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When Reward Meets Donation: A Paradoxical Dilemma

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Abstract

Reward-based crowdfunding platforms are increasingly incorporating donation options, allowing backers to financially support campaigns without receiving any tangible rewards in return. Although this option seems to create a novel fundraising channel, our quasi-natural experimental study highlights the potential negative impacts of individual donation occurrences, which ultimately lead to reduced total raised funds, as substantiated by robust empirical evidence. We explore two primary mechanisms responsible for the adverse effect. First, the bystander effect, where prior donations discourage potential backers from supporting the campaign, causing them to either forgo reward purchases or decrease their contribution amounts. Second, the social conformity effect, in which prior donations shape backers' perceptions of social norms and consequently lower their support levels. By offering a comprehensive understanding of behavioral dynamics in crowdfunding, our study enriches the literature on the design and management of crowdfunding platforms and provides valuable insights for industry practitioners.

Keywords: Reward-based crowdfunding, charitable giving, peer influence, crowding-out effect, social conformity effect

Introduction

Reward-based crowdfunding has emerged as a viable method for raising capital through the collective effort of individual backers. It greatly diminishes the difficulty in finding backers and provides fundraisers with direct access to the market even before their products are well-developed. According to Statista, crowdfunding platforms in North America raised nearly $74 billion in 2020.

Despite the prevalence of reward-based crowdfunding, many entrepreneurs face challenges in attracting enough backers and raising sufficient funds to meet their goals (Mollick 2014). To facilitate successful fundraising, platform managers have employed various strategies, including linking to social networks such as Facebook and Weibo (e.g., Jin et al. 2020), offering information control features (Burtch et al. 2015), using probabilistic uncertain rewards (Gong et al. 2020), or setting reward limits (Yang et al. 2020). This study aims to examine an increasingly popular strategy among reward-based crowdfunding platforms, including Indiegogo and Kickstarter (see Figure 1 and 2) — the provision of a donation option (i.e., allowing backers to contribute money without redeeming rewards).

A recent study by Chan et al. (2023) has paved the way for understanding the platform-level impact of integrating donation options into reward-based crowdfunding platforms, showcasing the crucial role donations hold in the success of these reward-based campaigns. Despite these advances, little is known about the impact of actual donation occurrences on micro-level reward buyer behaviors and their subsequent effects on achieving fundraising goals. Building on the insights provided by Chan et al. (2023), our investigation delves deeper into the long-term consequences and overall equilibrium effects of implementing donation options. We seek to establish causal connections between donation occurrences enabled by a donation option and subsequent reward buyers, while taking into account the dynamic responses of backers to the integration of the donation option. This focus allows us to uncover valuable insights for fundraisers aiming to devise effective strategies and equips platform managers with essential knowledge for refining the design and execution of donation options.

Donation occurrences on reward-based crowdfunding platforms have the potential to reshape the fundraising process, as earlier studies demonstrate the inter-temporal dynamics of support behaviors and the power of the crowd in both reward-based (e.g., Hong et al. 2018) and donation-based crowdfunding (e.g., Burtch et al. 2013). Our study closely aligns with Burtch et al. (2013), examining the impact of donation occurrences. Nevertheless, the generalizability of their findings to our focus on reward-based crowdfunding warrants further investigation, considering the distinct characteristics that differentiate donors and reward buyers. In contrast to donors, who enjoy the flexibility to contribute customized amounts to campaigns, reward buyers are restricted to pre-determined reward prices. Moreover, the motivations driving reward buyers encompass a mix of intrinsic incentives, such as the desire to help others, and extrinsic incentives, like tangible rewards. Conversely, donors are primarily propelled by intrinsic incentives. These differences underscore the importance of a nuanced understanding of donation occurrences' role within the context of reward-based crowdfunding platforms.

Little is known about how donations affect micro- and individual-level reward buyer behaviors, and ultimately, progress toward the fundraising goals. On one hand, the inclusion of a donation option introduces a new fundraising channel and gives backers the flexibility to contribute amounts that are lower than the lowest reward price. Also, previous literature has well documented the existence of the social conformity effect or herding behaviors in crowdfunding (e.g., Zhang and Liu 2012), suggesting that donations may accelerate the fundraising process. On the other hand, the nature of donations could unintentionally discourage potential backers by intensifying the bystander effect (Burtch et al. 2013). It is possible that gains from donations come at the expense of losing regular reward buyers, which could potentially lead to a worse-off outcome for both fundraisers and platforms. This study empirically examines whether and how donations influence prospective reward pledges and elucidate the underlying behavioral mechanisms.

To answer our research questions, we collaborate with a leading reward-based crowdfunding platform in China to study the impact of donations. We leverage a quasi-experimental research design in which a subset of campaigns receives donations. Following Hu et al. (2015), we dissect the decision-making process for potential reward buyers into two steps: (1) deciding whether to purchase (i.e., purchase decision) and (2) deciding which reward option to choose (i.e., amount decision), and then explore how donations affect this two-step process. We initially examine the impact of prior donations on daily-level contribution and pledging behaviors. Next, we leverage the bystander and social conformity effects to explain the mechanisms through which prior donations drive changes in reward buyers' pledging behaviors.

Our analyses reveal several notable findings. First, we observe that campaigns with donations struggle with a decrease in total contribution levels. This phenomenon is intriguing, considering that the donation option has the potential to attract donors and generate more contributions. Upon further examination, we attribute this negative impact to the negative externality of prior donations on subsequent reward buyers. Specifically, we find that potential reward buyers tend to reduce their support levels, either by opting out of reward purchases or by decreasing their contribution amounts. Second, our study indicates that the bystander effect plays a dominant role in shaping backers' purchase decisions. This is evidenced by the negative changes observed in the total number of backers and reward buyers. Lastly, we find that the negative changes in the total amount of money contributed by backers or pledged by reward buyers can be attributed to a combination of both the bystander and social conformity effects.

Our study offers several key contributions to the existing body of literature. First, we enhance the understanding of reward-based crowdfunding platforms' design by investigating the role of a unique design artifact — the donation option — in affecting subsequent backers. In contrast to previous studies, our focus lies on the influence of peers' donations rather than the mere introduction of the donation option by the platform. Additionally, we delve deeper into the underlying mechanisms by concentrating on micro-level decisions instead of campaign-level outcomes. Second, our research expands the extant literature on social influence by investigating the cross-channel peer influence between donating and reward pledging. We distinguish between the purchase decision and the amount decision, uncovering that the dominant mechanism may vary between these two decisions. Specifically, the bystander effect governs the purchase decision, while both the bystander and social conformity effects serve as main drivers for the amount decision. Third, we contribute to the literature on the impact of charitable giving by examining how peer donations affect the purchase behaviors of subsequent backers.

