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Sustainability of Rewards-Based Crowdfunding:
A Quasi-Experimental Analysis of Funding Targets and Backer Satisfaction

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Abstract

Rewards-based crowdfunding presents an information asymmetry for participants due to the funding mechanism used. Campaign-backers trust creators to complete projects and deliver rewards as outlined prior to the fundraising process, but creators may discover better opportunities as they progress with a project. Despite this, the all-or-nothing (AON) mechanism on crowdfunding platforms incentivizes creators to set meager funding-targets that are easier to achieve but may offer limited slack when creators wish to simultaneously pursue emerging opportunities later in the project. We explore the related issues of how funding targets seem to be selected by the creators, and how dissatisfaction with the rewards outcomes may arise for the backers. We constructed a *quasi-experimental* (QE) *research design* based on an extensive dataset from Kickstarter with nearly 390,000 campaigns. Our findings show that creators who set particularly meager funding-targets for their campaigns are more likely to receive sufficient funds but are less likely to satisfy backers with the project outcomes they deliver. We also test the moderating roles of creator and campaign characteristics. Overall, this study provides evidence that the funding mechanism used in rewards-based crowdfunding may be unsustainable in its current form, unless new mechanisms are introduced to realign the diverging incentives for creators and backers.

Keywords: Causal inference, computational social science (CSS), fintech, fundraising, incentives, information asymmetry, platforms, propensity-score matching (PSM), quasi-experiment, rewards-based crowdfunding.

Brief Bios

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Introduction

Many entrepreneurs and small businesses have benefitted from new ways to bring products and services to market in recent years, including new platforms for attracting and fundraising from crowds of backers. The global crowdfunding market was worth about USD 13.3 bn in 2019 [77, 78] and is projected to grow further by 2026 to as much as USD 39.79 bn. In the U.S., the crowdfunding segment is projected to pull in more than USD 1.05 bn by late 2021, with a 3.3% *compound-annual growth-rate* that will lead to a market-wide total of USD 1.2 bn by 2025.

The benefits of crowdfunding, a form of *fintech intermediation* [36], depend on projects receiving the resources they need to be carried out effectively.[1] This explains why *crowdfunding campaign-creators* appear so focused on fundraising when designing campaigns [66]. Fundraising is only the first step though. The fundraising target and the associated conditions will likely affect what creators are willing or able to do later in the project, and what creators need to do to deliver satisfaction to their backers. For example, in *rewards-based crowdfunding*, backers offer funding in return for prespecified material rewards at some point in the future. When this is the case, where an agreement is reached but some of the work has yet to be performed, *threshold contracts* (a form of delayed-payment agreement) are usually preferred to share the risk between parties. Funding mechanisms in rewards-based crowdfunding typically require down-payments in advance by backers, often made weeks or months before project outcomes are due [60]. This is a major reason why crowdfunding has attracted so much attention from entrepreneurs and innovators, as consumers are transformed into investors or partners based on the timing of the exchange.

This arrangement between creators and backers is naïve, however. Crowdfunding platforms create natural conditions associated with goal-setting, information sharing, and risk asymmetry that challenge their fintech intermediaries [21]. This type of principal-agent problem has been recognized for almost half a century [71]. Insufficient effort has been expended on developing formal governance approaches to manage the resulting agency problems in crowdfunding though. This insight is important given that creators are incentivized to attract funds, even if they do not generate positive outcomes for a campaign's backers. The possible circumstances when this can happen are notable: for example, if a new component technology is released while a funded project is underway, if a new business partner approaches the creator to customize the product or service, or if the market feedback for the funded product or service calls for changes. Indeed, a degree of drift can be expected if we assume creators discover some new opportunities with greater market potential during the course of a project. We consider this to be a problem with *diverging incentives*, reflected by self-interest and fiduciary interest that drift over time away from the details of the specifications of crowdfunding contracts [72, 86]. This has implications beyond crowdfunding, as it challenges the underlying principle of having consumers commit to a venture earlier in the innovation process.

This study empirically explores two research questions that arise as a result of these observations using a quasi-experimental research design applied to a large dataset. Answers to the questions are important for the viability of the stakeholder relationships in the crowdfunding market mechanism and the agency problems that characterize them, similar to other digital economy transaction platforms [19, 62]:

- Do incentive differences during crowdfunding affect creators' fund-seeking behavior and campaign-backers satisfaction about the eventual project outcomes?
- Do the requirements for creators to set a funding target and describe the rewards for backers at the outset of a project impact issues that later arise from their diverging incentives?

Theoretical Background for Rewards-Based Crowdfunding

We next consider the literature and theoretical background related to: creators, backers and rewards; agency theory, moral hazard, risk asymmetry, and incentives; the setting of campaign funding-targets; and how campaigns are funded under the *all-or-nothing* (AON) mechanism.

Creators, Backers, and Rewards

Crowdfunding platforms connect commercial, social, charitable, and artistic projects with crowds of potential backers, so these projects become an alternative to traditional sources of financing, such as banks or venture capitalists [82]. Different platforms facilitate different types of crowdfunding. Some focus on interest-based loans, while others on the purchase of equity, and still others on prosocial and charitable donations [9]. However, rewards-based crowdfunding has arguably produced the most disruptive outcomes.

Rewards-based crowdfunding appeals to creators and backers for various reasons. First, some believe that crowdfunding supports mutually-beneficial, short-term financial benefits. Creators can obtain capital when they need it, while backers get valuable discounts or assets that they rationally require to incentivize participation. Second, many creators believe that crowdfunding generates interest among potential consumers and user groups and contributes to viral marketing. Third, some backers and creators believe that the grass-roots approach of crowdfunding will create shared value and social benefits. Policy-makers, as a result, often encourage the growth of these platforms, building on evidence that crowdfunding campaigns create opportunities for entrepreneurs and stimulate local economies [51].

These benefits assume such projects can deliver on their promised rewards. This observation has been a topic of interest and controversy since the emergence of crowdfunding though. Some highlight the risk of fraud, others are concerned by creators' inexperience or poor planning, and still others point to systemic coordination and communication challenges that emerge as projects grow in size.[2] The reasons why projects disappoint backers vary: not delivering or only delivering rewards after long delays; lacking creator-backer collaboration; or having a clash of expectations or poor fit with later business partnerships.

Moral Hazard, Risk Asymmetry, and Counterparty Incentives

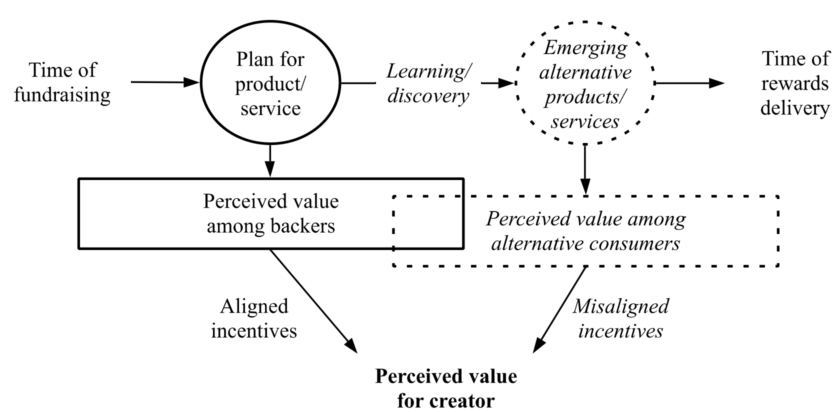
Crowdfunding differs from other forms of crowdsourcing in two ways. First, the "crowd" in crowdfunding platforms does not usually participate directly in the value-creation process. Instead, they entrust design and development to the creator, limiting the role of backers to onlookers, who can make suggestions and appeal to the creator's sense of community. As a result, creators often influence projects indirectly via their ongoing interactions with the crowd and their public discourse [34, 35]. Second, the crowd must commit its support to a project at the outset, rather than withhold funding until the backers are satisfied with the outcomes. So, they may pre-commit to outcomes that may change as a project unfolds.

This is a *principal-agent relationship* [71]. The *agent* – the project campaign-creator – must take actions and make decisions to reflect the interests of the *principal* – backers here – in the presence of information asymmetries that allow the agent to hide certain actions and information. Such principal-agent relationships create conditions for their goals to diverge, as a result of the "*frictions that lie at the center of agency* *problems*" [72, p. 45]. The principal has limited means to monitor and verify the agent's actions though. There are multiple related issues: (1) *moral hazard*, where the agent can pursue opportunistic and selfish behaviors unseen or poorly understood by the principal [50]; (2) *adverse selection*, so agents present themselves as more capable of succeeding than they actually are [54]; and (3) *risk-attitude asymmetry*, so the principal and agent may prefer contrasting actions because their goals are impacted differently by their respective risk sensitivities and the incentives in a given setting [73].

Crowdfunding is susceptible to moral hazard and adverse selection, as backers are often inexperienced investors, and subject to asymmetry in their risk attitudes. While campaigns have implicit contracts, their backers cannot negotiate specific commitments with project creators. Backers may provide funding, but they lack little legal recourse to enforce penalties or oversee the distribution of rewards once a campaign is underway. This is true if the creator has delivered rewards to the backers – even if the rewards are of disappointing quality, not timely, lack support, or fall short of being a new product [10].

Some of the touted benefits for creators we noted earlier include the ability to experiment, test market demand, and explore new opportunities for subsequent products and/or services. In fact, creators always strive to discover more desirable products and services in the process of development, often after they have committed to initial proposals. This situation impacts the parties' incentives, as creators are discouraged from committing resources to the initial proposal beyond the minimum that is required. Backers lack this ability: they have committed their resources. It also leaves them at the mercy of creators should the latter begin redirecting their attention to emerging opportunities. (See Figure 1.)

Figure 1. Learning, discovery, and incentives in rewards-based crowdfunding



Under these conditions, there are still shared benefits between creators and backers. Creators are incentivized to excite backers by generating a positive public image. They also seek to avoid the types of failures that could result in legal action. There may also be backers who prefer the emerging products or services to the ones initially proposed. However, the sharing of benefits between creators and backers becomes increasingly short-term over time, as backers become less representative of long-term consumers.

Such short-term benefit-sharing in principal-agent relationships can actually have an undesirable effect: it may encourage the agent to use the principal's resources as part of its own short-term strategies to maximize its earnings [71]. This situation occurs because agents have the power to walk away from the long-term relationship, so they are more apt to weight short-term benefits more than long-term risks. Such risks are not an abstract threat in rewards-based crowdfunding. For example, the creators may agree to difficult requests while the project is ongoing to avoid public conflict, even if they believe backers will be disappointed with the eventual results. Creators may also prioritize interaction with backers or media appearances, even if that time would be better spent on product or service development. They may spend an excessive amount of time solving development issues that are only partially relevant to the proposed outcomes but are highly relevant for subsequent opportunities, too.

