An Empirical Study of the Dynamic and Differential Effects of Prefunding

Xiahua Wei
School of Business
University of Washington, Bothell, Washington 98011
xhwei@uw.edu
Phone: (425) 352-3233
Fax: (425) 352-5277
(Corresponding author)

Ming Fan
Michael G. Foster School of Business
University of Washington, Seattle, Washington 98195
mfan@uw.edu
Phone: (206) 543-7525
Fax: (206) 543-3968

Weijia You
School of Economics and Management
Beijing Forestry University
35 Qinghua East Rd, Haidian District, Beijing, 100083, China
wjyou@bjfu.edu.cn
Phone: +86 10 62338802

Yong Tan
Michael G. Foster School of Business
University of Washington, Seattle, Washington 98195
ytan@uw.edu
Phone: (206) 616-6785
Fax: (206) 543-3968

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Abstract

This paper investigates the dynamic and differential effects of prefunding on reward-based crowdfunding markets plagued by information asymmetry. Prefunding, an innovative feature in crowdfunding, enables founders to share project information with potential backers before fundraising begins. By collecting and analyzing daily project-level panel data from one of the world's largest crowdfunding platforms, we found that projects with the prefunding feature were more likely to succeed in reaching their funding goals and the effects of prefunding on the amount of funds raised remained positive and significant over time. In probing why this occurred, we used text analyses and revealed that the mechanisms driving the funding premium were the specific types of prefunding information shared between founders and potential backers (volume, length, and sentiment). Further, in examining the sources of funds, we found that prefunding information first attracts funding from regular backers, followed by lottery backers. This herding behavior creates two intertwined funding streams—a primary and a secondary—for prefunding projects. Finally, using counterfactual decomposition analysis, we identified the types of projects that benefited the most from prefunding and found that prefunding democratizes funding outcomes. These findings and insights into information sharing, herding, and differential effects of prefunding contribute to the OM-IS research on operational designs of reward-based crowdfunding platforms that serve early-stage ventures in online environments with minimal informational oversight and regulations.

Keywords: Crowdfunding, Information Asymmetry, Prefunding, Dynamic Effects, Herding, Counterfactual Decomposition

1. Introduction

Crowdfunding over the Internet allows entrepreneurs to raise relatively small amounts of money from large numbers of people to fund their early-stage ventures (projects) in short periods of time (Mollick 2014). It has become a worldwide phenomenon. The global crowdfunding markets grew at an average rate of 120% each year from 2011 ($1.47 billion) through 2015 ($34.4 billion) (Massolution 2015). The World Bank estimated that crowdfunding would reach $90 billion by 2020, surpassing venture capital and angel capital as a means of financing (Barnett 2015). A prominent type of crowdfunding, reward-based crowdfunding, offers founders, who are the creators of projects, low-cost opportunities to raise funds to support product research, development, and production for innovative ideas, and to test market demand before committing extensive investments (Belleflamme et al. 2014). In exchange for funding the project, backers have the opportunity to receive products produced in the future.

Despite the popularity of reward-based crowdfunding, its success is not guaranteed (Agrawal et al. 2018). Unlike other types of crowdfunding, such as equity-based crowdfunding where information disclosures are governed by strict regulations,[1] reward-based crowdfunding is unregulated (Cascino et al. 2019). Consequently, while founders have more private information about their projects than potential backers who may fund them, founders might not share it, including information on the founder's credibility, the likelihood of achieving funding success, and possible issues in product development, manufacturing, production, and delivery processes (Agrawal et al. 2014). Such potential information asymmetry in unregulated environments presents a classic "lemon market problem" that can cause backers to withhold their funding or withdraw from the market, leading to market inefficiencies or failures (Akerlof 1970). Hence, it becomes essential for reward-based crowdfunding platforms to address information asymmetry through effective design mechanisms that improve information sharing and market efficiency.

[1] Equity-based crowdfunding is regulated by national regulatory authorities, such as the Securities and Exchange Commission (SEC) in the U.S., regarding the types of information entrepreneurs must provide to potential equity investors.

The design of crowdfunding platforms is operational in nature. It has cultivated a flourishing research stream at the interface of operations management (OM) and information systems (IS). Our paper extends this research stream through a study of *prefunding*, an innovative design feature offered on JD Crowdfunding, one of the largest reward-based product crowdfunding platforms in the world.[2] With prefunding, founders can engage and communicate with potential backers *prior to* raising funds (Garimella et al. 2017). These actions are analogous to the prefunding efforts of startups before their initial public offering (IPO), such as executive presentations at IPO roadshows (Blankespoor et al. 2017) and communications with potential investors on social media (Blankespoor et al. 2018), which can play an informational role and create value for the company (Saboo and Grewal 2013). Likewise, prefunding can bring value for crowdfunding projects through its information shared with prospective backers. Integrating perspectives from OM, IS, information economics, and entrepreneurship, our research examines whether and how prefunding serves as a channel that facilitates information sharing and improves crowdfunding outcomes.