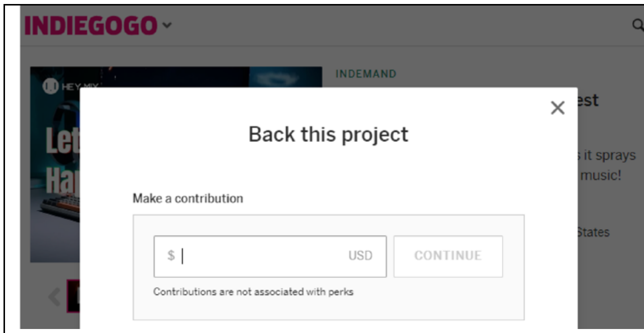


Figure 1. Donation Option on Indiegogo

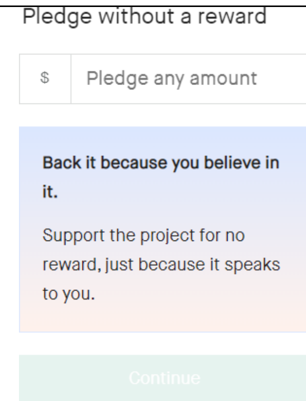


Figure 2. Donation Option on Kickstarter

Our study yields valuable managerial insights for managers of reward-based crowdfunding platforms. By illustrating the potential negative consequences of incorporating a donation option on the success of fundraising campaigns, our results urge managers to carefully consider the implementation and design of such options. Furthermore, our study provides actionable recommendations for improving the design of donation options, such as showcasing only donation records that surpass the minimum reward price. Employing these guidelines could augment the effectiveness of donation options, ultimately leading to more successful crowdfunding campaigns. More broadly, our practical significance extends beyond crowdfunding platforms, as it can inform a wide range of business contexts that incorporate donation options. For instance, in the context of live-stream shopping, consumers may opt to tip online influencers alongside purchasing promoted items. In this case, tipping mirrors donating, while buying promoted items resembles reward pledging. Likewise, on specific digital content platforms (e.g., Zhihu), users can choose to tip authors as an alternative to article subscriptions. Given that both tipping and donating signify support, these concepts are virtually synonymous in such instances. The findings of our study hold the potential to transform the design and implementation of donation and tipping options across various platforms and industries, ultimately benefiting practitioners and organizations alike.

Literature Review

Factors Affecting Backers' Contribution Patterns

Campaign Attributes & Platform Design

The attributes of a campaign can substantially influence the contribution patterns of backers in crowdfunding. For example, the campaign description, the extent of information disclosure, the ambitiousness of the fundraising target, and the presentation of reward options can have a significant impact on backers' support levels. Additionally, the characteristics of the fundraiser, including his/her funding outcomes from previous crowdfunding campaigns, demographic information, and geographic location can also shape backers' contribution behaviors.

While campaign attributes are undoubtedly critical factors in determining the success of crowdfunding campaigns, the design of crowdfunding platforms plays a similarly vital role. Researchers have conducted extensive studies on various strategies aimed at attracting and retaining backers. For example, Burtch et al. (2018b) demonstrate that adopting a provision point, which refers to an all-or-nothing scheme, can effectively deter fraudulent activities and abuse. In addition, Xiao et al. (2021) reveal that allowing fundraisers to post communicative messages, such as updates on the campaign, has a positive impact on the volume of contributions received. Jin et al. (2020) suggest that linking crowdfunding platforms with social networks could enhance the influx of contributions while Kim and Viswanathan (2018) propose that identifying "experts" with prior investment experience can assist the crowd in making informed investment decisions.

This study seeks to bridge a gap in the existing literature on the design of reward-based crowdfunding platforms by investigating the impact of a unique design element — the donation option. Despite the prevalence of donation options on reward-based crowdfunding platforms, little is currently known about how their presence influences the behavior of subsequent backers, especially those who may be interested in purchasing rewards. In this regard, our work closely aligns with Chan et al. (2021), which explored the impact of introducing a donation option on reward campaigns with prosocial causes. Through an unannounced site change, they observe that incorporating the donation option increases the success rate of reward campaigns by attracting donations and leading to a "crowd-in" effect. Our study diverges from their work in two fundamental aspects. Firstly, we emphasize the externalities of "peer" donations rather than the platform's implementation of the donation option. Secondly, we provide a more nuanced understanding of the underlying mechanisms of the donation option by concentrating on micro-level decisions instead of campaign-level outcomes.

Social Factors

Social factors are equally critical in determining the outcomes of crowdfunding campaigns. Extensive studies have demonstrated that a variety of social factors, such as the identity of early contributors (Kim and Viswanathan 2018), the engagement of backers on the platform (Xiao et al. 2021), the momentum of contributions throughout the fundraising process (Burtch et al. 2013), and the concurrent presence of other campaigns (Geva et al. 2019), have a significant impact on crowdfunding outcomes. Our study focuses on one crucial social factor, i.e., peer influence, which arises from the transparency inherent to crowdfunding platforms.

Previous research has extensively examined the role of peer influence across diverse online crowdfunding markets, including donation-based (Burtch et al. 2013), reward-based (Kuppuswamy and Bayus 2017), financial lending (e.g., Zhang and Liu 2012), and equity crowdfunding markets (Bapna 2019). The visibility of contributions from peers has been found to greatly affect the willingness of potential backers to contribute to a campaign.

However, the impacts of peers can vary based on the types of peer influences. One type of peer influence that may result in negative consequences is called the bystander effect. This effect illustrates the tendency of individuals to refrain from intervening in emergencies when others are present. This phenomenon occurs due to the diffusion of responsibility, where individuals assume that someone else will take action, leading to inaction. The bystander effect has been extended to the context of crowdfunding, where individuals may be less inclined to support a campaign if they perceive that others have already contributed. For example, Burtch et al. (2013) have documented the bystander effect in a donation-based market, where higher prior donating frequencies could result in reduced subsequent donating amounts. A possible underlying mechanism is that donors experience a decrease in the utility of donating when they perceive themselves as less important to the fundraiser.