This problem could be compounded if creators balance other forms of investment that prioritize the firm's long-term success over products or services, including venture capital or personal savings. Repaying the investment may become harder if a creator perseveres with the outcomes that it agreed to with backers, instead of pursuing newly-discovered products or services with greater market potential.

Thus, the theory suggests that rewards-based crowdfunding encourages creators to focus disproportionately on fundraising, as the desired development outcomes may change once the project is underway. Because backers are focused on the development outcomes that were proposed initially, this kind of crowdfunding creates agency problems. Specifically, between campaign-creators and backers, it results in incentive problems – especially *incentive misalignment*, as defined by Zhang et al. [86]. This problem may occur as perceptions of behaviors and incentives change over time, diminishing the incentive compatibility of the crowdfunding arrangements they have and how they understand the implied contract between them.

In economic theory, agents (as creators in our setting) are known to behave differently across various individual tasks due to discrepant incentives and the nature of *monitoring* that principals use (as backers in our setting) [44, 61]. Thus, the counterparty incentives in our research context recognize that the creator-backer relationship evolves during a project due to unavoidable uncertainties. Any misalignment, thus, is temporal, emergent, and situational in nature, although at the outset the terms and conditions of a campaign are incentive-compatible for creators and backers so crowdfunding is feasible.

Setting Funding Target Levels

Creators launch crowdfunding campaigns with multiple kinds of goals. They include the *financial target for money raised* for the underlying project and its crowdfunding set-up, activities lifecycle, platform intermediation fees, and tax costs. They further include sampling for *evidence of marketplace demand* for new product innovation, and creating a *foundation for growing market interest* in early-cycle product or service development [60]. Our research focuses on the financial goals that a campaign-creator selects and implements for project funding, so we only consider a subset of these issues.[3]

Incentives. Campaign performance problems typically are not revealed in most empirical studies. In fact, to our knowledge only a handful of published research works have treated the alignment of creator-backer incentives in online crowdfunding campaigns. A key study is by Havrylchyk [40], who asserted that diverging incentives may occur between campaign creators and their investing backers on loan-based crowdfunding platforms. A crowdfunding platform's first responsibility, as a fintech intermediary that promotes the viability of its transaction and market-matching mechanism [36, 49], is to ensure campaign-backers that they can effectively avoid adverse selection by performing risk-management checks for platform and creator due diligence. This aids backers to avoid losses due to insufficient information about likely problems with some the intermediary or the campaign-creators. Banks face similar problems with lending money to creditors for whom they have not conducted thorough *know-your-customer* (KYC) checks with proposed lending relationships. Another consideration is whether platforms operate with inappropriate *moral hazard* levels and lax risk management schemes, as occurred with home mortgage lenders in the U.S., paving the path toward the Financial Crisis in 2007-2008.[4]

Rewards-based crowdfunding and market microstructure. Beyond Burtch et al. [12, 13] in the IS discipline on the role of provision points, Gabison [32] explored incentive problems under the AON *market microstructure* for crowdfunding. First, there may be insufficient incentive for the platform to implement pre-emptive due diligence because of the number of problematic campaigns it hosts. The process requires a digital intermediary to pass on risk assessment to the campaign's creators and backers, flag campaigns for removal, and refund their backers' investments.

Second, there may also be problems with a creator's incentives to disclose negative or costly information. AON crowdfunding is likely to require convincing potential backers to be supportive. The process demands that creators yield sufficient investments to meet a campaign's minimum funding-target compared to *keep-it-all crowdfunding* [24]. Under that market mechanism, the creator will retain any funds raised without a required minimum on the targeted funding level.

Third, when a platform relies more on campaign investors for due diligence, investing backers may not wish to share negative information that diminishes the likelihood of success of AON funding. They also may misinterpret information they receive from others because they make insufficient effort to understand it, or may not expend the effort to acquire information. Instead, they may rely on guesses that may misinform others who are swept up by herd decision-making.

Effects of campaign overfunding and underfunding. Gabison [32] further proposed that the overfunding of campaigns, which occurs when backers provide funding in excess of a creator's funding target, especially creates problems with AON crowdfunding. The impact on backers is that they have less incentive to assess project quality: a critical mass of backers has already given a "thumbs up." Potential backers also take no risk that the project will not be funded at the required provision point-based, AON level. So, the creator's target is important related to the quality of the crowdfunding-market overall. Past work suggests that overfunded campaigns tend to be more attractive than underfunded campaigns, and more often associated with projects that are late to reach completion [43]. A key thing occurs though:

underfunding and overfunding relative to the creator's target tend to shift risk between the campaign-creator to the backers. Thus, a creator's choice of target has the potential to distort the related project information.[5] Asking for too little may create a higher likelihood for funding, but it misinforms potential backers who are not privy to a creator's private information about how much money truly is needed for a project to succeed – along with the increased likelihood of failure. Setting the target too high, by the same token, will result in some likelihood of failure too, with risks for the creator and the backers, though it may suggest higher project quality.[6]

How All-or-Nothing Rewards-Based Campaigns Are Crowdfunded

The process of launching a campaign is not as simple as it may seem. The majority of backers on many popular platforms support only a single project, suggesting individual networks are vital for attracting backers. Thus, before creators begin the formal process, quite a bit of groundwork is needed so creators can generate the awareness and social capital needed, especially for encouraging early contributions [20]. Once projects create sufficient momentum, these early contributions enable herding effects to arise later in the fundraising period that help campaigns to reach their targets. For example, statistics from Kickstarter suggest that once campaigns surpass 40% of their AON funding-targets, the failure rate drops to 7%.[7]

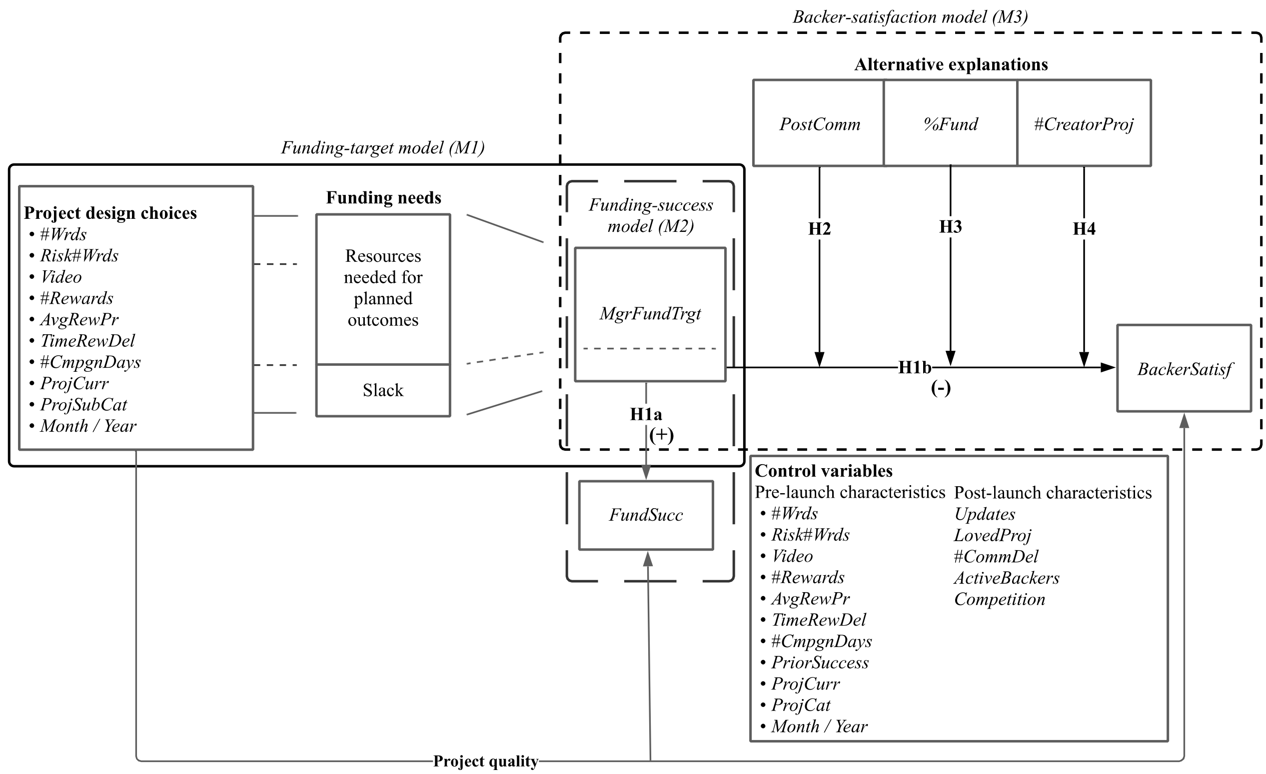
Once creators have a set of rewards, a timeline, and an AON funding-target in mind, they can begin creating their campaign. Creators typically pick a category in which to fundraise (e.g., art, fashion, games, technology). Then they enter details of their campaign to set up a draft for review. Once approved, creators can choose to launch their campaign when they are ready and begin collecting contributions. Funding usually lasts for about 30 days, and creators frequently add updates and respond to potential backer queries. They often add stretch goals for new benefits which incentivize backers to continue contributing once the provision-point targets are met, such as free perks for backers who have backed the campaign above a specific level. Backers of campaigns that did not meet AON funding-targets receive refunds. For projects that did meet their targets, funds are transferred to the creator – minus platform and payment fees.

Transfer of funds kicks off a work-intensive time for creators after the fundraising concludes. They stay in touch with backers via the crowdfunding platform and update them on progress made toward the delivery of their rewards. In turn, backers often write comments on the project to inquire about its status, and possible deviations from the planned schedule and rewards delivery. They often ask for more information or express concerns, while the creators reassure them and explain how they are managing various challenges. The majority of projects are delayed but most deliver rewards of varying quality, with few cases where backers are left empty-handed. Comments and updates typically continue for a certain period after the rewards are delivered, at which time communication gradually stops or moves to other platforms.

Model and Hypotheses for Crowdfunding Targets and Outcomes

Creators are motivated by a combination of multiple factors, including the desire to: develop a specific product or service that needs additional funds; test the market's appetite for a product or service; or build hype through viral sharing. Based on this, creators design projects according to key parameters, such as how long a project might take and what rewards might be offered. Creators then estimate a funding target, considering the resources needed for development, for profit, but also for contingencies and unforeseen challenges. Once the target has been set, creators engage in the fundraising process. Success depends on the reactions of potential backers. Finally, creators will carry out the project to completion and the rewards delivery process will begin. Fulfilling their obligations to backers though backers may or may not find their rewards satisfying. We hypothesize multiple relationships for this in the following. (See Figure 2.)