Specifically, we studied the following questions: (1) What are the dynamic effects of prefunding on funds raised throughout the fundraising period? (2) What are the effects of prefunding on the different types of backers? (3) What are the differential effects of prefunding across projects? To address these questions, we proposed hypotheses based on theories of information asymmetry, operational transparency, and herding. We tested these hypotheses using daily information from a project-level panel dataset consisting of 3,878 projects between April 2015 and July 2016 from JD Crowdfunding.

We find that projects that feature prefunding are more likely to succeed and raise considerably more funds than those that do not. This positive effect of prefunding is persistent throughout the funding period. To investigate why this occurred, we applied text analyses to the communication between founders and backers. We find that prefunding information, measured by volume, length, and sentiment, has strong explanatory power for funds raised. We also find that the additional information flow that prefunding

[2] The transaction value of the crowdfunding market in China was $5 billion in 2017; JD Crowdfunding had the largest market share at 20% (Yuan and Chen 2018).

creates first attracts a larger number of informed backers, who are then followed by uninformed backers. Finally, by using counterfactual decomposition analysis, we find that the return of prefunding is the highest for projects in the lower quantiles of the funding distribution.

Our study makes the following contributions. First, with in-depth research into a novel feature in crowdfunding (prefunding), our findings and insights extend the OM-IS literature on the optimal operational designs of crowdfunding platforms that serve early-stage ventures in an online environment with minimal information requirements. Second, we are the first to evaluate the dynamic effects of prefunding throughout the funding period. Third, we reveal that the specific types of prefunding information from founder-backer communications are the underlying mechanisms driving the funding premium associated with prefunding projects. Fourth, we verify that prefunding information induced herding behavior across two types of backers which then created two intertwined funding streams. Fifth, by identifying the types of projects that are most advantaged by prefunding, we show that this design feature levels the crowdfunding playing field. Sixth, our insights into the operational designs of crowdfunding platforms are of value to all crowdfunding stakeholders: founders, backers, platforms, policymakers, and the general public.

In the following sections, we first review the literature (Section 2), propose our hypotheses (Section 3), describe our data (Section 4), present empirical analyses and results (Section 5), perform robustness checks (Section 6), and conclude with our findings, contributions, and limitations (Section 7).

2. Literature Review

The design of digital platforms is at the core of OM-IS research (Kumar et al. 2018, Cohen 2018, Kornish and Hutchison-Krupat 2017). Designing a crowdfunding platform involves the understanding of factors, at both the project and platform levels, that influence crowdfunding success (Burtch et al. 2013). At the project level, the crowdfunding literature has identified various project characteristics as factors of funding success, such as project duration, funding goal, industry, pictures, videos, project description, available backing choices, and third-party endorsements (e.g., Bi et al. 2017, Mollick 2014, Kunz et al. 2017, Bapna 2019).

Additionally, the entrepreneur's characteristics and actions including gender (Gorbatai and Nelson 2015), social and intellectual capital (Ahlers et al. 2015), backing history (Colombo et al. 2015), and communications with backers (Courtney et al. 2017) have been found relevant to crowdfunding outcomes. We incorporate and extend many of these factors in our study.

At the platform level, several design features have been studied. For example, Cumming et al. (2019) evaluated all-or-nothing (AON) versus keep-it-all (KIA) revenue models for crowdfunding platforms and found that they led to different funding outcomes.[3] Gong et al. (2020) showed that a lottery backing feature could cannibalize funding if lottery backers crowded out other backers.

Other studies at the OM-IS interface use analytical modeling to optimize operational designs in crowdfunding platforms. For instance, Hu et al. (2015) investigated optimal product lines and pricing strategies in a two-period game where backers make decisions sequentially. In an AON scenario where backers have an incentive to strategically wait until success is certain before participating, Chakraborty and Swinney (2019) demonstrated that optimal reward menu designs can mitigate such strategic behaviors. Taking a different approach, Zhang et al. (2017) developed a dynamic model to optimize both the funding pledge level and the campaign duration to maximize revenue. In terms of moral hazard risks such as founders misappropriating funds and misrepresenting products, Belavina et al. (2020) compared two deferred payment mechanisms and showed that stopping campaigns once funding goals are met outperforms escrowing excess funds.