On the other hand, another type of peer influence, known as the social conformity effect, may result in positive consequences. This phenomenon refers to the tendency of individuals to adjust their behaviors to conform to the perceived social norms of their peers (Cialdini and Trost 1998). In the context of crowdfunding, this implies that the presence of peer contributions can establish a social norm that affects potential backers' contribution decisions. For example, Zhang and Liu (2012) have shown that people are more likely to support a campaign when they realize that their peers have contributed to it as well. It is worth noting that the social conformity effect can also yield negative consequences, since the direction of change in social norms can be either positive or negative.

We add to the extant literature by investigating the cross-channel peer influence between donating and reward pledging. In particular, we examine the possible externality of donations on subsequent reward buyers and utilize the bystander and social conformity effect to explain the underlying mechanisms. By shedding light on the interaction between two types of contribution behaviors, our study offers practical implications for platform managers to better leverage social influence theory. Through centrally managing the donation option, platforms can mitigate the negative externality and improve the overall efficacy of crowdfunding campaigns.

Impacts of Charitable Giving

Scholars have highlighted the psychological benefits of charitable giving for donors, such as its positive association with reported states of true happiness. Moreover, previous studies have delved into the positive impacts of charitable giving on recipients, including improvements in health outcomes and educational attainment in low-income communities. However, the role of social factors in the context of charitable giving has been relatively understudied, despite their potential salient influence on recipients. With the increasing prevalence of online crowdfunding platforms, the visibility of others' social behaviors may further amplify the impact of social factors. In this regard, Burtch et al. (2013) have demonstrated that higher prior donating frequencies could significantly affect potential donors, which leads to reduced subsequent donating amounts.

While Burtch et al. (2013) have established the within-channel social influence, research on cross-channel social influences remains limited. One sub-stream of literature on charitable giving has focused on the impact of corporate charitable giving on potential consumers. Cause-related marketing, which involves linking a company's products or services to a particular social or environ- mental cause, has been shown to have positive effects on customers' attitudes toward the company and their purchase behaviors (e.g., Arora and Henderson 2007). Notably, the outcomes of a cause-related marketing campaign are significantly moderated by the donation amount (Koschate-Fischer et al. 2012).

However, there exists a research gap concerning the cross-channel peer influence between donating and reward pledging, and how the extent of donations may moderate this effect. Our study addresses this gap by examining the impact of peer donations on subsequent backers, with a specific focus on the moderating effect of peers' donation amounts and volume.

Hypothesis Development

Our theoretical foundation is grounded in the bystander and social conformity effects. The bystander effect posits that donation occurrences may inadvertently crowd out potential reward buyers, who would have otherwise supported the campaign, thereby leading to a decrease in purchase incidences. Conversely, the social conformity effect suggests that donation occurrences may encourage individuals who could otherwise not back at all to become reward buyers, ultimately increasing purchase incidences. Consequently, the influence of donation occurrences on *reward volume* hinges upon the predominance of either effect. If the bystander effect dominates the social conformity effect, we would observe a negative impact of donation occurrences on *reward volume*. By contrast, if donations successfully mobilize enough new backers, the *reward volume* will experience a positive effect. In sum, we propose the following hypothesis.

Hypothesis 1 (Reward Volume). *Donation occurrences exert either a (a) negative or (b) positive impact on subsequent reward volume.*

As discussed earlier, the relationship between donation occurrences and subsequent *reward amount* can be examined through two primary mechanisms: the bystander effect and the social conformity effect. The bystander effect suggests that individuals may reduce their support levels if they perceive that others have already contributed by either opting for less expensive rewards or forgoing monetary support (i.e., not supporting the campaign). Ultimately, this could lead to a decrease in *reward amount*. Similarly, the social conformity effect implies that donation occurrences can adjust social norms and subsequently affect potential backers' contribution decisions. Although the backing amount of donors is not necessarily lower than the reward price, customized donation amounts are generally lower than the minimum pre-determined reward prices. As a result, the existence of prior donations may establish a less favorable social norm (i.e., one with a lower average contribution level), leading to reduced *reward amount*. It is important to note that either mechanism, or both, could lead to a decline in *reward amount*, necessitating further investigation. Accordingly, we propose the following hypothesis.

Hypothesis 2 (Reward Amount). *Donation occurrences have a negative impact on reward amount, which can be attributed to (a) the crowding-out effect, (b) the social conformity effect, or (c) a combination of both.*

Research Context and Data

Data Source: The Platform

Our study is based on a leading reward-based crowdfunding platform in China that was established in 2013. This platform shares similarities with other major reward-based platforms such as Kickstarter and Indiegogo. Please note that this platform offers a donation option for all its campaigns. Specifically, backers can pledge money by choosing from a range of reward items at pre-determined prices. Alternatively, they can choose to donate without redeeming any rewards with customizable donation amounts. This platform caters to a variety of crowdfunding genres, including agriculture, arts, entertainment, publication, science, and more.

When launching a campaign on this crowdfunding platform, fundraisers are required to make critical decisions on various campaign features, such as the campaign description, fundraising target, and the planned duration of the fundraising period. In addition, fundraisers are obligated to devise a reward scheme that encompasses a menu of reward offerings, consisting of reward items and their corresponding prices.

Potential backers can easily get access to all campaign details, cumulative prior contributions, and all contribution records by visiting the campaign page. Once a backer decides to support a particular campaign, he/she can choose to make a reward pledge or a donation. Upon making their decisions, the details of their contributions will be automatically displayed on the campaign page. Figure 3 presents a screenshot of anonymized contribution records. The platform provides information on prior contribution behaviors, including backer ID, contribution amount, contribution date and time, and whether it was a donation. Employing an all-or-nothing scheme, the platform ensures that rewards are distributed to buyers if the fundraising target is achieved within the predetermined time window. However, if the campaign fails to meet its funding goal, all backers (including both reward buyers and donors) will receive a refund.

Data Description and Variable Definition

We have acquired a proprietary dataset from the focal crowdfunding platform, containing data on over 4,000 campaigns initiated between November 2014 and May 2018. Among these campaigns, nearly 700 did not receive any donations, thereby constituting our control group. The comprehensive dataset consists of detailed campaign-level information, such as campaign descriptions, genres, fundraising targets, start and end dates, and reward schemes. To augment our identification strategy, which is explained in the next section, we gather summary statistics of reward prices for each campaign, such as count, average, minimum, and standard deviation. Additionally, the dataset contains information on fundraisers' geographic locations and their past fundraising efforts. Furthermore, it keeps records of each contribution, including the backer ID, amount, type (i.e., reward pledge or donation), and timestamp. Overall, the dataset follows a panel structure with approximately 600,000 contribution-level observations. We construct our dataset as panel data at the campaign level, with each observation corresponding to a campaign and each time period representing a day. Using this dataset, we conduct two sets of analyses in our study.