Figure 2. Conceptual model



Funding Success When Campaign-Creators Set Meager Funding-Targets

Many commercial principal-agent relationships begin with a contract of some sort, in which both parties negotiate the financial compensation required for the principal to assume specific outcomes and their associated risk [47, 59]. The estimation of outcomes and risk is challenging, as the goals specified for complex endeavors are vague, evolving, and can even be paradoxical in principal-agent settings [11, 71]. Crowdfunding projects are vulnerable to these challenges because they are often early-stage ventures where creators are exploring new markets and backers are not particularly knowledgeable.

A solution that addresses uncertainty is to overestimate the compensation required for individual projects. The resources available are always limited and under scrutiny though. So, principals may judge whether a project will maximize their allocated resources, with the result that the agents must compete partly on price [83]. This encourages a supplier to bid low to secure a supply chain contract, for example, either because the supplier underestimates the requirements, intends to make quality compromises, or is willing to take more risks than its competitors [69].

Thus, the temptation for a creator in rewards-based crowdfunding is to select a meager funding-target. By *meager*, we mean a funding-goal that is relatively lower than the estimated funding needed when compared with other projects of similar complexity and scope. Such projects are more likely to reach their funding milestones [22]. Backers are more willing to fund smaller projects, perhaps due to the lower initial investments required or due to a focus on smaller markets that appeal to niche groups. Crowdfunding platforms have a limited pool of backers though, so creators must compete for attention and funding from the backer community [84]. Thus, even though crowdfunded projects must initially be incentive compatible for the participants, the divergence of creator-backer incentives over time will reflect their pursuit of funding, risk tolerance, and rewards to be delivered. As a consequence, some creators will have rational expectations that leads them to set meager funding-targets for their project [6]. This makes them more likely to hit their funding targets, though backers must accept increased rewards uncertainty. So, we offer:

> **Hypothesis 1a (Meager Funding-Targets Yield Successful Funding):** *Campaigns with meager funding-targets are more likely to meet their targets and receive full funding, compared with other project campaigns of comparable scope, complexity, and market type.*

Meager Funding-Targets and Backer Satisfaction

When information asymmetry is high and resources are sparse, agents may opportunistically leverage ambiguities in contractual agreements. Low monitoring and uncertain returns will tempt agents to shirk some responsibilities and take additional risks to achieve appropriate returns. Principals often manage this temptation by creating new incentives to “sweeten the relationship” for the agent. Often, the prospect of repeat business incentivizes agents to emphasize longer-term strategies to build trust and long-term relationships with principals [33]. Such incentives are less likely in rewards-based crowdfunding. Sometimes, crowdfunding may include long-term relationships, especially if creators launch or back multiple crowdfunding projects [20]. Most view crowdfunding campaigns as a springboard for projects to reach larger markets though, at which point their relationships with campaign-backers may become less important [85].

Another way for principals to discourage agent shirking is to provide compensation beyond the minimum another agent might accept. The opportunity becomes more desirable to agents than the alternatives, so creating a form of loyalty makes sense because agents do not wish to be identified as shirking or relegated to other inferior alternatives [3]. It also affords agents the slack to explore new opportunities while maintaining sufficient focus on core contractual items. Efficient agents are likely to create more opportunities over time, so they tend to encounter stronger competing opportunities [53].

Meager funding-targets, thus, will affect creator-backer alignment over the course of a crowdfunding relationship, as they increase the stress on resources allocated to initially-planned outcomes. Assuming creators may then shirk on those initially-planned outcomes, backers have few contractual controls. While some backers may be risk-tolerant and understanding when unforeseen or unmanaged threats undermine projects, others will likely become vocal about being dissatisfied. A number of well-known factors influence the degree of their dissatisfaction, such as delays, poor communication from creators, or an unwillingness to accept community input. However, our theoretical perspective suggests that inappropriate meager funding-targets and poor risk management are tied to subsequent dissatisfaction of backers. So, we assert:

> **Hypothesis 1b (Meager Funding-Targets and Backer-Dissatisfaction):** *Campaigns with meager funding-targets are less likely to satisfy backers with project outcomes, compared with other project campaigns of similar scope, complexity, and market type.*

Alternative Explanations and Moderating Influences

Setting a funding target is complex. We propose alternative explanations as to why a meager target may cause a reduction in backer satisfaction; explanations that are not based on diverging incentives.[8] These explanations are not intended to be exhaustive. They support our attempt to model and test moderation effects to explain the reasons for the hypothesized impact of meager funding-targets on backer satisfaction.

Creators who seek less funding may be less passionate about their projects. It makes sense that backers who are less committed to a project will prefer streamlined activities and ask for less money. If so, low backer-satisfaction should not be attributed to incentive issues, as creators discover new product or service opportunities over the course of a project. Instead, creators asking for less funds may intend to make less effort from the outset. So, the problem is common adverse selection and moral hazard.

This alternative explanation assumes that creator effort can offset the problem. Less well-funded projects may overcome insufficient reserves by their creators making compensatory effort, for example, by working longer hours for timely delivery or forfeiting payments to avoid escalating costs when effort is needed. They may divert expected profit to other efforts too, sacrificing returns for better product or service outcomes. Also, they may draw on their backers' voluntary efforts to offer valuable guidance and information, or creative contributions [29]. So, they will form their judgments of legitimacy and distinctiveness from feedback provided by other backers [81], who have varied backgrounds and interests.

Each of these scenarios requires that creators seek and receive sufficient feedback from backers. Feedback is a key component of monitoring activities in agency relationships, as it allows the principal a means of expressing encouragement or dissatisfaction, both to the sender and to other recipients. Monitoring helps the agent to gauge the principal's intent and priorities, and gives the agent a means to judge the effectiveness of their communication and to respond to the principal in negotiation.

Monitoring in agency relationships suggests that principals (as backers in our context) must often request and validate communications from agents (as creators in our context) to reduce *information asymmetry* [23]. While individuals may ask questions, creators' responses are usually visible to all backers. Thus, individual crowd members often lack in-depth and integrated knowledge from experts. As a result, they must rely on collective judgement to spot obvious problems and inform their own judgments of legitimacy with feedback provided by other backers. Greater levels of interaction create a sense of project connection. So, creators must treat backers as in-group members and avoid opportunism. This is likely to benefit all projects but it is especially important where agents are otherwise likely to shirk responsibilities, such as when a crowdfunding campaign creator's initial commitment is low. Thus, we will test:

> **Hypothesis 2 (Backer-Creator Interaction Effects):** *The negative effect of meager funding-targets on backer satisfaction with project outcomes will be weaker when there are more interactions between backers and creators – after the fundraising campaign concludes and before any rewards are due.*

Creators may seek meager funding because a project has low market appeal. Another reason why meager funding-targets may cause lower backer-satisfaction is that these projects are less attractive to backers. Setting a meager target is thus a decision forced on the creator by the practical realities of their products and services, and not necessarily due to incentive issues. This prediction is reasonable, if we assume a minority of new ventures succeed and funding on crowdfunding platforms gravitates toward the most promising projects, regardless of their funding targets. This is supported by the fact that many successful projects exceed their funding targets. Such "blockbuster" project legitimize new project types and tend to precede a surge in successful funding for subsequent related endeavors [75]. It appears that projects which barely make their funding targets may have prosocial motivations [24]. There may be a lack of demand for such projects and, perhaps, the target is in line with the estimated maximum demand.

This alternative explanation posits that the relationship between a meager funding-target and lower backer-satisfaction should be weaker if it substantially exceeds that target by harvesting more money from the market. This suggests market demand is higher than expected, and so predicts higher backer-satisfaction. Thus, it will demonstrate increased demand to the creator. This effect is likely to be stronger for projects when agents were previously skeptical about that market demand, such as when a crowdfunding campaign's creator initially set a meager funding-target. The creator may see additional reason to focus on the quality and timeliness of the planned outcomes, further reinforcing the moderation effect. We proffer:

> **Hypothesis 3 (Fundraising Beyond the Specified Target):** *The negative effect of meager funding-targets on backer satisfaction with project outcomes will be weaker when fundraising exceeds the initial funding target.*

Creators also may seek meager funding because they are forced to start small and build a reputation among backers. The opportunities available to an agent often change over the course of multiple tasks, as they can accumulate valuable reputation and trust over repeated interactions [53]. A form of deferred compensation may emerge that incentivizes the agent to expend effort and not be opportunistic, selfish or short-sighted. This deepens the principal-agent relationship, assuming the agent intends to continue in a future similar role. Further, the mutual benefits of having a trusted and successful long-term partner means the agent will share the costs of missing the principal's goals, such as delays, or shares the benefits of meeting them, such as for firm or product performance [57]. An agent's willingness to accept deferred compensation also allows them to demonstrate a commitment to long-term outcomes [7].

In the crowdfunding context, a meager funding-target may represent a gesture of good faith, in which the agent demonstrates their efficiency with limited resources. After the project, these creators return to the platform to fund new products and services. Over time, creators rely on the backer community to repay their demonstration of efficiency by building awareness and hype. Such examples also benefit backers, who become more invested in the products and services proposed by the creator and so less likely to express dissatisfaction that may damage the product's market potential, service, or the company with a negative public image. Similarly, creators who spent time building up these reputational and relational assets are incentivized to compensate for meager funding-targets with free labor, long hours, or less profit.

If this explanation were true, the relationship between meager targets and lower backer-satisfaction should decrease for creators who fundraise for multiple projects. Further, the effect will be stronger for projects when resources cannot be easily reallocated to account for unforeseen issues such as when a campaign's creator set a meager funding-target. So, we further assert:

> **Hypothesis 4 (Creators' Relationships with Platform Users in Repeated-Campaigns):** *The negative effect of meager funding-targets on backer satisfaction with project outcomes will be weaker when creators have ongoing relationships with other platform users in repeated crowdfunding-campaigns.*

Data and Variables

Research Setting and Dataset

We selected Kickstarter as a research setting. As of January 2021, over 193,000 projects were funded through this platform, raising USD 5.5 bn from 19 mm backers. We gathered a dataset that covers the period from the launch of Kickstarter in April 2009 until December 2020. It includes over 500,000 projects launched on the platform during that period. For this study, we limited our dataset in these ways. First, we excluded campaigns that did not provide an estimated delivery date for the offered rewards. This information is essential for our analysis: it defines the start date for the period in which we expect backers to express their satisfaction or dissatisfaction with the rewards they were supposed to receive. Providing this information was possible for creators from August 1, 2011 onwards. Second, we excluded campaigns that were canceled by the creator or suspended by Kickstarter (e.g., for copyright violations). The final dataset consists of 389,064 campaigns, of which 163,840 were successful. Our dataset contains basic campaign information, such as the project descriptions and funding targets, but also the text of more than 20 mm comments written by backers about these projects.