While analytical studies on crowdfunding are growing in the operations literature, empirical evidence has been scant (e.g., project updates by Mejia et al. 2019 and project promotion strategies by Li et al. 2020). Our research contributes to this nascent class of empirical studies on operational designs (Chen et al. 2019, Allon and Babich 2020). While an important finding in the literature attributes early traction as

[3] Under AON, the entrepreneur receives all funds raised only if the campaign is successful and nothing otherwise; under KIA, the entrepreneur keeps all funds regardless of the campaign's outcome. JD Crowdfunding, our research context, utilizes the AON model: if founders do not meet their funding goals during the specified funding period, then all funds are returned to backers and the campaign is terminated.

a success factor in crowdfunding (e.g., Kuppuswamy and Bayus 2018), our study explains *how* founders garner that early traction.

3. Theory and Hypotheses

Our study draws from theories on information economics, operations management, finance, and entrepreneurship and develops testable hypotheses on how prefunding affects the fundraising process, induces the herding behavior of uninformed backers, and generates differential impacts across projects.

3.1. Information Asymmetry

Like other financial markets, crowdfunding markets are inherently plagued by information asymmetry (Cascino et al. 2019). In reward-based crowdfunding, information asymmetry between founders and backers at the project level is *the difference between the project information possessed by founders and the project information provided by the founder and used by backers*. Such information asymmetry is prevalent in crowdfunding (e.g., Courtney et al. 2017, Chakraborty and Swinney 2019); it can hinder fundraising, leading to market inefficiencies or failures including adverse selection, moral hazard, and the collective actions of backers (Akerlof 1970, Agrawal et al. 2014).

On the one hand, founders have disincentives of disclosing full information lest revealing information to competitors that harms their intellectual property, releasing potentially undesirable information to backers that could materially disadvantage the project, and diverting resources and time to manage communications with the crowd. On the other hand, backers have limited opportunities to perform due diligence in an online environment, have less credible information, and face high risks of founder incompetence (stemming from operational inexperience), fraud (due to the manipulation or falsified information exacerbated by the lack of repeated interactions and backers' underinvestments in due diligence), and project failure (inherent in early-stage ventures). Specific to reward-based crowdfunding, the additional uncertainty that surrounds the development and manufacturing of innovative, future products can exacerbate information asymmetry (Belleflamme et al. 2015). If founders do not voluntarily provide project information beyond the minimal requirements on the platform, backers would rationally respond by providing fewer or no funds.

Regulations can intervene and improve the functionality of markets that have amplified information asymmetry (Cascino et al. 2019). An alternative approach, at the core of OM-IS research, attempts to devise platform features that improve the operations of crowdfunding. These features can leverage the signaling mechanism (Spence 1978), where an informed party (e.g., founders) sends observable signals and discloses information on unobservable characteristics to the less informed party (e.g., backers) (Ahlers et al. 2015). Entrepreneurial actions that signal founder credibility and project potential can help attract funding from backers (Vismara 2016).

Prefunding, potentially a signaling mechanism, provides a channel of information sharing and communications between founders and prospective backers before fundraising begins. It is likely that the founders of projects with strong potential would be eager to communicate additional project information to backers. Therefore, their use of a prefunding feature could serve as an effective signal that the project is valuable, the founder is credible, and additional project information will be disclosed. First, during prefunding, a founder has an opportunity to showcase a product prototype or beta version, demonstrating product attributes in detail and releasing updates on product development. Second, founders are likely to receive inquiries from potential backers regarding product specificities, with subsequent discussions publicly displayed on the project webpage. The information generated in this manner can be pertinent to potential backers as it addresses their questions and concerns about the project. Third, prefunding can improve transparency and improve backers' perceptions of a project's value. In the operations management literature, operational transparency—the disclosure of operational information to external actors—has been found to improve customers' perceptions of a company's trustworthiness and effort, and results in higher valuations of the company (Buell and Norton 2011, Buell et al. 2017). Likewise, operational transparency in the context of crowdfunding such as campaign updates can increase funding success (Mejia et al. 2019).

Therefore, based on the theories of information asymmetry and operational transparency, if the founder adopts prefunding, *ceteris paribus*, the project is likely to be more valuable to backers and subsequently, succeed in achieving their funding goals.[4] This leads to the following hypothesis:

Hypothesis 1 (H1): Prefunding increases the likelihood of crowdfunding success.