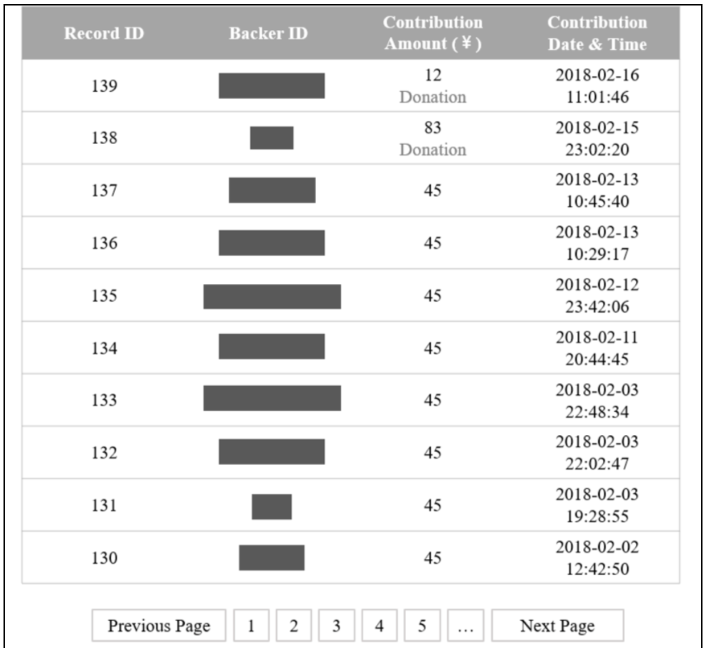
First, we examine the possible externality of donations on subsequent reward buyers. As such, our primary independent variable of interest is the treatment indicator, *donation dummy*$_{it}$, which indicates whether campaign i has received donations by day t. Our key dependent variables include day-level *backer volume*, *back amount*, *reward volume*, and *reward amount*. The variables *backer volume*$_{it}$ and *reward volume*$_{it}$ denote the number of backers and reward buyers for campaign i on a specific day t, respectively. Meanwhile, *back amount*$_{it}$ and *reward amount*$_{it}$ indicate the amount in Chinese Yuan contributed by backers or pledged by reward buyers to campaign i on a given day t.

Second, to gain a deeper understanding of the underlying mechanisms, we examine several additional variables, including:

- *pre donor volume*$_{it}$: the cumulative number of donors for campaign i by day t.
- *pre donation amount*$_{it}$: the cumulative amount of money donated to campaign i by day t.

- *high–priced reward volume*$_{it}$: the number of high-priced (i.e., above the median price) reward buyers for campaign *i* on a specific day *t*.
- *low – priced reward volume*$_{it}$: the number of low-priced (i.e., below the median price) reward buyers for campaign *i* on a specific day *t*.
- *hist avg donation amount*$_{it}$: the historical average amount of money donated to campaign *i* by day *t*, which could reflect the change in social norms attributed to peer donations.
- *hist avg reward amount*$_{it}$: the historical average amount of money pledged to campaign *i* by day *t*.
- *pre reward amount*$_{it}$: the cumulative amount of money pledged to campaign *i* by day *t*.
- *pre reward volume*$_{it}$: the cumulative number of reward buyers for campaign *i* by day *t*.

It is important to note that all variables, with the exception of the treatment indicator (i.e., *donation dummy*$_{it}$), undergo a log transformation.



Record ID	Backer ID	Contribution Amount (¥)	Contribution Date & Time
139	[redacted]	12 Donation	2018-02-16 11:01:46
138	[redacted]	83 Donation	2018-02-15 23:02:20
137	[redacted]	45	2018-02-13 10:45:40
136	[redacted]	45	2018-02-13 10:29:17
135	[redacted]	45	2018-02-12 23:42:06
134	[redacted]	45	2018-02-11 20:44:45
133	[redacted]	45	2018-02-03 22:48:34
132	[redacted]	45	2018-02-03 22:02:47
131	[redacted]	45	2018-02-03 19:28:55
130	[redacted]	45	2018-02-02 12:42:50

Previous Page 1 2 3 4 5 … Next Page

Figure 3. Example of Contribution Records

Identification Strategy

Main Specification

When identifying the possible effects of prior donations, it is crucial to acknowledge that campaigns receiving donations (i.e., the treatment group) may exhibit substantial differences from those that do not (i.e., the control group). To address this concern, we utilize a matching technique to generate a group of campaigns, ensuring that the campaigns within the treatment group are comparable to their counterparts in the control group. By applying this matching method, we can organize our data to resemble a controlled experiment, thereby enabling more accurate identification of the causal effects of earlier donations on subsequent reward pledges. To further refine our analysis, we adopt the difference-in-differences (DID) technique as our main regression specification. This approach, which is commonly used to estimate the effect of an exogenous treatment by comparing changes in outcomes over time between treatment and control groups, has been used in various studies. The DID method is well-suited to our research context, given that we observe a fundamentally quasi-experimental design where treatments (i.e., donations) are applied to a subset of campaigns at different time points, while many other control campaigns remain untreated. Particularly, for campaigns in the treatment group, we anticipate that subsequent reward pledges will be affected by donations after the treatment. In contrast, no such effect is expected for campaigns in the control group.

Propensity Score Matching (PSM)

As previously mentioned, the selection of treatment campaigns that receive donations is not entirely exogenous. Donors chose treatment campaigns based on a number of observable campaign characteristics, potentially leading to differences between treatment campaigns and their control counterparts. This bias may confound our findings. As a result, to reduce systematic discrepancies between treatment and control campaigns, we rely on two matching specifications to generate a sample of control campaigns that is comparable to the treatment campaigns in terms of observable campaign attributes. Essentially, each campaign with donations is paired with a control campaign that is not "treated" but is almost identical to its counterpart in the treatment group in terms of its likelihood of receiving treatment. This approach facilitates a fair comparison between the two sets of campaigns.

First, for static and categorical characteristics such as *campaign genre* and *fundraiser's geographic location*, we use exact matching to pair campaigns. Only campaigns within the same genre and province are matched.

In addition to the aforementioned exact matching, we implement propensity score matching (PSM) on the numerical characteristics of the matched samples from the prior phase to enhance the validity of the matching process. Recall that our dataset differs from others in that each treatment campaign has a distinct treatment time (i.e., campaigns receive donations at various times), whereas none of the control campaigns have a treatment, making them incompatible with conventional PSM methods. Consequently, we apply a technique known as two-stage PSM, which has been used in previous studies encountering similar issues. This method's ability to dynamically match time-varying characteristics, such as *fundraising completion rate* and *competition level*, provides an advantage over the traditional static PSM.