Variables

Dependent variables. The dependent variables in our study are twofold. First, we use a variable for funding-target success (*FundSucc*), to indicate whether a campaign reached its AON funding target. Second, we use backer satisfaction (*BackerSatisf*) by evaluating the average valence encoded in their textual comments after the designated reward delivery date and for a period of up to 12 months after. On average, creators planned to deliver the first reward 55 days after the campaign deadline elapsed, while they estimated it would take another 73 days for the final reward to be delivered to backers.

During this waiting period, 6 mm comments were written by backers, averaging 15 per campaign (std. dev. = 268). Similar to Saifee et al. [68], we examined the sentiment represented in these comments using the R package, SentimentR. Its sentiment analysis goes beyond simply comparing words in a given text to a list of words with negative and positive sentiment polarity and intensity scores. Rather, it considers N-grams and thus also words that appear in close proximity to a word with a negative or positive connotation.

As such, the tool considers several types of valance shifters, such as negators (e.g., "`not good`") or those that should amplify the polarity and intensity scores (e.g., "`very good`"). To fine-tune the analysis, we added 12 words and corresponding scores relevant to crowdfunding (e.g., "`refund`").

Based on the continuous sentiment scores provided by SentimentR, we derived a binary operationalization for *BackerSatisf*, in which we considered backers to be satisfied with the outcome of the campaign and their rewards if their average sentiment score was 0 or above and dissatisfied otherwise.[9] We did so as we are primarily interested in whether backers were satisfied with the outcome of the campaign or not and less interested in the specific sentiment score. To avoid bias, we included only those campaigns that received at least one comment in the mentioned period, and we ignored comments by project creators.

Independent variable. Our main independent variable is meager funding-target (*MgrFundTrgt*). It captures whether creators set a meager funding-target for their crowdfunding campaign compared to other projects of comparable scope, complexity, and market type, reflecting diverging expectations. (For the measurement details, refer to the last paragraph of the next section.)

Moderators. To test Hypotheses 2 to 4, we used three moderators. First, post-fundraising comments (*PostComm*) indicates how many comments were posted by the project creators and backers after the campaign concluded, but before any rewards were due at the end of the project. Second, *%Fund* indicates the percentage of funding obtained compared to the funding target. Third, we measure how many campaigns were launched by the creators *(#CreatorProj*), as a way to proxy for their experience with crowdfunding.

Control variables. Crowdfunding research has examined how different campaign characteristics predict backer commitment during the fundraising process. To control for identifiable heterogeneity that might suggest alternative explanations, we included control variables in our models suggested by past research. We defined the review scope for identifying the campaign characteristics most commonly associated with fundraising in rewards-based crowdfunding. We focused on campaign characteristics that were partially or totally visible to backers during fundraising. Rather than exploring and interpreting the different qualities that vary by project context, we limited the focus to empirical studies that performed quantitative analyses of multiple projects. We included studies from a range of disciplines that achieved a high level of methods scrutiny. So, we conducted a systematic literature review of Financial Times 50 journals (FT50) limited it to the period, January 2010 to January 2020, avoiding work when crowdfunding was emerging.

Our search terms included two words that could appear anywhere in the articles (“`crowdfunding`” and “`crowd funding`”) and two popular platform names (“`kickstarter`” and “`indiegogo`”). They also could occur in case studies of crowdfunding platforms in other research streams, and where the authors chose not to refer to the platform type. Our work produced an initial set of 132 articles from 22 of the 50 journals. We eventually identified 40 quantitative studies on rewards-based crowdfunding.[10] We noted that none of the sampled papers focused on backer satisfaction, so we used a concept-centric matrix to synthesize the common campaign characteristics linked to funding success.[11] Further refinement gave us a list that was grouped into pre-launch and post-launch sets of campaign characteristics.

We considered the following pre-launch campaign characteristics. First, we built dummy variables for the 15 Kickstarter categories, as well as for the respective subordinate categories, in which creators launched their campaigns. Second, we created dummies for the currency used for collecting the funds. Third, though our dataset has a cross-sectional structure, it spans 2010 to 2020. So, we included dummy variables for years and months in which a campaign was launched to control for the unobservable time-varying effects of a changing platform. Fourth, the amount of information shared by creators was proxied by the word count in the campaign description as well as the statement on the project risks. Fifth, the written information was complemented by a pitch video. Sixth, we considered the number and average price of rewards, which specify the deliverables that backers may expect. While the details of the different rewards vary, their number typically indicates the breadth of commitments creators made to backers. A higher number offers backers more choices but increases project complexity. Seventh, we also included the number of days the campaign accepted funds and the expected time to delivery of the first material reward to backers. Finally, we assessed how many prior campaigns of a given creator have been successfully funded.

We also included post-launch characteristics. For those, we first counted how many updates creators posted for a project during the fundraising period. Second, we assessed whether the focal campaign was assigned the label “project we love” by Kickstarter, which indicates the platform’s decision to further promote a campaign within the first few days after its launch. Third, we counted how many comments backers wrote in the delivery period during which they expected to receive their rewards. Finally, as a means to control for platform growth and competition, we control for the number of investments (in hundred thousands) made by backers during the quarter in which the respective campaign ended and the number campaigns in the same subcategory that were active on the day the respective campaign launched. (See Table 1 for descriptive statistics and variable descriptions.[12])

Table 1. Descriptive statistics and variable descriptions

VARIABLE	MEAN	SE	DESCRIPTION	ADDITIONAL INFORMATION
Dependent variables				
FundSucc	0.421	0.493	Campaign met AON target (0/1)[(a)]	Creators selected an AON funding-target
BackerSatisf	0.928	0.259	Backers considered satisfied if average sentiment score 0 or above (0/1)	Valence of backer comments written for up to 12 months after rewards were due
Independent variables				
FundTrgt	37,681.11	985,385	AON campaign funding-target (USD)	Funding-targets were converted to USD
MgrFundTrgt	0.124	0.330	Meager funding-target set by creators (0/1)	Equal to 1 if funding target is 1 SD (15.7%) below the predicted *FundTrgt*
Moderators				
PostComm	4.747	125.039	# comments posted in waiting period	Comments posted after funding period has ended but before rewards were due
%Fund	429.7	36,926.92	Percentage of funding target obtained	
#CreatorProj	0.601	2.63	# of prior projects developed by creator	Proxy for creator-experience
Control variables				
Pre-launch characteristics				
ProfCat	–	–	Project category (15 total)	Dummy variables for each category[(b)]
ProjSubCat	–	–	Project subcategory	Dummy variables for each subcategory
ProjCurr	–	–	Project currency	Dummy variable for currency
Month	–	–	Month campaign launched	Dummy variable for each month
Year	–	–	Year campaign launched (2011-2020)	Dummy variable for each year
#Wrds	579.832	603.661	# words in campaign description	Proxy for amount of info shared
Risk#Wrds	98.548	104.015	# words indicating project risk	Proxy for project risk
Video	0.702	0.457	Campaign had a video (0/1)	Measures richness of campaign info
#Rewards	7.892	5.868	# rewards offered to backers	Flexible to suit creator’s project needs
AvgRewPr	437.773	3,462.005	Average reward-price for backers	Proxy for reward-value expectation
TimeRewDel	88.128	108.021	# days before 1st reward to be delivered	
#CmpgnDays	33.186	11.651	Duration, # days for fundraising	For different project types
PriorSuccess	0.409	2.255	# prior successful campaigns by creator	Proxy for creator experience
Post-launch characteristics				
Updates	5.005	9.412	# updates made by a creator	Proxy for creator attentiveness
LovedProj	0.099	0.299	Kickstarter showcased project (0/1)	Campaign featured on separate webpage
#CommDel	15.279	267.540	# of comments written by backers during delivery period	Comments written after rewards were due and for up to 12 months thereafter
ActiveBackers	15.872	3.501	# of investments (in hundred thousands) made by backers during quarter when the respective campaign ended	Backer-investment activity is to proxy for how much they engage in crowdfunding over time

Competition	118.549	110.059	Number of active campaigns in same subcategory on the day of launch	Indicates to which campaigns of a similar type are competing with one another

Notes. [(a)]AON = All-or-nothing funding; [(b)] 15 Kickstarter categories are: Art, Comics, Crafts, Dance, Design, Fashion, Film & Video, Food, Games, Journalism, Music, Photography, Publishing, Technology, and Theater.

Quasi-Experimental Research Design and Econometric Estimation

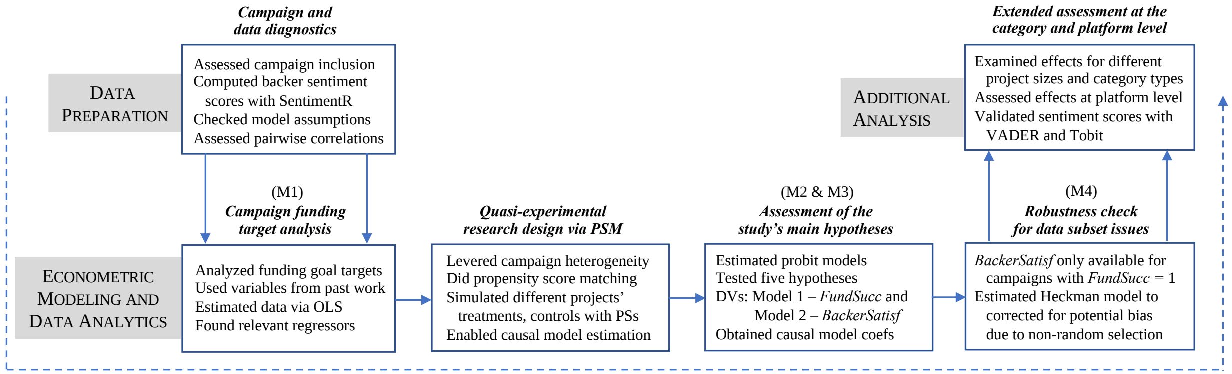
The approach we use to test the primary hypotheses in the crowdfunding market mechanism is a *quasi-experimental* (QE) *research design*. It reflects contemporary *computational social science* (CSS) methods [14, 55] involving big data and causal inference [16, 17]. Establishing causal relationships is important in empirical assessments of business, political, public and environmental policy. It offers a way to obtain an unbiased reading of the strength of the underlying relationships through data analytics [65], while retaining an appropriate level of validity to make evidence-based policy-making realistic [28]. Further, when carrying out a randomized and controlled experiment is not an option [26], it is possible to use identification strategies including QE designs that address selection issues due to unobservable variables that are likely to have discoverable effects [38]. The testing strategy for causal inference depends on the sources of variation in the dependent and independent variables associated with the treatment and the data.