Moreover, if founders use prefunding to signal their intent to continually provide more information not only during the prefunding period but throughout the funding period, then through a steady cascading of information, we expect that prefunding projects would persistently raise more funds than non-prefunding projects throughout the entire funding period. Over time, non-prefunding projects could also disclose pertinent information and begin to gain momentum in fundraising. Therefore, the funding premium gained by prefunding could stay positive throughout the funding period, but its magnitude could dampen over time, leading to our next hypothesis:

Hypothesis 2 (H2): Prefunding increases the amount of funds raised and this effect decreases over time.

3.2. Herding of Uninformed Backers

The effects of prefunding on alleviating information asymmetry between founders and backers could vary depending on the costs and incentives of the backers in acquiring and processing the information. While crowdfunding lowers the barriers to entry for entrepreneurial financing and democratizes broader participation, it presents a new challenge as it attracts large, heterogeneous groups of investors (Agrawal et al. 2014, Ahlers et al. 2015). On JD Crowdfunding, there are two principal types of backers: regular backers who provide funds in exchange for a future product reward and lottery backers who wager a small bet to speculate on winning the product.

Theories of information costs in finance and accounting, coupled with the classical assumption of rationality in economics, suggest that acquiring and integrating information into decision making is costly, which explains why there are informed and uninformed agents in capital markets even when the same

[4] The theory of information asymmetry suggests that if information asymmetry exists at a high degree, it can result in an underprovisioning of funds from backers (Agrawal et al. 2014). A corollary to this logic provides an underlying premise of our study: if prefunding improves funding outcomes, then we can infer that prefunding information is effective in reducing information asymmetry.

information is available to everyone (Blankespoor et al. 2014, Bushee and Miller 2012). Likewise, while both regular and lottery backers observe the same prefunding information, not all backers will acquire or utilize this information because of their cost-benefit calculations. Different types of backers may rationalize different levels of due diligence and engage disproportionally in information acquisition and integration, leading to distinct backing behaviors of informed and uninformed backers.[5] Regular backers, who provide more than 80% of project funding, have rational incentives to be more meticulous in gathering, scrutinizing, analyzing, and making decisions around the prefunding information. Therefore, regular backers are more likely to be informed and prefunding may have a greater impact on them, which leads to the following hypothesis:

Hypothesis 3 (H3): Projects with prefunding attract a larger number of informed, regular backers.

On the other hand, lottery backers are likely to have fewer or no incentives to acquire and process prefunding information, thus remaining uninformed. The finance literature has extensively documented herding behaviors in financial trading due to costly information extraction and explained why uninformed investors tend to free-ride on their informed predecessors (e.g., Froot et al. 1992, Hirshleifer et al. 1994, Yang 2011). Consistent with this literature, we expect that free-riding on informed backers, or herding, could be a rational strategy for lottery backers. Facing relatively lower stakes in backing, a small chance of winning the product, and thus low or even negative expected returns if incurring information costs, lottery backers would find it optimal to voluntarily forego the prefunding information (remain uninformed) and instead imitate the choices of informed regular backers at no cost which can generate higher expected returns.[6] The number of regular backers who support projects with conspicuously growing funds can serve as informational cues, signal the project's value, and trigger the naïve herding of lottery backers (Zhang and Liu 2012). Hence, while prefunding may eventually attract more backers including lottery backers,

[5] Backers determine if there is a net benefit associated with accessing and integrating the prefunding information and may decide to avoid those costs if they exceed expected benefits or if there is substitute information available at lower costs. In those cases, backers might not access the prefunding information.

[6] It is relatively costless for lottery backers to identify well-funded projects with large numbers of regular backers, as JD Crowdfunding enables backers to sort projects by the amount of funds raised.

prefunding is unlikely to have a direct and immediate effect on lottery backers. Instead, regular backers could mediate their relationship as prefunding attracts regular backers first, who then influence lottery backers. This leads to the following hypothesis:

Hypothesis 4 (H4): The number of regular backers mediates the relationship between prefunding and the number of lottery backers.

3.3 Differential Effect of Prefunding

A stylized fact in crowdfunding is that the distribution of funds is highly skewed across projects (Agrawal et al. 2014). For instance, on Sellaband, 0.7% of projects accounted for more than 73% of funding from 2006 to 2009 (Agrawal et al. 2015). From 2009 to 2015, Kickstarter's top 1% (10%) of successful projects accounted for \$590 million (\$1 billion), or 42% (76%) of total funds raised throughout the platform (Agrawal et al. 2018). How would prefunding change the distributions of funds across projects? We investigate the *quantile treatment effect on the treated* (Firpo 2007) across projects to address this question.

