward campaigns is that the observed effects might occur spuriously because of 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 Online 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 two-step matching and 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 find that the donation channel exerted both primary and secondary effects. 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; there is no detail on how they arrive at the decision. However, in 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 2019). 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 beneficial and only produces 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 find that the added donation scheme enhances 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 in which the platform only hosts reward campaigns.

Second, our findings speak to the literature on the interplay between tangible rewards and prosocial motives, specifically relating to crowding-in effects. Whereas there are studies on how offering tangible rewards may crowd out (or, in some cases, crowd in) prosocial behavior (Burtch 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, creating a unique crowd-in effect. This finding is interesting because the literature mainly focuses on the one-way crowding effect from rewards to prosocial motives, whereas we show the reverse type of crowding-in can 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 they can only use one funding scheme. In particular, we show that the addition of a donation scheme can increase the success rate of reward campaigns substantially. However, the added donation channel does not always improve crowdfunding outcomes. As demonstrated in our study, this positive effect only works on campaigns that have prosocial causes. Hence, to make the added donation scheme more effective, crowdfunding sites should provide mechanisms for finding reward campaigns with prosocial causes, for example, by providing tags or search filters related to prosocial causes and promoting or featuring such campaigns more prominently. Second, similarly, campaign owners should take steps to uncover and highlight the prosocial aspects of their crowdfunding campaign, for example, by revising campaign descriptions to include prosocial keywords/tags. Third, our findings of a crowding-in effect of early donations means that campaign owners could play an active role in encouraging early donations to their campaign. The owner's direct social network is a potential source for gaining such early donations (Kuppuswamy and Bayus 2013). Relatedly, the campaign owners could benefit from spreading the word about the early donations they receive.

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 in which a random sample of reward campaigns could be used as controls. Second, the match process itself is imperfect as it cannot match observable factors. Whereas 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 provides 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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Endnotes

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

[2] While our manuscript was under review, we discovered a working paper by Keele et al. (2019) that offers a proof of a similar approach. As our manuscript was first submitted in 2015, our work was dated much earlier than Keele et al. (2019) and is developed independent of their work.

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

[4] Whereas 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.

[5] This precautionary step allows the sample of pretreatment 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.

[6] The image-processing model, BRISQUE, is used to compute the image quality scores for the images. Please see Online Appendix C for more details about this image quality measure.

[7] The chief information officer of the site further validated this insight.

[8] In the first step in which we match charity-based campaigns across preperiods and postperiods, 270 out of 398 charity campaigns in the preperiod were matched. In the second step of the matching, 270 out of 1246 reward campaigns in the preperiod were matched, and 268 out of 2,152 reward campaigns in the postperiod were matched.

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

[10] There is no significant difference between the average number of backers for charity campaigns in the preshock period (M = 54.27, SD = 90.87) and that in the postshock 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 preshock period (M = 92.29, SD = 214.61) and that in postshock 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 the preshock period (M = 13,521.44, SD = 64,415.77) and that in the postshock period (M = 8,484.81, SD = 25,048.45); $t(536) = 1.19$, $p = 0.23$.

[11] 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.

[12] The pretreatment weeks close to the treatment shock have fewer campaigns to begin with as there are not as many campaigns with crowdfunding durations lasting two 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.

[13] 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 postshock weeks.

[14] 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 nonresponse may cause these backers to lose confidence in these owners, resulting in a reduced propensity to contribute to their campaigns.

[15] 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.

[16] The average target amount of postperiod reward campaigns that received any donation is $39,000.96, 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 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 $18,024.69. For the first type of campaign, the donation-induced reward amount raised in the second half is 0.28 × 18,024.69 = $5,047, which represents (5,047/39,000.96) × 100 = 13% of the target goal of the focal campaigns. For the second set of campaigns, the donation-induced reward amount raised in the second half is 0.39 × 18,024.69 = $7,029, which represents (7,029/39,000.96) × 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 the secondary effect increases with the early donation amount received, that is, 52% to 60%.

[17] According to the Charities Act 2011 of the United Kingdom (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).

[18] Whereas 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 with contribution frequency as campaigns are governed by an all-or-nothing rule.

[19] Because these campaigns are matched by duration, matched campaigns have the same pretreatment and postshock durations.

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