In the two-stage PSM, the first stage estimates campaign *i*'s overall propensity score as a logistic function of a vector encompassing all static numerical characteristics (e.g., *fundraising target*, *number of prior campaigns attributed to the fundraiser*, summary statistics of reward prices, etc.). Here, we utilize summary statistics of reward prices, such as count, average, minimum, and standard deviation, as proxy indicators for available reward schemes. To be specific, campaigns with similar summary statistics of reward prices are considered to possess analogous reward schemes. One-to-three nearest neighbor matching without replacements is employed to identify several closely matched control-and-treatment campaign pairs. In each pair, the treatment time for the treatment campaign serves as a "hypothetical" treatment time for the untreated counterpart. The second stage extracts the value of the time-varying characteristics, including *pre reward volume*, *pre reward amount*, *fundraising completion rate*, and *competition level*, at the "hypothetical" treatment time, and performs a logistic function calculation to approximate campaign *i*'s overall propensity score based on both static and time-varying characteristics. One-to-one nearest neighbor matching is used to create matched pairs, which results in 668 pairs of campaigns and 101,223 records of reward pledges. Following this two-stage matching, the difference in campaign characteristics prior to treatment between the treatment and control campaigns is minimized.

To evaluate the effectiveness of the PSM analysis, we compare the overall distributions of propensity scores for matched and unmatched samples. The propensity score distribution for treatment and control groups is shown in Figure 4. It is evident that the discrepancy in propensity scores between treatment and control units prior to matching is substantially eliminated, and that the distributions of propensity scores after matching are nearly equal across both treatment and control units.[1] Additionally, we perform a balance test to compare all numerical covariates used in the matching process, as shown in Table 1. The results indicate no significant difference in any variables between treatment and control groups, suggesting that the control group is comparable to the treatment group before the intervention.[2]

In summary, our final dataset consists of 1,336 campaigns with 16,323 campaign-day-level observations. Comprehensive summary statistics for all relevant variables for the main analysis are presented in Table 2. It is important to note that these statistics are calculated across both pre- and post-treatment periods and across treatment and control campaigns.

Note1: During the PSM stage, no control campaigns are dropped. Therefore, the propensity score distribution of the control group in Figure 4 remains unchanged.

Note2: For categorical covariates included in the PSM stage, it is not feasible to concisely aggregate, present, and compare their values. However, please be aware that we employ exact matching to ensure no systematic difference exists between treatment and control groups.

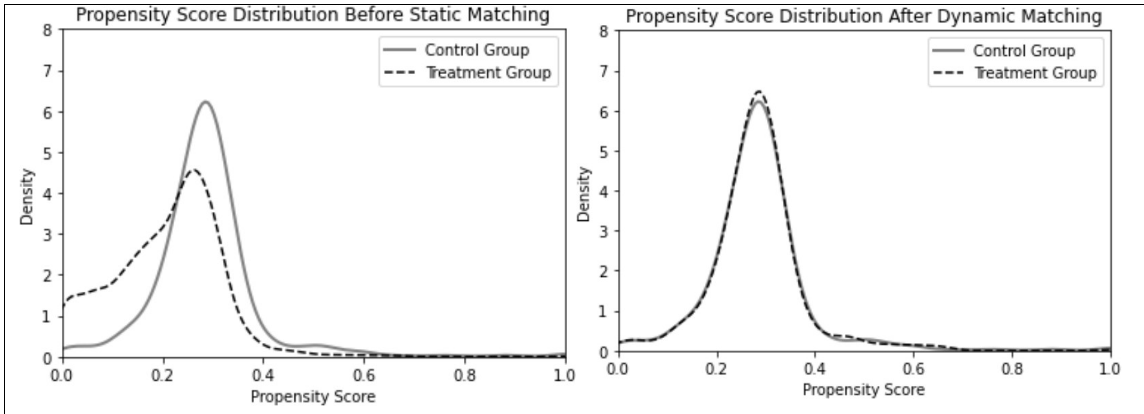


Figure 4. Distributions of Propensity Scores for Unmatched and Matched Groups

	Treatment				Control				Difference
Variables	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max	*p*-value
Fundraising Target	13,935.210	20,352.830	249	260,000	14,001.540	35,432.320	89	500,000	0.955
# of Prior Campaigns Attributed to Fundraiser	1.243	3.047	0	23	1.186	2.708	0	22	0.635
Average Level of Reward Prices	1,086.425	1,691.776	1	30,000	1,043.690	6,516.029	5	110,048.600	0.865
Minimum Level of Reward Prices	91.237	460.885	1	10,000	303.596	4,496.934	1	99,650	0.224
Standard Deviation of Reward Prices	723.220	2,134.032	0	28,284.27	1,101.852	8,151.016	0	187,749	0.227
Count of Reward Tiers	3.723	1.633	1	12	3.796	1.450	1	11	0.276
Pre Reward Volume	37.383	21.876	0	281	39.668	223.497	0	5,199	0.793
Pre Reward Amount	8,937.501	9,025.754	0	198,710	9,113.395	45,574.27	0	985,260	0.922
Prior Fundraising Completion Rate	0.646	0.755	0	10.219	0.693	2.650	0	49.213	0.666
Prior Competition Level	80.045	37.256	7	143	80.045	37.256	7	143	-

Table 1. Balance Tests on Numerical Covariates (Pre-treatment) after Matching

Variables	**Mean**	**Std. Dev.**	**Min**	**Max**
Donation Dummy	0.379	0.485	0.000	1.000
Backer Volume	6.864	152.083	1.000	16,589.000
Back Amount	1,112.823	9,185.411	1.000	498,020.000
Reward Volume	6.201	151.403	1.000	16,589.000
Reward Amount	1055.277	8981.446	1.000	498,020.000

Table 2. Summary Statistics

Difference-in-differences (DID)