Propensity-Score Matching (PSM) to Support the QE Research Design

Causal inference from data has been a central concern in several disciplines, when it is not possible to randomly-assign observations to treatment and control groups. As such, systematic differences between groups may lead to biased results. We could not design a randomized field experiment, though we can take advantage of the participants, by leveraging information for what may differentiate them. Further, campaigns with meager targets may be systematically different from other campaigns and these differences may be the true cause of any effects we see.[13]

Kim and Steiner [52] cautioned us that different ways to leverage QE designs to produce causal inferences are used: among them, *instrumental variables* (IVs) and PSM. Imbens and Rubin [46] further reported that if there are *"reliable measures of all confounding covariates, then matching or propensity-score* (*PS*) *designs to balance groups on observed baseline covariates and thus enable the identification of causal effects*" (quoted in [52, p. 400]).[14] *Matching methods* are effective to pair treated and control observations based on observable pre-treatment characteristics. We use PSM for matching based on campaign characteristics determined before campaigns are launched: description length, risk description length, project video, project rewards, average reward price, campaign duration, and time to rewards delivery.[15]

Figure 3. Research process and methods



We next present our use of PSM to create a QE research design. We discuss econometric considerations and the empirical approach to test the proposed hypotheses to uncover causal connections. (See Figure 3.) After assessing campaigns to include in the dataset for analysis, the creation of computed variables for some constructs, and the basic model assumptions and variable checks (upper left block), we next did campaign funding-target analysis (*FundTrgt*) with Model 1 (M1). For that, we derived a measure that indicates whether a campaign had a meager funding-target (lower left block). (See next section.) To test the hypotheses for the overall effects of meager funding-targets on campaign funding-success and backer satisfaction, we implemented PSM (2nd block from the left). This was to address campaign heterogeneity, and make the relatively low and high funding-targets in campaigns serve as QE design elements. Thus, we could approximate a treatment-control design that made causal inference from the modeling estimates possible [45].

Then, we used models to capture the nature of our operationalizations for funding success (*FundSucc*) and backer satisfaction (*BackerSatisf*) with Models 2 (M2) and 3 (M3), respectively. *FundSucc* was mapped to [0,1] for success (2nd block from the right). In this case, the estimation was for whether the AON target was met. In the case of backer satisfaction (*BackerSatisf*), we assessed whether a binary-valued variable for the valence of the campaign-backers' aggregate sentiment was positive (satisfied) or negative (dissatisfied) for a campaign. (See Appendix B of the online supplemental material for alternative measures.)

We also used Heckman's [41] model to account for the dependent variable, *BackerSatisf*, only being available for successful campaigns to avoid selection bias [31]. Our assessment of category-level and platform-level effects came last (top right block).

Precursors to Creator-Backer Incentives

The logic of the information structure in the applied setting suggests that the exact process of how creators decide on and set a particular funding-target on Kickstarter is opaque to outsiders. Thus, we lacked such information. However, we note that creators will likely compare their own targets to those set by other creators who launched similar campaigns in the same subcategory in preceding weeks and months.

To identify comparable funding-targets, we ran a linear model with a log-transformed funding-target as the dependent variable for the total 389,064 campaigns. We estimated it with ordinary least squares (OLS) and used campaign pre-launch characteristics as regressors that are likely linked to lower or higher funding-targets. We measured the length of the project description (*#Wrds*) as well as the risk description text (*Risk#Wrds*) and assessed whether a video was included in the campaign (*Video*). To proxy for a creator's desire to test market demand and/or develop a viable product or service, we assessed the number of different rewards offered (*#Rewards*) as well as their average price (*AvgRewPr*). Higher-price rewards resemble sales, not tokens of appreciation. We also captured the campaign's duration (*#CmpgnDays*) as well as the length of time between the funding deadline and the planned delivery of the first rewards (*TimeRewDel*). Finally, we controlled for the chosen campaign currency (*ProjCurr*), the subcategory (*ProjSubCat*), and the month and year the campaign launched (*Month, Year*). These reflected a creator's choice of markets.

Table 2. Funding-target model predictions

VARIABLES	Funding-Target Model (M1)	
	COEF	SE
ln (*#Wrds*)	0.116***	(0.003)
ln (*Risk#Wrds*)	0.110***	(0.002)
Video	0.308***	(0.006)
ln (*#Rewards*)	-0.206***	(0.005)
ln (*AvgRewPr*)	0.510***	(0.002)
TimeRewDel	0.002***	(0.000)
#CmpgnDays	0.019***	(0.000)

Constant	3.601*** (0.029)
ProjCurr *ProjSubCat* *Month / Year*	Dummies included but details omitted due to space limits.
Obs.	389,064
Adj. R^2	39.8%

Notes. Dep. var.: ln(*FundTrgt*); * $p < 0.05$; ** $p < 0.01$, *** $p < 0.001$; SEs are in parentheses.

The proposed model explains about 40% of the observed variation in funding targets. (See Table 2.) We used the model to obtain a *predicted, appropriate funding-target* for each campaign in our sample and assessed how much each campaign's creator-chosen target diverged from this prediction. The binary meager funding-target (*MgrFundTrgt*) variable was set to 1 if the actual funding-target was at least one standard deviation below the predicted value. This applied to 48,418 of the 389,064 campaigns. Campaigns with meager funding-targets typically have a target that is in the 1st quartile in the respective subcategory.

Results

We next present the empirical results on the hypotheses' main variables and moderators. We used econometric models that implemented our research design for the outcome success in the crowdfunding setting, especially related to whether the AON funding-target was met and campaign backers expressed satisfaction with project outcomes. We then discuss the robustness of our identification strategy and post hoc analyses.

Effects of Meager Funding-Targets

We estimated a Funding-Success Model (M2) for the dependent variable, *FundSucc*, and a Backer-Satisfaction Model (M3) for the dependent variable, *BackerSatisf.* As our dependent variables are binary, we estimated probit models with robust standard errors. (See Table 3.)

Table 3. Probit estimation results

VARIABLES	FUNDING-SUCCESS MODEL (M2)		BACKER-SATISFACTION MODEL (M3)	
	COEF	SE	COEF	SE
MgrFundTrgt	0.847***	(0.008)	-0.098***	(0.020)
ln (#Wrds)	-0.004	(0.003)	0.017*	(0.007)
ln (Risk#Wrds)	-0.046***	(0.003)	0.022**	(0.008)
Video	0.134***	(0.007)	0.048*	(0.020)
ln (#Rewards)	0.237***	(0.006)	-0.059***	(0.016)
ln (AvgRewPr)	-0.104***	(0.002)	0.015*	(0.007)
TimeRewDel	-0.002***	(0.000)	-0.002***	(0.000)
#CmpgnDays	-0.016***	(0.000)	-0.001	(0.001)

Updates	0.996***	(0.004)	0.105***	(0.009)
LovedProj	0.531***	(0.010)	0.063***	(0.018)
ActiveBackers	-0.007***	(0.002)	0.005	(0.004)
Competition	-0.000	(0.003)	-0.007	(0.007)
PriorSuccess	0.587***	(0.009)		
#CommDel			0.241***	(0.008)
Constant	-0.663***	(0.036)	1.277***	(0.097)
ProjCurr *ProjCat* *Month / Year*	Dummies included but details omitted due to space limits.			
Obs.	389,064		83,745	
Pseudo-R^2	47.7%		7.6%	

Note. Dep. var = *FundSucc* in Model *2* and *BackerSatisf* in Model 3; signif. and dummy variables handled as before. SEs are robust.

The *MgrFundTrgt* coefficient in M2 was positive and significant. Looking at the marginal effects, we found that campaigns with meager funding-targets (*MgrFundTrgt* = 1) were over 18% more likely to reach their funding target, supporting the Meager Funding-Targets Yield Successful Funding Hypothesis (H1a).

Likewise, the coefficient for *MgrFundTrgt* in the Backer-Satisfaction Model (M3) was negative and significant. Marginal effects revealed that campaigns with meager funding-targets were over 2% less likely to satisfy backers, supporting the Meager Funding-Targets and Backer-Dissatisfaction Hypothesis (H1b).

Empirical results after PSM was applied. As imbalance in the covariates may have affected our main results, we performed the same analysis again after applying PSM [42]. Table 4 shows the estimation results after PSM was applied. They are similar to our main results with only slight differences in coefficients, which provides further support for our hypotheses.

Table 4. Probit estimation results after PSM was applied

VARIABLES	FUNDING-SUCCESS MODEL (M2)		BACKER-SATISFACTION MODEL (M3)	
	COEF	SE	COEF	SE
MgrFundTrgt	0.857***	(0.011)	-0.139***	(0.027)
ln (#Wrds)	0.032***	(0.006)	0.012	(0.014)
ln (Risk#Wrds)	-0.036***	(0.006)	0.036*	(0.015)
Video	0.050***	(0.012)	0.021	(0.030)
ln (#Rewards)	0.264***	(0.012)	-0.030	(0.029)
ln (AvgRewPr)	-0.110***	(0.005)	0.014	(0.013)
TimeRewDel	-0.001***	(0.000)	-0.002***	(0.000)
#CmpgnDays	-0.014***	(0.000)	-0.002	(0.001)
Updates	1.012***	(0.007)	0.100***	(0.017)
LovedProj	0.593***	(0.028)	0.070	(0.041)
ActiveBackers	-0.005	(0.003)	-0.006	(0.007)
Competition	-0.012*	(0.006)	0.004	(0.013)
PriorSuccess	0.522***	(0.015)		
#CommDel			0.238***	(0.014)
Constant	-0.868***	(0.072)	1.184***	(0.176)
Obs.	96,836		21,636	
Pseudo-R^2	46.7%		6.9%	

Note. Dep. var. = *FundSucc* in Model 2 and *BackerSatisf* in Model 3; signif., dummies, and SEs handled as in prior tables.

Moderating Effects

In the analysis of the moderating effects, we first focused on how the main effect of a meager funding-target (*MgrFundTrgt*) is moderated by the interaction between creator and backers, measured as the number of comments posted after the funding period concluded (*PostComm*). The second moderator variable, *%Fund*, indicates the percentage of funding obtained compared to the funding target. The final moderator is creator experience, measured as the number of crowdfunding project campaigns launched by a creator before the focal campaign (*#CreatorProj*). The estimation results are shown in Table 5.

We found that the coefficient for the main effect of *PostComm* was insignificant and there was no support for the Backer-Creator Interaction Effects Hypothesis (H2), as the moderating effect of *PostComm* was also insignificant (See Table 5, Moderator A).