We focus on two quantile distributions of outcomes: the *actual* funding outcomes of prefunding projects vs. their *potential* funding outcomes had those same projects not been treated by prefunding (counterfactual).[7] The two distributions may differ and the difference might be more pronounced on one tail than the other. To explain this potential disparity, it becomes necessary to disentangle how much the funding outcomes stem from the prefunding effect versus from inherent, idiosyncratic characteristics of the project.

On the one hand, for projects that would have raised a lot of money without prefunding (right-tail/upper quantiles of the potential outcome), leveraging prefunding would help them even more, compared with projects that would have raised little money without prefunding (left-tail/lower quantiles of the potential outcome). These right-tail projects may be endowed with certain idiosyncratic attributes (e.g., creative marketing, founder reputation) that can elevate them to become top-funded even without prefunding. Prefunding, with positive signaling and increased information sharing, may enable these

[7] All distributions discussed in this section refer to quantile distributions: the amount of funds raised against their quantiles.

projects to attract even more funds and entrench their success. In other words, prefunding may help right-tail projects more than left-tail projects. We thus hypothesize:

Hypothesis 5A (H5A): The effect of prefunding is stronger for projects that would have raised more funds without prefunding (right-tail) than for projects that would have raised fewer funds without prefunding (left-tail).

On the other hand, the possibility that prefunding can assist projects with less endowed characteristics is also compelling. Some projects at the lower quantiles of the potential funding outcomes may have been marginal due to their entrepreneurial endowment (e.g., avant-garde concepts, fewer founding resources). Prefunding may democratize opportunities for these projects; they can leverage a prefunding period to better communicate with prospective backers about their background and the project's potential to create innovative products, thus generating funding momentum. As a result, prefunding may have a greater effect on these projects which would otherwise find it difficult to raise enough funds. Therefore, we propose the following alternative hypothesis:

Hypothesis 5B (H5B): The effect of prefunding is stronger for projects that would have raised fewer funds without prefunding (left-tail) than for projects that would have raised more funds without prefunding (right-tail).

4. Data

4.1. Data Source and Research Context

Our data from JD Crowdfunding consist of a daily, project-level panel dataset compiled from April 2015 to July 2016. Each project includes a webpage on the platform that details the product, funding goal, rewards (products) of various backing choices, cumulative funds raised, funding progress (percentage of funds relative to the funding goal), and number of days until the funding period ends. In addition, if founders elect to initiate a prefunding period, they may share additional project information with prospective backers prior to the funding period (prefunding information). Regardless of whether founders use prefunding or not, they are allowed to provide information and engage with potential backers via discussion forums throughout the funding period.

Our paper focuses on reward-based crowdfunding, where founders provide tangible products as a reward for funding while backers provide funds with the expectation of receiving that product reward. Charity projects do not offer tangible products as a reward and are excluded from this study. Finally, since JD Crowdfunding recommends that the funding duration should not exceed 60 days, we removed projects with funding durations beyond that time frame. These exclusions result in a sample of 3,878 projects which represent 95% of the total projects from the original dataset.

4.2. Variables and Summary Statistics

Key variables of interest in this study can be classified into five categories: funding, backers, project and founder characteristics, discussions between founders and potential backers during the prefunding period, and founder-backer interactions during the funding period. Table 1 describes these variables with their summary statistics.[8] The definitions of the major variables are provided as follows.

[Place Table 1 here]

First, among variables related to funding, cumulative funds (*Total Funds*) represent the total amount of funds the project raises from both regular backers and lottery backers. *Success* is a binary indicator of whether a project's cumulative funds at the end of the funding period has reached the target amount of funds (*Goal*). We normalized performance with a funds-to-goal ratio to measure the funding progress, defined as the cumulative funds divided by the funding goal (*Ratio*).

Second, there are two major types of backers in our dataset. *Regular Backers* provide a specific amount of money in exchange for a tangible product at a certain quantity. *Lottery Backers* wager a small bet (usually less than $0.25 USD) to enter a lottery with a pre-specified chance of winning the product (usually less than 1%). For an average project on JD Crowdfunding, about 20% (80%) of backers are regular

[8] The correlation matrix for major non-categorical variables is in Online Appendix A, Table A1.

(lottery) backers, who collectively contribute 80% (20%) of all funds. The amount of funds from regular and lottery backers are designated as *Regular Funds* and *Lottery Funds*, respectively.