Upon establishing a comparable treatment group and control group based on static campaign characteristics and dynamic campaign variables before the treatment, we employ the DID regression to discover the causal effects of prior donations. In line with Hu et al. (2015), we decompose the decision-making process for potential reward buyers into two stages: (1) deciding whether to make a purchase (i.e., purchase decision), and (2) deciding the reward option (i.e., amount decision). Then, we explore how donations affect this two-stage process. In particular, we formulate our regression specification for the day-level analysis as follows:

$$y_{it} = \alpha + \beta \times donation\ dummy_{it} + campaign_i + time_t + relative\_time_{it} + weekday_{it} + \epsilon_{it}, \quad (1)$$

where y_{it} includes *backer volume*$_{it}$, *back amount*$_{it}$, *reward volume*$_{it}$, and *reward amount*$_{it}$ for campaign i on day t. The independent variable of interest, *donation dummy*$_{it}$, indicates whether campaign i has received donations as of the observation time. If campaign i belongs to the treatment group and time t occurs after receiving the first donation, the treatment indicator (i.e., *donation dummy*$_{it}$) is set to 1. To account for time-invariant unobserved factors specific to the campaign that may influence reward pledges (for example, campaign quality), we incorporate a campaign-fixed effect term $campaign_i$. To account for time-variant unobservables that affect all campaigns, we include a time-fixed effect term $time_t$, which captures seasonality in the change of reward pledging. Recognizing that pledging behaviors may change over different phases of the fundraising cycle (Kim et al. 2020), and that the phases for different campaigns vary at a certain time, we further include a relative-time fixed effect term *relative time*$_{it}$ to control for fundraising-phase-specific unobserved heterogeneity. The relative time refers to the time difference (by month) between the observation time t and the time of the first purchase for the same campaign. Lastly, $weekday_{it}$ represents the weekday of time t. This specification enables us to estimate the impact of prior donations on subsequent reward pledges by observing the crucial parameter β. To alleviate heteroscedasticity concerns, we leverage standard errors that are clustered at the campaign level.

Relative Time Model

The validity of our primary identification strategy, which makes use of PSM and DID, relies critically on the pre-treatment parallel trend assumption (i.e., there is no significant difference between treatment and control campaigns before the treatment). To test this assumption, we utilize the relative time model with lead and lag periods. In this model, we add a number of time dummies that indicate the relative temporal distance between the observation time t and the moment when campaign i receives its first donation. For the analysis of day-level contribution behaviors, we specify our relative time model as follows:

$$y_{it} = \sum_j \tau_j\, pre_{it}(j) + \sum_l \omega_l\, post_{it}(l) + campaign_i + time_t + relative\_time_{it} + weekday_{it} + \epsilon_{it}, \quad (2)$$

in which y_{it} represents *backer volume*$_{it}$, *back amount*$_{it}$, *reward volume* or *reward amount* for campaign i on day t. The terms $campaign_i$, $time_t$, $relative\_time_{it}$, and $weekday_{it}$ denote the campaign-fixed effect, time-fixed effect, relative-time-fixed effect, and weekday-fixed effect, respectively. The newly added term $pre_{it}(j)$ is an indicator function that equals 1 if time t is j month(s) prior to campaign i's treatment. Analogously, the term $post_{it}(l)$ is an indicator function that equals 1 if time t is l month(s) after the first donation is received. As a result, the coefficient τ_j for j = -3, -2, and -1 reflects the pre-treatment trend of the impact of donations, whereas the coefficient ω_l for l = 0, 1, 2, and 3 captures the effect of donations in each post-treatment period. By normalizing the coefficient of $pre_{it}(-1)$ to zero, we set a period prior to the time of treatment as the baseline, which is consistent with prior work.

Empirical Results

Relative Time Model

To begin with, we report the findings of the relative time model to verify the adherence of the parallel pre-treatment trend assumption, which in turn affirms the validity of our standard PSM + DID specification. The results, as depicted in Table 3, show that none of the coefficients associated with the pre-treatment dummies, *pre*(j), are statistically significant with a p-value of less than 0.10. This result substantiates the lack of any discernible pre-treatment discrepancies in contribution behaviors among campaigns, regardless of whether they receive donations or not, following the matching process. Consequently, we can confidently assert that the parallel pre-treatment assumption holds true in our analysis.

DV:	log backer volume	log back amount	log reward volume	log reward amount
pre(3)	-0.393	-0.425	-0.337	-0.073
	(0.359)	(0.298)	(0.342)	(0.414)
pre(2)	-0.076	-0.239	-0.038	-0.969
	(0.208)	(0.495)	(0.198)	(0.648)
pre(1)		Baseline		
post(0)	-0.047	0.039	-0.084*	-0.013
	(0.046)	(0.171)	(0.044)	(0.169)
post(1)	-0.300***	-0.316*	-0.300***	-0.339*
	(0.050)	(0.185)	(0.048)	(0.183)
post(2)	-0.112	0.080	-0.121*	0.071
	(0.069)	(0.271)	(0.065)	(0.269)
post(3)	0.032	0.309	-0.007	0.590
	(0.100)	(0.344)	(0.095)	(0.351)
Time FE	Yes	Yes	Yes	Yes
Relative time FE	Yes	Yes	Yes	Yes
Weekday FE	Yes	Yes	Yes	Yes
Campaign FE	Yes	Yes	Yes	Yes
Observations	16,323	16,323	16,323	16,323
Adj. R-Squared	0.349	0.352	0.321	0.354

Note: robust standard errors in parentheses;

* $p < 0.1$; ** $p < 0.05$; and *** $p < 0.01$.

Table 3. Parallel Pre-treatment Trend

Impact of Prior Donations

The estimation results regarding the impact of prior donations on subsequent backers are shown in Table 4. We observe a substantial and statistically significant decrease in both the number of new backers and the total contribution levels (i.e., *backer volume* and *back amount*) following the receipt of prior donations. This finding suggests that potential backers are less inclined to support campaigns that have already received donations. Moreover, the willingness to pay of potential backers for a campaign with donations is considerably diminished. Given that the donation option opens up an additional fundraising channel that is capable of attracting donors and donations, this negative impact should be attributed to the adverse externality of prior donations on subsequent reward buyers.

Table 4 further illustrates the estimated effects of prior donations on subsequent reward buyers, confirming the presence of this negative externality. First, the existence of prior donations leads to a decrease in the number of subsequent reward buyers for campaigns (i.e., *reward volume*$_{it}$). That is, upon observing peers' donations, potential reward buyers will not convert to donors. Instead, they will choose not to support the campaign. This finding is consistent with our theoretical expectation that the bystander effect drives the changes in the daily number of purchase incidences. Second, we identify a pronounced decline in the total amount of money pledged by subsequent reward buyers to a campaign with donations (i.e., *reward amount*$_{it}$). In other words, after observing peers' donations, potential reward buyers will lower their willingness to pay. This decrease in reward amounts can be attributed to either the bystander effect, social conformity effect, or a combination of both, as customized donation amounts typically fall below the minimum pre-determined reward prices. In the following section, we further investigate the mechanisms underlying the change in reward amounts.