Table 5. Probit moderator estimation results

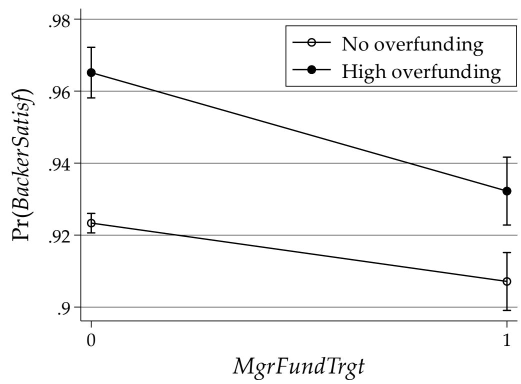
VARIABLES	*POSTCOMM* MODERATOR A		*%FUND* MODERATOR B		*#CREATORPROJ* MODERATOR C	
	COEF	SE	COEF	SE	COEF	SE
MgrFundTrgt	-0.096***	(0.023)	0.209	(0.115)	-0.100***	(0.024)
ln (*PostComm*)	0.009	(0.009)				
MgrFundTrgt × *ln* (*PostComm*)	0.000	(0.018)				
ln (*%Fund*)			0.118***	(0.016)		
MgrFundTrgt × *ln* (*%Fund*)			-0.069***	(0.021)		
ln (*#CreatorProj*)					0.056***	(0.012)
MgrFundTrgt × *ln* (*#CreatorProj*)					-0.012	(0.023)
ln (*#Wrds*)	0.017*	(0.007)	0.016*	(0.007)	0.017*	(0.007)
ln (*Risk#Wrds*)	0.022**	(0.008)	0.024**	(0.008)	0.024**	(0.008)
Video	0.048*	(0.020)	0.064**	(0.020)	0.057**	(0.020)
ln (*#Rewards*)	-0.058***	(0.016)	-0.062***	(0.016)	-0.063***	(0.016)
ln (*AvgRewPr*)	0.015*	(0.007)	0.021**	(0.007)	0.018*	(0.007)
TimeRewDel	-0.002***	(0.000)	-0.002***	(0.000)	-0.002***	(0.000)
#CmpgnDays	-0.001	(0.001)	-0.000	(0.001)	-0.000	(0.001)
Updates	0.104***	(0.009)	0.097***	(0.009)	0.104***	(0.009)
LovedProj	0.062***	(0.018)	0.058**	(0.018)	0.064***	(0.018)
ActiveBackers	0.005	(0.004)	0.006	(0.004)	0.005	(0.004)
Competition	-0.008	(0.007)	-0.008	(0.007)	-0.007	(0.007)
#CommDel	0.238***	(0.008)	0.218***	(0.008)	0.238***	(0.008)
Constant	1.282***	(0.097)	0.687***	(0.126)	1.252***	(0.097)
Obs.	83,745		83,745		83,745	
Pseudo-R^2	7.6%		7.8%		7.7%	

Note. Dep. var. = *BackerSatisf*; signif., dummies, and SEs handled as earlier.

We found a positive main effect for the second moderator, *%Fund*, which suggests that, in general, campaigns that get overfunded have a higher likelihood of satisfying backers. However, against our

Fundraising Beyond the Specified Target Hypothesis (H3), the moderating effect of *%Fund* was negative, suggesting that campaigns with meager funding-targets (*MgrFundTrgt* = 1) benefit less from overfunding in terms of backer satisfaction, compared with other project campaigns of similar scope, complexity, and market type. (See Table 5, Moderator B.) The marginal effects of the absence versus the presence of high overfunding are shown in Figure 4.

Figure 4. Moderating effect of overfunding for *BackerSatisf*



Finally, for the Creators' Relationships with Platform Users in Repeated-Campaigns Hypothesis (H4), we proposed that creators' relationships with backers and their involvement in campaigns will moderate the effect of diverging incentives so experienced creators who set meager funding-targets will benefit more from their experience. While the main effect of *#CreatorProj* was positive and significant, suggesting that more experienced creators were more likely to satisfy backers, the moderating effect was not significant. (See Table 5, Moderator C.) We thus found no support for H4.

Table 6. Heckman estimation model results

VARIABLES	FUNDING-SUCCESS MODEL (M2)		BACKER-SATISFACTION MODEL (M3)	
	COEF	SE	COEF	SE
MgrFundTrgt	0.710***	(0.012)	-0.126***	(0.021)
ln (#Wrds)	-0.003	(0.004)	0.017*	(0.007)
ln (Risk#Wrds)	-0.051***	(0.004)	0.025**	(0.008)
Video	0.133***	(0.010)	0.045*	(0.019)
ln (#Rewards)	0.323***	(0.009)	-0.072***	(0.016)
ln (AvgRewPr)	-0.090***	(0.003)	0.019**	(0.007)
TimeRewDeliv	-0.003***	(0.000)	-0.002***	(0.000)
#CmpgnDays	-0.014***	(0.000)	-0.000	(0.001)
Updates	1.135***	(0.005)	0.052**	(0.018)
LovedProj	0.653***	(0.012)	0.038*	(0.019)

ActiveBackers	-0.000	(0.002)	0.005	(0.004)
Competition	0.029***	(0.004)	-0.009	(0.007)
PriorSuccess	0.665***	(0.009)		
#CommDel			0.241***	(0.007)
Constant	-1.985***	(0.049)	1.431***	(0.107)
atanh(ρ)[(a)]	-0.09** (0.026)			
Obs.	308,971		83,745	

Note. Dep. var. = *FundSucc* in Model 2, *BackerSatisf* in Model 3; Signif., dummies and SEs handled as in prior tables. [(a)] In *atanh*(ρ), ρ is the variance-covariance matrix which correlates the model error term with the error term of the selection equation used in estimation. The stat *atanh*(ρ) is a step to obtaining the best estimate of ρ via arctanh(ρ).

Robustness Checks

Our dependent variable, *BackerSatisf,* was only available for successful campaigns in which backers expected to receive rewards, so a selection bias may exist in the models [31]. As the underlying selection criterion is known (i.e., only campaigns that succeed in reaching the funding target will have a value for *BackerSatisf*) and the selection process is driven by observable characteristics (i.e., what characteristics drive *FundSucc* are known), we adopted the Heckman-type probit model to account for the selection process [41]. To model the selection process, we considered the same set of covariates as in our Funding-Success Model (Table 3, Model 2). The estimation results of the Heckman-type model, considering the selection process, are presented in Table 6. The coefficients are largely consistent with our main results.

Post Hoc Analyses

While the focus of our study is on uncovering relationships at the campaign level, we also extended our main findings to provide additional analyses at the category and platform level.

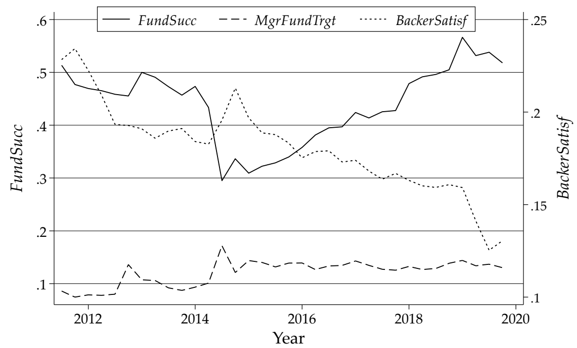
Category-level effects. On Kickstarter, projects in the various subcategories differ in terms of scope, complexity, and market type. For instance, in subcategories such as Wearable Technology, the focus of projects is on the development of hardware technology products with high fixed-costs. Selecting a particularly-meager funding-target in these categories may be especially costly. In other subcategories, projects often have low or no fixed costs and can be completed on a lower budget, as long as the reward's marginal costs of production can be covered with the collected funds. For instance, projects launched in subcategories focused on digital goods production, such as e-books, will be able to scale down the product itself, ship it partially completed to a backer, and typically have no or very low marginal costs.

To compensate for differences among subcategories, we ran two sets of sub-sample analyses. First, we made used of the fact that, for each reward, entrepreneurs must indicate whether it is a physical reward that needs shipping. Based on this information, we checked per category and subcategory whether most products developed were physical or digital. We found that 74% of categories and subcategories were focused on the development of physical goods, while the others were focused on digital goods. The marginal effect of selecting meager funding-targets for backer-satisfaction differs only a little for categories and subcategories focused on digital (-2.8%) versus physical goods (-2.5%). (Sub-sample results are omitted due to space.)

Second, as our measure, *MgrFundTrgt*, is based on the percentage discrepancy between the actual and predicted funding-target, the absolute discrepancy might be rather small for projects in categories and subcategories that typically host small-scale projects. In turn, absolute discrepancies will be large among other projects that have a need for more capital on average. To check whether this influenced our results, we split the categories and subcategories into quartiles based on their median funding-targets. In the 1st quartile (with the lowest values of *MedFundTrgt*), the marginal effect of selecting meager funding-targets for backer-satisfaction yielded essentially the same result as our main analysis: a 2.2% lower likelihood of satisfying backers. Further, the effect of *MgrFundTrgt* was not significant for projects in the 2nd quartile (with a *MedFundTrgt* between USD 3,300-5,000). For the 3rd quartile, the marginal effect was highest with 3.2% and in the 4th quartile it was 2.0%. Thus, surprisingly, the largest projects based on their funding-targets had a lower likelihood of dissatisfying backers if they chose a meager funding-target.

Platform-level effects. We next plotted average values for *MgrFundTrgt*, *FundSucc*, and *BackerSatisf* (as a continuous variable) per calendar quarter over the observation period. (See Figure 5.) *FundSucc* and *BackerSatisf* fell until 2014, when Kickstarter dropped mandatory campaign screening [84]. After, *FundSucc* grew steadily from ~30% to ~55% in 2019, while *BackerSatisf* continued to decline, leading to a widening gap between both measures. The percent of campaigns with meager funding-targets also grew steadily from around 8% in 2011 to over 13% in 2019. Diverging expectations may be the cause of these longer-term problems for Kickstarter – a relationship that deserves further investigation.

Figure 5. Diverging *FundSucc* and *BackerSatisf* over time



Discussion

This study explored the relationship between creators' decisions to set relatively low fundraising targets on a crowdfunding platform, and the subsequent funding and market mechanism outcomes. We performed a quasi-experiment using a large sample of projects from Kickstarter to test this relationship, as well as several moderators. The results present three key findings.

Support for the Effects of Meager Funding-Targets

Our results indicate a causal relationship between a key campaign-design decision, setting the AON funding-target, and subsequent project outcomes. The concept of an AON funding target is an important component of rewards-based crowdfunding. Previous research has demonstrated that adoption of provision-point targets weakens the signaling relationship between a campaign's prior capital accumulation and subsequent backers' decisions to contribute [13]. Utilization of AON fundraising signals confidence on behalf of the creator. This willingness to gamble on themselves reaching a specific provision point provides additional social proof of their competence, making backers less reliant on other social cues such as herding. Past research concluded that mandatory AON targets may be a superior market mechanism.