Third, in terms of project characteristics, founders decide the funding durations of their projects before launching, measured by the number of days of the funding period (*Duration*). Founders may also provide a menu of funding choices with different reward levels (*Options*) for backers. We calculated the median price of these funding choices to measure the inherent product value (*Value*) and use it to explain the amount of *Total Funds*.[9] For founder characteristics, we measured the founder's learning-by-doing experience by the number of prior founded and completed projects (*Expn_Launch*) and the number of prior projects they have backed (*Expn_Back*). In addition, we singled out the founder's specific experience with prefunding: the number of prior prefunding projects completed (*Expn_Launch_Pref*) and the number of prior prefunding projects initiated by other founders that they have backed (*Expn_Back_Pref*).[10] To capture any herding effects, we calculated the cumulative number of other prefunding projects on the platform that the founder was not involved in launching or backing (*Others_Pref*) before the focal project.

Fourth, prefunding discussions contain additional information exchanged between founders and backers during the prefunding period. We performed text analyses on prefunding discussions and created three categories of variables pertinent to prefunding information: volume, length, and sentiment, aggregated at both the project level and respectively for founders and potential backers of each project.

Specifically, the amount of prefunding information for a project is calculated as the cumulative number of discussion postings during the entire prefunding period (*Volume*). When measuring the length of a posting, we focused on the amount of objective information it contains. Hence, we normalized length as the proportion of non-sentiment words. Thus, the average length of prefunding discussions for a project

[9] A typical project usually has a few funding choices that are priced higher compared with the majority of choices, thus making the distribution of funding choices highly skewed to the right. Hence, we used the median price of the funding choices. We also used the mean for our robustness check, resulting in no changes in our subsequent findings. Lastly, for some projects, the number of funding options and their prices changed over the funding period.
[10] We only observed the prefunding status for projects during the sample period. Hence, the variables are not necessarily the total numbers of prior projects launched or backed by the founder since joining JD Crowdfunding.

is the average normalized length for all of its prefunding discussions (*Length*).[11] We also distinguished the total volume and average length of discussions by founders and potential backers: *Volume_Founder* vs. *Volume_Backer* and *Length_Founder* vs. *Length_Backer*.

To measure sentiment, we employed a text mining technique to extract sentiments from the linguistic context of prefunding discussions. Classification algorithms based on the sentiment dictionary, e.g., naïve classifier, are widely used in studies on online behaviors (Chen et al. 2014, Das and Chen 2007, Goh et al. 2013). Here, we used the National Taiwan University Sentiment Dictionary (NTUSD), the first Chinese dictionary for sentiment analysis, as the lexicon. We first collected text (in Chinese characters) from each project's discussion postings. Then, each word was checked against the lexicon and assigned a value of +1 (-1) if positive (negative) words were matched. Words not listed in the dictionary were regarded as neutral and assigned a value of zero. The valence of each posting was calculated as the net positivity of all lexicon-matched words, i.e., the number of positive words minus the number of negative words. The text was deemed positive (negative) if the value is greater (less) than zero; otherwise, the text was regarded as neutral. We calculated the sentiment score via scaling the valence of each posting by its word count so that the sentiment score is in the [-1, 1] range. We aggregated the average sentiment of all discussion postings at the project level. The sentiment scores of founders (backers) were averaged over all postings from founders (backers) across all prefunding days.

Lastly, the interactions between founders and backers during the funding period can also explain project funding outcomes. Hence, we used the numbers of "likes" from the crowd (*Likes*), project updates from the founders (*Updates*), questions and answers (*Q&A*), and discussions (*Discussions*) as potential factors to explain the amount of funds and funding success.

[11] We used the word count, number of characters, and the number of non-sentiment words as robustness checks. See Section 6.

5. Empirical Analyses and Results

Our empirical analyses start with creating a matched sample (section 5.1) and model-free evidence (Section 5.2). We then focus on the effects of prefunding on funding success (Section 5.3), on funds (Section 5.4), and on backer behaviors (Section 5.5), as well as the differential effect of prefunding (Section 5.6).

5.1 Matching

To mitigate the potential selection bias of prefunding, we matched prefunding projects (treatment group) with non-prefunding projects (control group) based on project and founder characteristics. Matching is a non-parametric method of reducing imbalances in covariates between treatment and control groups, which can control for potential confounding influences of the covariates. Specifically, we applied Coarsened Exact Matching (CEM), a method that bounds the degree of model dependence and causal effect estimation errors without requiring a separate procedure to restrict data to the common support (Iacus et al. 2012). CEM coarsens data temporarily, performs exact matching on the coarsened data, and then retains only the original uncoarsened observations from the matched data to estimate the causal effect (Blackwell et al. 2009).

We matched our coarsened data on various project and founder characteristics including the funding goal, duration, number of backing options, number of pictures, whether a video is available, delivery lag, and the founder’s experience of launching and backing. This resulted in a matched sample of 3,159 projects, of which 2,062 are prefunding projects and 1,097 are non-prefunding projects. The matched sample, with reduced imbalances in project and founder characteristics between the treatment and control groups (top panel in Online Appendix A, Table A2), is utilized in all subsequent analyses.