DV:	log backer volume	log back amount	log reward volume	log reward amount
donation dummy	-0.546***	-0.688***	-0.476***	-0.657***
	(0.036)	(0.082)	(0.033)	(0.082)
Time FE	Yes	Yes	Yes	Yes
Relative time FE	Yes	Yes	Yes	Yes
Weekday FE	Yes	Yes	Yes	Yes
Campaign FE	Yes	Yes	Yes	Yes
Observations	16,323	16,323	16,323	16,323
Adj. R-Squared	0.381	0.360	0.351	0.362

Note: robust standard errors in parentheses;

* $p < 0.1$; ** $p < 0.05$; and *** $p < 0.01$.

Table 4. Effect of Prior Donations

Mechanism Analysis

While our main analyses focus on assessing whether and to what extent prior donations causally influence subsequent reward buyers with respect to their purchase and amount decisions, our mechanism analysis aims to complement these primary analyses. In this section, we conduct further analyses to understand the underlying mechanisms driving the observed changes in reward buyers' pledging behaviors as a result of prior donations.

Recall that our theoretical foundation is grounded in the bystander and/or social conformity effect. Previous studies have consistently demonstrated that the within-channel behaviors of subsequent backers are influenced by their earlier peers (e.g., Burtch et al. 2013). Given that making a reward pledge is similar to making a donation, as both are two-stage contribution decisions, we expect a similar cross-channel impact between prior donations and subsequent reward pledges.

In terms of backers' purchase decisions, prior donations might trigger the bystander effect on one hand, thereby discouraging potential backers' support (i.e., lowering purchase incidences). On the other hand, potential backers may be motivated to support campaigns donated by others due to the social conformity effect. As for backers' amount decisions, either mechanism (or both) could yield the same outcome, namely a decline in reward amounts, as customized donation amounts are generally lower than the minimum pre-determined reward prices. To be specific, under the bystander effect, the presence of prior donations can cause potential backers to perceive themselves as less important to the campaign, thus leading to lower reward amounts. Similarly, under the social conformity effect, the existence of prior donations may establish a less favorable social norm (i.e., one with a lower average value) and thus lead to reduced reward amounts.

Note that our main analyses have already shed light on the underlying mechanism behind the observed changes in *reward volume*. Based on the DID specification, a decrease/increase in *reward volume* captures the shift in potential backers' purchase decisions on whether to support a campaign that receives donations. Such a change can be attributed to the bystander/social conformity effect. However, the mechanism behind the extent of support remains unclear. To further explore this aspect, we carry out additional empirical analyses. First, we expand our discussion on the bystander effect by illustrating the moderating effects of *pre donor volume* and *pre donation amount*. Second, we examine the heterogeneous treatment effects, taking into account different types of reward buyers. Lastly, we verify that both the bystander and social conformity effects collectively affect backers' amount decisions.

Moderating Effect of Donation Degree

Our main analysis has revealed a negative externality of prior donations on subsequent reward buyers. We argue that this negative outcome can be amplified by the magnitude of prior donations, including both the number of prior donors and the total amount donated.

To investigate our hypothesis, we incorporate the extent of prior donations, denoted as *pre donor volume* and *pre donation amount*, and interact them with the treatment indicator (i.e., *donation dummy* × *pre donor volume* and *donation dummy* × *pre donation amount*) into our DID model. This approach enables us to capture the moderating effects. The modified model specifications are presented below:

$$y_{it} = \alpha + \beta \times donation\ dummy_{it} + \gamma \times donation\ dummy_{it} \times pre\ donor\ volume_{it}$$

$$+campaign_i + time_t + relative\_time_{it} + weekday_{it} + \epsilon_{it} \qquad (3) \text{ and}$$

$$y_{it} = \alpha + \beta \times donation\ dummy_{it} + \gamma \times donation\ dummy_{it} \times pre\ donation\ amount_{it}$$

$$+campaign_i + time_t + relative\_time_{it} + weekday_{it} + \epsilon_{it} \qquad (4)$$

in which all specifications align with those in Equation (1), except for the inclusion of the two moderators *pre donor volume* and *pre donation amount*. Specifically, *pre donor volume* refers to the cumulative number of donors for campaign i up to day t, whereas *pre donation amount* represents the cumulative amount of donations made to campaign i up to day t.

We report our results in Table 5. As can be seen, the coefficients for *pre donor volume* and *pre donation amount* in all regressions are statistically negative, indicating that the extent of prior donations can indeed amplify the negative externality of prior donations on subsequent reward buyers.

Heterogeneous Effects by Types of Reward Buyers

We hypothesize that the treatment effect may differ across various types of reward buyers. To be specific, backers who prefer low-priced rewards may perceive a lower value in the campaigns they support, which makes them more sensitive to peer influences. In contrast, backers who favor high-priced rewards are likely to place a higher value on the campaigns throughout the fundraising process. As a result, they might be less influenced by the donation levels of peers when making their amount decisions.

Given the difficulty of directly observing backers' perceived value, we focus on those backers who have already decided to contribute to campaigns, using the money they contribute as a proxy for their perceived value of the campaign. We then examine the differential impacts of prior donations on different types of reward buyers. In particular, we categorize reward buyers into two broad groups based on the price they pay for campaign rewards (i.e., low and high). "High-priced" reward buyers are those who choose a reward with a price exceeding the median reward price, while "low-priced" reward buyers opt for a reward price at or below the median. For example, if a campaign offers reward prices of $10, $20, and $50, the median price is $20. All reward buyers contributing more than $20 to the campaign are deemed high-priced reward buyers, whereas the remaining buyers are classified as low-priced reward buyers.

Following this classification, we use two separate dependent variables, namely *high–priced reward volume* and *low–priced reward volume*, and replicate the DID model to capture the heterogeneous effects regarding buyer types. Our model specification is same as Equation (1), except that y_{it} represents: (1) *high–priced reward volume*, which denotes the number of high-priced reward buyers for campaign *i* on day *t*, and (2) *low–priced reward volume*, which indicates the number of low-priced reward buyers for campaign *i* on day *t*.