We built on these findings by examining Kickstarter, where all projects must adopt the AON mechanism. Our study uncovered new issues with the use of AON targeting. Specifically, our results suggest that the possibility to set their own funding target encourages some creators to select relatively low targets. Such projects are likely to be successful with funding, but less likely to satisfy backers with their outcomes.

One explanation is that, having removed the opportunity for creators to communicate confidence when choosing their funding mechanism, setting a low fundraising target becomes a signal, allowing creators to demonstrate their confidence in a different way. Creators who signal confidence with AON funding are punished if their confidence is misplaced. They are incentivized, as a result, to be cautious when sending this signal. Those who signal confidence with meager targets are rewarded short-term (when they are highly invested) and punished longer-term (when they disengage). The costs of sending the signal are therefore reduced, opening the door for the degree of divergent incentives to influence creators' decision-making.

Evidence on the Role of Incentives in Rewards-Based Crowdfunding

Our results present evidence on how backer and creator incentives may differ on rewards-based crowdfunding platforms. The literature has widely acknowledged the imperfect overlap between backers' social goals and creators' commercial ambitions [10, 25]. So, some incentive differences in the creator-backer relationship are natural. We identified their manifestation on Kickstarter and linked them to a defining element of crowdfunding platform design: the requirement for AON targets. This is a vital step toward aligning the incentives better, rather than accepting the arising issues for rewards-based crowdfunding.

We investigated the role of meager funding-targets and their ramifications by hypothesizing and testing three alternative explanations. First, we proposed that creators who seek less money may be less passionate about their projects, and more interaction between creators and backers should attenuate the relationship between meager funding-targets and backer-satisfaction. The data did not support this explanation though.

Second, we proposed that creators may seek less funding due to a project's lower market appeal; excess fundraising may address this, but we observed the opposite effect. It makes sense based on the creator's post-fundraising learning and discovery. Additional resources are likely to accelerate this process of learning and discovery, paradoxically increasing the distance between emerging opportunities and initially planned outcomes. The added validation of the creator may also increase their desirability among other principals, so reducing the relational costs of disappointing backers.

Third, we proposed creators may seek less funding if they are forced to start small and build a reputation among backers. So, creators who launch more projects on Kickstarter should be less susceptible to the negative impacts of setting relatively low fundraising targets. Again, the data did not support this though.

Evidence of a Pooling Equilibrium and Deterioration in Primary Market Mechanism

Though we found evidence of issues with AON funding, there are no external regulations that require crowdfunding platforms to address them. Still, one could argue that it is in Kickstarter's short-term interest that campaigns be successfully funded because the firm collects 5% commission only if campaigns are successful. Meager funding-targets increase the success rate and reduce the waste of reviewing, hosting, and promoting unsuccessful campaigns. Kickstarter also has incentives to encourage funding that exceeds the provision-point targets, due to the guaranteed commissions they yield for the intermediary. Such funding also legitimizes subsequent projects in the same genre, creating a ripple effect of success.

Our results present evidence that diverging project-level incentives in the setting of AON funding-targets is part of a larger, potentially dangerous *pooling equilibrium*, in which information on different kinds of creators and projects are not available in the signaling game that characterizes Kickstarter's market mechanism. Akerlof [2] wrote about a similar *market for lemons* for signal-undifferentiated quality for used cars. He argued that it was due to the inability of sellers to make their private-held information about car quality available to buyers. He further asserted the theoretical diminution of the market's quality.

Our Kickstarter platform-level evidence demonstrates that aggregate funding and backer-satisfaction have shifted to exhibit opposing trajectories, perhaps represented by the growing trend of creators who set relatively low funding-targets. As a result, backers can no longer easily distinguish high-quality from low-quality projects. The creators' increasing adoption of meager funding-targets has been occurring to the detriment of project outcomes and backer interests, and so is correlated with their satisfaction – which coincides with our observation of deteriorating participation by backers on Kickstarter. This suggests that incentive divergence is not a marginal issue counterbalanced by other improvements in platform design. Instead, incentive divergence may be why Kickstarter has contracted in recent years.

Similar issues with uncertainty and asymmetric information have forced other online platforms that rely on consumer judgment and provision points for fundraising to revamp their mechanisms. Prosper.com, the first U.S.-based P2P lending website in 2005, initially adopted an auction system to calculate loan repayment rates. Lenders offered loans by bidding different interest rates and loan-seekers assembled loans from the lowest rates available to acquire their target funds. A *hold-up problem* developed for loan-seekers who did not know the interest rates that they would obtain before applying. Since then, this process has come to be known for its regulatory issues, such that P2P lenders are no longer able to forgo stating the rates on loans that they intermediate [40]. This problem resonates with us due to the evidence we obtained about Kickstarter. Its creators do not know the market potential of their planned products or services in a precise way. Thus, campaign-backers are left having to absorb the effects of lacking private information on project quality. Prosper.com, in an analogous way, abandoned its bidding mechanism in 2009 in favor of pre-set interest rates and tighter screening of loan-seekers.

Another example is U.S.-based Groupon.com, the group-buying e-commerce website founded in 2008. The firm initially used a provision-point mechanism similar to Kickstarter, which required a minimum number of buyers before product or service offerings were activated, thus assuring the digital intermediary some minimum level of revenue. This market mechanism created surges in demand and bottlenecks that often frustrated individual buyers looking to redeem their "groupons" for products and services, as had been observed in many similar group-buying business models around the world [48]. A related impact was that the perceived value of Groupon's business model among consumers was driven down, creating further downward pressure on the quality of sellers. In response, Groupon had to become selective of sellers allowed on the platform and further added maximum participant thresholds to limit undesirable pooling.

A further example is Priceline.com, a U.S.-based online travel agency (OTA) founded in 2007. It offered deep discounts on air travel, hospitality reservations and rental car contracts. It also was a major player with other OTAs (e.g., Orbitz.com, Expedia.com, Hotels.com) in the destabilization of *global distribution systems* (GDSs) [37]. Priceline, now part of Booking Holdings, initially allowed consumers to state their preferences and location when searching for deals, and then "name-your-own-price" to make a bid. Consumers then had to pay in advance – without knowing the hotels, airlines, or cars they would get. Similar to campaign-backers on Kickstarter, Priceline's consumers expected greater efficiency and lower prices to compensate them for their uncertainty. Meanwhile, participating providers were incentivized to find other value from these consumers, such as information about market demand or collateral consumer spending at hotel sites, or extending rental car contracts. Priceline moved to a more standard booking approach, dropped its "name-your-own-price" in 2016, but implemented the option of "pricebreaker deals" for hotels, in which users are offered lower prices if they are willing to accept any one of three named hotels for a given stay.

Each of these examples demonstrates a consistent pattern where consumer uncertainty drives down their willingness-to-pay for supplier services. A ripple effect on the quality of products and services offered, we argue, was created by the digital intermediaries. The remedy for Prosper, Groupon, and Priceline has been to reinstate consumer certainty at the point-of-purchase, since it is at the heart what could make their intermediation more incentive-compatible overall. Kickstarter has a different set of constraints, of course, as its focus on enabling creative projects causes the riskiness of their outcomes to be a basic characteristic that backers must accept – similar to all investment settings. To be successful going forward, it appears that Kickstarter will need to become a more traditional digital commerce platform – as the firms have that are our examples demonstrated. A new approach with dynamic pricing is required to manage the forces that lead to pooling, and enhanced monitoring tools will help backers to assess changing incentive compatibility.

Contributions and Limitations

The main insight from this study is that rewards-based crowdfunding may not be sustainable in its current form, unless new market mechanisms are introduced to solve fundamental problems. Though Kickstarter has established many fundraising practices in this type of crowdfunding and launched many high-profile technology and art projects, systemic issues in incentive structure seem to be contributing to a decline in campaign-backers' collective satisfaction and loyalty. The observed decline in satisfaction and participation accelerated when Kickstarter decided to reduce the restrictions on who can launch projects [84].

Crowdfunding presents a dilemma of *mechanism-based co-dependence*, which makes it so the participants "can't have one without the other." In other words, it is clear that both creators and backers need to support a market mechanism that balances the creator's desire for a reliable and efficient source of capital, while the backers need to be satisfied about their rewards and outcomes. So, if an *incentive-balanced market mechanism* is not found, the increasing severity of the problems when a platform expands will cast doubt on the *present value of growth opportunities* (PVGO) for crowdfunding in the future.

Theoretical Contributions

Several previous studies have explored the relationship between the design of crowdfunding campaigns and fundraising success. We sought to contribute a causal inference-focused approach for assessing how creator-backer incentives diverge over time in rewards-based crowdfunding. Our work lays a foundation for three streams of future research. First, causal modeling of the drivers of funding-success should help to assess the existing screening procedures for creators, as well as expectation-setting for campaign-backers and the drivers of their dissatisfaction with crowdfunding rewards. Risk-tolerant creators are not necessarily undesirable, as long as the backers have similar attitudes toward project risk. For campaign processes, experimental designs to assess how creator-backer incentives change over time should help to better understand how ongoing interactions impact their essential information asymmetry. In addition, developing ways to study the related mechanisms in more detail will allow future research to trace project outcomes back to key events and design decisions that influence how crowdfunding campaigns operate. If crowdfunding markets are to mature to become levers for key innovations, this will be important [51]. Further, no studies of which we are aware of link the design of crowdfunding campaigns to eventual backer satisfaction – a critical oversight. The business sustainability of Kickstarter, and other rewards-based crowdfunding platforms, requires an engaged population of backers. Thus, it is vital to identify the types of campaigns to which backers respond positively, so platforms can build and sustain their all-important communities.

Our second contribution is focused on modeling backer satisfaction. This represents a new direction for the crowdfunding literature, which has focused heavily on either the process of fundraising or its economic and commercial impacts. The prior emphasis takes for granted the growth of crowdfunding and its prevailing market mechanisms. Our findings suggest continued growth is not certain, especially if large numbers of backers are regularly disappointed by project outcomes. Empirically modeling backer satisfaction is important for this reason, we assert, so new theoretical perspectives can be developed that enrich our understanding of factors leading to positive backer experiences. Adding backer satisfaction is also important for studies about the macro-impacts of crowdfunding. Causal connections between regional trends and the number of successful campaigns may be incomplete or even misleading without also modeling backers' reactions to outcomes in geospatial terms – an opportunity for advancing other empirical research methods. It also will permit modeling geospatial information-spillovers and revealing their impacts in crowdfunding.

Other potential progress that is possible in our work is to explicitly identify the relevance of *dynamic incentive alignment*, as a way to leverage further engagement between creators and backers over the time of crowdfunding campaign project completion. The idea is to match developments in dynamic agency theory over the past 15 years and shift toward dynamic controls to maximize value for the participants [70].