5.2 Model-Free Evidence

The matched prefunding and non-prefunding projects contrast significantly in funding outcomes (bottom panel in Online Appendix, Table A2): prefunding projects attracted more funds and backers, achieved higher funds-to-goal ratios, and had greater chances to succeed than non-prefunding projects. Specifically, the average total funds raised was ¥323,578 CNY per prefunding project and ¥156,352 CNY per non-prefunding project at the end of the funding period (more than twice as many).[12] The average percentage of prefunding projects that succeed in reaching their funding goals is close to 80%, while that of non-prefunding projects is about 68%.

We indexed projects by their funding day rather than by calendar day. For example, even though project A started raising funds on January 1, 2015, and project B started on March 15, 2016, both projects have an equivalent first day of funding (funding day 1), second day of funding (funding day 2), and so on. Thus, we normalized and grouped projects by their funding days to compile our data.

Given the same funding duration, prefunding projects are observed to raise more funds (*Total Funds*) and have greater funding progress (*Ratio*) than non-prefunding projects, and this advantage persisted over time. For instance, close to 46% of the projects in our sample have a funding duration of 30 days, the highest percentage among all durations. The average cumulative funds (*Total Funds*) per project is higher for prefunding projects than non-prefunding ones on each funding day of the 30-day duration (Online Appendix, Figure A1).

5.3 Prefunding and Crowdfunding Success

We first analyzed the effect of prefunding on crowdfunding success. To obtain a baseline estimation of the prefunding effect, we started with the CEM matched sample to estimate the sample average treatment effect on the treated. The result shows that prefunding projects are more likely to succeed; the odds-ratio is 0.50 (significant at the 1% level) which suggests that the probability of reaching the funding goal for prefunding projects is 1.67 times higher than for non-prefunding projects.[13]

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[12] The averages are equivalent to \$52,190 USD and \$25,218 USD, respectively, based on the exchange rate of \$1 USD = ¥6.20 CNY during the sample period.

[13] We also applied Propensity Score Matching (PSM) to the CEM matched sample to refine the baseline estimation, as the CEM algorithm can improve traditional matching methods such as PSM (Blackwell et al. 2009). The matching variables used for PSM include project characteristics (goal, duration, video, pictures, product categories) and founder experience (launching and backing), leading to a significant overlap over the common support for the propensity score distributions (Online Appendix, Figure A2). The estimation result of the PSM matched sample again confirms that prefunding projects have a higher probability of success. The average treatment effect is 0.80 (significant at the 1% level), indicating that prefunding projects are 2.2 times more likely to succeed than non-prefunding projects.

Formally, to account for the possible endogeneity in prefunding (unobservable project or founder characteristics that influence the choice to use prefunding), we applied a control function approach where residuals from the selection model are calculated and then included in the estimation of potential outcomes.

We first modeled the choice of using prefunding or not for a project in a selection equation:

$$Prefunding_i^* = \alpha + \gamma Z_i + \varepsilon_i \quad (1)$$

$$Prefunding_i = \begin{cases} 1, & \text{if } Prefunding_i^* > 0 \\ 0, & \text{if } Prefunding_i^* \leq 0 \end{cases}$$

where $Prefunding_i^*$ is a latent endogenous variable that determines the prefunding status of project i; Z_i includes project characteristics (funding goal, duration, and product category), the founder's experience with prefunding (number of prefunding projects launched and completed *Expn_Launch_Pref* and number of prefunding projects backed *Expn_Back_Pref*), and the potential herding effect of prefunding on the platform (*Others_Pref*); ε_i contains unobservable project attributes. We only observed whether a project involves a prefunding period or not, i.e., $Prefunding_i$ = 1 or 0. Prefunding is postulated to be adopted in a project when $Prefunding_i^*$ is above 0.

We estimated Model (1) with a probit estimator, obtained the residual $\widehat{\varepsilon_i}$, and then used it to estimate the potential outcomes and the average prefunding treatment effect on the treated (prefunding projects). The outcome of funding success or not is observed for projects both with and without prefunding ($Prefunding_i$ = 1 and $Prefunding_i$ = 0). The binary success outcome is modeled as another probit model:

$$Success_i^* = \alpha + \beta_1 \widehat{\varepsilon_i} + \beta_2 X_i + \eta_i \quad (2)$$

$$Success_i = \begin{cases} 1, & \text{if } Success_i^* > 0 \\ 0, & \text{if } Success_i^* \leq 0 \end{cases}$$

where X_i includes project characteristics and the founder's overall experience (number of projects launched and completed *Expn_Launch* and number of projects backed *Expn_Back*) while η_i includes the unobservables. In the estimations of Models (1) and (2), all non-categorical variables are log-transformed due to their highly skewed distributions; robust standard errors are clustered at the founder level.