DV:	log reward volume	log reward volume	log reward amount	log reward amount
donation dummy	-0.107**	-0.142***	-0.175	-0.294**
	(0.054)	(0.047)	(0.116)	(0.132)
donation dummy × log pre donor volume	-0.266***		-0.348***	
	(0.037)		(0.061)	
donation dummy × log pre donation amount		-0.090***		-0.098***
		(0.011)		(0.026)
Time FE	Yes	Yes	Yes	Yes
Relative time FE	Yes	Yes	Yes	Yes
Weekday FE	Yes	Yes	Yes	Yes
Campaign FE	Yes	Yes	Yes	Yes
Observations	16,323	16,323	16,323	16,323
Adj R-Squared	0.366	0.361	0.365	0.363

Note: robust standard errors in parentheses;

* $p < 0.1$; ** $p < 0.05$; and *** $p < 0.01$.

Table 5. Moderating Effects of Donations

The results are shown in Table 6. By comparing the coefficients of *donation dummy* for *high–priced reward volume* and *low–priced reward volume*, we find that low-priced reward buyers are more affected by prior donations. We further conduct our regression analysis for an additional dependent variable, *ratio of high–priced reward buyer*, which is calculated using *high–priced reward volume* divided by *reward volume*. The significantly positive coefficient of *donation dummy* reinforces our finding that low-priced reward buyers are more sensitive to prior donations. Please note that we may underestimate the change in *low–priced reward volume* since potential backers with high perceived values could shift to low-priced buyers due to peer influences.

Social Conformity Effect

As previously discussed, the observed changes in *reward amount* can be attributed to the bystander effect, social conformity effect, or a combination of both. In our earlier analyses, we have demonstrated the existence of the bystander effect. In this subsection, we conduct additional analysis to establish the existence of the social conformity effect when potential backers make their amount decisions.

The social conformity effect refers to individuals' tendency to adjust their behavior to conform to the perceived social norm of their peers (Cialdini and Trost 1998). In our context, the perceived social norm regarding the level of support is based on peers' contributions (including both reward pledges and donations) to the campaign. For campaigns in the control group, the social norm is set by the historical average amount of money pledged to them (i.e., *hist avg reward amount*). We believe that peer donations can significantly alter the perceived social norm. To capture its impact, we construct an independent variable of interest, *hist*

DV:	log high-priced reward volume	log low-priced reward volume	ratio of high-priced reward buyer
donation dummy	-0.171***	-0.380***	0.027**
	(0.025)	(0.031)	(0.012)
Time FE	Yes	Yes	Yes
Relative time FE	Yes	Yes	Yes
Weekday FE	Yes	Yes	Yes
Campaign FE	Yes	Yes	Yes
Observations	16,323	16,323	16,323
Adj R-Squared	0.390	0.600	0.258

Note: robust standard errors in parentheses;

* $p < 0.1$; ** $p < 0.05$; and *** $p < 0.01$.

Table 6. Heterogeneous Effects

avg donation amount, which denotes the historical average amount of money donated to the campaign. To account for potential changes in reward amounts driven by the bystander effect, we further include two control variables for cumulative contribution amounts, namely *pre donation amount* and *pre reward amount*. Our model specification is as follows:

$$y_{it} = \alpha + \beta \times donation\ dummy_{it} + \gamma \times hist\ avg\ doantion\ amount_{it}$$

$$+\delta_1 \times hist\ avg\ reward\ amount_{it} + \delta_2 \times pre\ donation\ amount_{it} + \delta_3 \times pre\ reward\ amount_{it}$$

$$+campaign_i + time_t + relative\_time_{it} + weekday_{it} + \epsilon_{it}, \qquad (5)$$

where the dependent variable y_{it} refers to the amount of money pledged by reward buyers to campaign i on day t (i.e., *reward amount*). This specification enables us to test the existence of the social conformity effect by examining the critical parameter γ. To be specific, if the change in *reward amount* is partially driven by the social conformity effect, we can expect a significantly positive γ. Otherwise, we would observe an insignificant γ.

The estimation results are presented in Table 7. The coefficients for *pre donation amount* and *pre reward amount* once again confirm the existence of the bystander effect. More importantly, the coefficients for *hist avg reward amount* and *hist avg donation amount* provide evidence for the existence of the social conformity effect. To be specific, the significance of the parameter γ substantiates that higher peer donations can alter the perceived social norm, consequently leading to an increase in *reward amount*.

Conclusions

Collaborating with a prominent reward-based crowdfunding platform in China, we explore the impact of prior donations on subsequent reward buyers. Our finding reveals that the increase in donations stemming from the donation option fails to compensate for the significant loss in reward pledges, leading to a considerable decline in the overall amount raised by a campaign. We offer two plausible explanations for this observed negative change in contribution levels: the bystander effect and the social conformity effect. Specifically, the bystander effect is responsible for the decrease in reward volume, while both the bystander and social conformity effects drive the decline in reward amount.

DV:	log reward amount
donation dummy	-0.150
	(0.140)
log hist avg donation amount	0.168**
	(0.069)
log hist avg reward amount	0.300***
	(0.043)
log pre donation amount	-0.143***
	(0.052)
log pre reward amount	-0.288***
	(0.031)
Time FE	Yes
Relative time FE	Yes
Weekday FE	Yes
Campaign FE	Yes
Observations	16,323
Adj R-Squared	0.374

Note: robust standard errors in parentheses;

* $p < 0.1$; ** $p < 0.05$; and *** $p < 0.01$.

Table 7. Social Conformity Effect

This research, therefore, sheds light on the complicated contribution patterns of crowdfunding campaigns and underscores the importance of understanding the cross-channel peer influence between donating and reward pledging. Ultimately, this study makes substantial contributions to both the literature and practice.

With respect to the literature, we extend the existing literature on the design of reward-based crowdfunding platforms by examining the impact of a donation option on subsequent backers. We also enrich the literature on social influence by identifying different types of peer influences at various stages of backers' decision-making processes. Lastly, we contribute to the literature on the impacts of charitable giving by broadening the context to reward-based crowdfunding and peer donations.

Additionally, our research offers valuable managerial insights for practitioners, especially crowdfunding platform managers. First, our finding caution that incorporating a donation option may not always hasten the success of fundraising campaigns. Even though adding such an option could open up a new funding channel, it may potentially deter reward buyers. Second, our results can inform various improvement recommendations regarding the design of the donation option. For example, due to the presence of the social conformity effect, fundraisers should be permitted to set a minimum donation amount. Crowdfunding platform managers may also consider publicly displaying only those donation records that exceed the minimum reward price. Third, we believe that our study can reshape the design of donation/tip options across a wide range of business scenarios, such as live-stream shopping.

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