Practice Contributions

This research contributes to practice by addressing diminishing participation in rewards-based crowdfunding platforms such as Kickstarter. First, we recommend that platforms address incentive issues to connect funding and development outcomes. Platforms can adopt staggered payment models. This shift is becoming more common outside of Kickstarter, as platforms such as Patreon introduce subscriptions, and equity platforms use multiple, not single funding rounds. Other options may be to introduce contingent payments throughout the development cycle, or to increase creators' accountability in the event of disappointing project outcomes. This suggestion complements research by Belavina et al. [8], who showed how escrowing fundraising in excess of the target can deter misconduct and improve efficiency.

Second, platforms may embed fundraising in other websites and social media used by creators. Creators will then be more likely to experience long-term reputational costs and benefits for project outcomes. This approach is commonly used in principal-agent relationships: both parties benefit from the other's ongoing success. It lessens the temptation for moral hazard to develop among agents, and the negative consequences for the principal threaten the resources and principals' appetites for the relationship too. This encourages mutual learning to reduce adverse selection and information asymmetry.

Third, platforms may use explicit structures for creators to share the perceived risks at their campaigns' outset. This encourages them to reflect on these risks when they set funding targets. It also highlights possible risks for backers, so they can evaluate creators' planned responses, and provide feedback as appropriate. Kickstarter has added some of these features in its "Risks and Challenges" section online. More can be done, ranging from mandatory creator disclosures to scheduled and automated backer polling.

Limitations and Future Research

We acknowledge several limitations in this research. First, we focused on a single platform with a disproportionately North American presence. While crowdfunding platforms are relatively uniform across countries in terms of design, there are several environmental factors that may influence users' attitudes and behaviors. One is *regulation*. For equity crowdfunding and P2P lending fintech platforms, this has been evident for some time. Crowdfunding tends to overlap with national regulation around financial investment. Regulation, nevertheless, prevents creators in many countries from using rewards-based mechanisms. Regulation may become relevant when lawsuits are proposed against creators who fail to deliver their planned rewards. Another factor is *culture*. Different cultures have distinct attitudes toward entrepreneurial risk-taking, and risk in general. They may also have different perceptions of power distance and hierarchy. Other user populations may have varying levels of wealth, security, and disposable income too. These could affect how creators and backers interact, and the funding targets they set, generalizing our findings to crowdfunding platforms in other regions, such as StartNext in Germany or DemoHour in China.

Second, we focused on Kickstarter, an established platform that emphasizes creative projects. Other such platforms are newer or cater to different markets, including prosocial cause-based projects, artistic exhibitions, and technology and education. Backers' expectations on these platforms build on a different legacy, though many have been inspired by the early growth of Kickstarter. It is also a *public-benefit corporation* (PBC), so it must consider the impact of their decisions on society. Backers may react more strongly as a result, when they perceive creators are behaving selfishly and ignoring risks. Alternatively, it may cause them to be more understanding and accept personal losses as part of the larger social exchange that is occurring. More research is needed to understand these new approaches and platforms.

Third, we acknowledge that our ability to model fundraising success was stronger than our ability to model backer satisfaction, based on the fit of our econometric models. One explanation is that a larger range of factors influences backer satisfaction and related outcomes, given that they continue to accumulate information after fundraising, and their production and development activities create additional complexity. That highlights our study's value, for extending current theory to post-campaign activities. Another explanation is that our satisfaction measures were less sensitive than they needed to be. Whether fundraising reaches some preset target leaves little scope for alternative measures, while backer-satisfaction is more ambiguous. We measured sentiment analytics for backer comments in several ways, though many other measures are possible. They include other types of text analysis, including specific terms or phrases that indicate satisfaction and not just broadly "positive or negative" sentiments. It may also include measures of stakeholder-engagement on other media, such as growing numbers of social media followers as projects reach their conclusion. This approach would help to capture the evolution of backers' longer-term relationships with creators. Other measures could include self-reported data, such as surveys to capture the perceptions of backers directly. Triangulation across multiple measures is likely to increase the sensitivity of measurement and validity. Perhaps most fundamentally though, a broader set of measures could expand and clarify our understanding of what makes a project satisfying for backers on platforms such as Kickstarter. These issues clearly open up new pathways for future research.

Conclusion

This study identifies a significant issue with the funding model used in rewards-based crowdfunding platforms, such as Kickstarter. We show how the timing of AON funding is linked to falling backer satisfaction across Kickstarter. We believe this is a significant finding for crowdfunding research, which can now begin the search for new market mechanisms to amend or replace AON fundraising. We hope this work will inspire new mechanisms that can maintain incentive compatibility over the course of a crowdfunding project and bring through the next generation of crowdfunding platform design.

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Notes

[1] Crowdfunding is widely viewed as a form of digital financial intermediation in the fintech sector. The British rock band, Marillion, successfully raised GBP 39,000 (~USD 60,000) online in 1997. Then in 2000, another organization, ArtistShare (www.artistshare.com), succeeded in raising about USD 130,000 for a project, which led businesses and charities to set up fundraising platforms on the Internet. A little later in 2006, a video-blog entrepreneur coined the word *crowdfunding*, foreshadowing the success of other well-known start-ups, such as Kiva in 2005, Indiegogo in 2008, and Kickstarter in 2009.

[2] There are numerous examples, though we lack space to discuss them. For additional details, see Agrawal et al. [1] and Hervé and Schwienbacher [40] on economics, innovation, and crowdfunding.

[3] The practice literature, in contrast, emphasizes the importance of financial target-setting that can support the future success of a fundraising campaign [30]. Kickstarter, for example, has managed to achieve a level of 38.21% for successfully-funded projects that met their financial targets, while it has had to absorb a much higher level for its 61.79% unsuccessfully-funded projects [79]. This suggests its record has been surprisingly weak historically [80]. In response, industry consultants have emphasized that campaign-creators must establish realistic expectations for fundraising levels as the first matter of business.

[4] Although banks must absorb the first losses in credit activities, no such restrictions have been promulgated to ensure there is effective *risk retention* in crowdfunding. This would make it so that platform intermediaries will not be able to pass on their problems with losses to other investors downstream through a process possibly involving *crowdfunding securitization* [40].

[5] A similar interpretation applies to *initial public offerings* (IPOs) of stock handled by an informed financial intermediary. The key choice is the price at which the equity is sold to investors [18]. A low price increases the risk the new firm entrepreneur will give away ownership at too low a price relative to its *present value of growth opportunities* (PVGO). Too high a price will return an inferior yield to investors. An investment bank, the financial intermediary for an IPO, has an incentive to avoid failure and not permit the IPO issuer to wring every penny of value from it. A less-greedy approach gives the market confidence, supports investor risk-taking, and enables the stock's value to rise over time to match its theoretical PVGO, while creating a positive impression of value, increasing demand by future investors. When a successful balance of IPO price, demand for shares, investor interest and upside potential is achieved, typically the issuer will harvest capital quickly, and its investment banks will be profitable.

[6] Another setting in which target choice decisions occur is commercial lending. Large banks use lending function *value-at-risk* (VaR) assessment to establish firm identity, type and sector, and exposure limits for lending and financial risk management [39]. A line-of-credit is established for a customer, and the bank advises the borrower how much working capital it can access on an annual, revolving basis. This *advised line* is supplemented by a *guidance line-of-credit* approved by the bank, to identify how much money it can make available if the borrower has negative cash flow, a business slowdown, or adverse supply costs or sales reductions. Setting the advised line too low (or high) makes a bank vulnerable to losing a customer, dealing with higher credit risk that could lead to too a high debt-to-equity ratio and subsequent bankruptcy.

[7] Sites such as Kicktraq (kicktraq.com) reinforce this perception, allowing members of the public to view the probability that live Kickstarter campaigns will reach their funding targets.

[8] We thank the Guest Editor, Thomas Weber, and the anonymous reviewers for encouraging expansion of the theory for the funding targets and other observable and unobservable aspects of the process to support alternative explanations.

[9] We derived normalized, weighted composite scores of sentiment for each of the 6 mm comments. The unidimensional sentiment scores were mostly in the (-1,+1) interval (most negative to most positive). We then averaged the campaign scores as a basis. See Appendix B of the online supplemental material additional tests to the validity of this measure.

[10] 50 of these articles were not focused on crowdfunding, another 10 covered equity crowdfunding, 8 P2P lending, and 1 charity. So, these all were removed, leaving 63 articles on rewards-based crowdfunding. 11 articles were not empirical, another 10 focused on macroeconomic impacts of crowdfunding, and two were qualitative. There were also removed, resulting in 40 articles.

[11] This resulted in an initial set of 53 campaign characteristics with demonstrated fundraising correlations. For parsimony, these were refined to remove characteristics that met any of the following exclusion criteria: (1) they described qualities of the creator, especially their bias and prejudice (e.g., age, ethnicity); (2) they were theoretical outliers that had not received widespread attention (e.g., rhetorical signals, anonymity); or (3) they looked at interactions between campaigns and social contexts, each of which would have to be analyzed separately (e.g., location, early contributions from offline networks, social media interactions, etc.).

[12] We report detailed descriptive statistics and pairwise correlations in Appendix A of the online supplemental material.

[13] Most observers view experimental designs as more effective than designs with statistically-detectable associations, though the study of causality has broader intellectual and interdisciplinary foundations [63]. When a researcher seeks to learn from studying an experimental intervention, randomized-control trial designs are strongest. But this kind of design is not possible in a setting where a creator's decision to engage in such fundraising is observable but not controllable. Creators who decide to crowdfund a project campaign self-select the funding target, the crowdfunding market mechanism, and the platform to use [76].

[14] There is a long tradition in research inquiry on causal effects of treatments and interventions in settings that establish the basis for making such inferences. Those who conduct *causal inferenc*e-focused empirical analysis recognize limitations from testing based on *statistical association.* According to Ruiz de Villa [67], analysts can use techniques to quantitatively document causality. They include: control variables in multivariate regression [64]; regression discontinuity designs [56]; difference-in-differences [15]; instrumental variables for causal assessment [4, 5]; switching regression [74]; and *propensity-score matching*. The latter leverages heterogeneity of observational units in the data to create a basis for QE research designs [27].

[15] In econometrics for QE designs, IVs are a means to address problems with endogenous effects on the dependent variable. In the IS discipline, IVs have been used in a "one-off" way to adjust a particular variable for endogeneity. The key difference to PSM is that IV-based solutions in IS research have not addressed model-wide causality. In contrast, PSM can support such causal inference. So, it is not appropriate to think of IV as a substitute for the use of PSM. With IVs, we typically get variable-specific bias adjustment; with PSM though, model-wide treatment-control causality across all of its variables can be attained. Observation matching in the dataset is what permits this.