Our identification assumption is that the founder's observation of others' prefunding projects on the platform (*Others_Pref*) can influence their decision of prefunding for the focal project (learning/herding effect on prefunding adoption). When controlling for the founder's overall experience with crowdfunding (learning-by-doing effect on funding outcomes) and project-specific characteristics, *Others_Pref* may not directly affect the success of the focal project. In other words, the prefunding prevalence at the platform level affects funding outcomes of the focal project only through the prefunding decision.[14]

Table 2 reports the estimation result of the above endogenous treatment effect model. In terms of prefunding selection, the founders' prior experience in launching and backing prefunding projects, the number of other founders' prefunding projects on the platform, and the funding goal contribute to a greater likelihood of opting in prefunding for the focal project. Further, we found that projects with prefunding on average are 66.9% more likely to succeed in reaching their funding goals (significant at the 1% level), which provides corroborative evidence for H1: prefunding increases the likelihood of funding success.

[Place Table 2 here]

5.4 Prefunding and Funds Raised

Next, we investigated the effects of prefunding on the cumulative funds. An endogenous treatment effect model was applied to account for the prefunding selection by combining Model (1) and Model (3):

$$Total\ Funds_{it} = \alpha_i + \beta_1 Prefunding_i + \beta_2 X_i + \beta_3 X_{it} + \tau_t + u_{it} \quad (3)$$

where *Total Funds*$_{it}$ represents the cumulative funds for project i on funding day t; X_i includes project characteristics (funding goal, duration, number of backing choices, product value, product category, number of pictures, whether the project description has a video, and the number of days to deliver the product after the funding period concludes) and founder characteristics (experience in launching and backing); X_{it} contains activities of the founder and backers during the funding period, including the numbers of likes, updates, Q&A, and discussions. Additionally, τ_t has monthly dummies to account for seasonality; u_{it} includes unobservable project/founder characteristics not captured by the regressors. The error terms in

[14] We also took the ratio of 'the number of other founders' prefunding projects' to 'the total number of projects on the platform' and found similar results to using *Others_Pref*.

equations (1) and (3) are correlated as a bivariate normal distribution. All non-categorical variables are again log-transformed and their associated coefficients are interpreted as elasticity.

[Place Table 3 here]

The estimation results of the two-step treatment effect model are reported in Table 3. The positive coefficient of prefunding (significant at the 1% level) in Column 1 indicates that projects with prefunding tend to raise more funds, thus supporting part of H2: prefunding increases total funds raised. We find again that the founder's experience in prefunding projects and the number of other founders' prefunding projects increase the likelihood of choosing prefunding in the focal project.

To examine how the prefunding effect on funds evolves over time, we included in Model (3) an interaction term between prefunding and the funding duration. While the coefficient of prefunding remains positive and highly significant, the negative coefficient of the interaction term (significant at the 1% level) suggests that the prefunding effect, although always positive, decreases with the length of the funding period (Column 2). This moderation effect might imply that the prefunding premium is the greatest for projects with shorter funding periods. We also introduced another interaction term between prefunding and funding days. Besides the significant main effect of prefunding, the results show that the magnitude of the coefficient on the interaction term diminishes as funding days move forward (Column 3). Together, H2 is supported: prefunding increases the total funds and its effect declines over time.[15] We infer that the use of prefunding signals the founder's willingness to communicate not only during the prefunding period but throughout the funding period, which creates long-lasting, positive fundraising effects.

So far, prefunding has been treated as a binary indicator in our analysis. Considering that founders can communicate with potential backers during the prefunding period, we probe deeper into discussions between the two parties which may unveil the mechanism of how prefunding increases funds. Hence, we performed text analyses on prefunding discussions with three sets of new variables: discussion volume,

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[15] We used two alternative funding outcome variables: the funding progress (*Ratio*) and the average funds per backer (cumulative funds divided by the number of backers) and found similar results.

length, and sentiment. Prefunding discussions exist only for prefunding projects, so we included these new variables in a Heckman two-step model that addresses the potential sample selection of prefunding.

Specifically, we first estimated the prefunding selection Model (1) that generates the estimated parameter $\hat{\gamma}$ to calculate the inverse Mills ratio: $\lambda_i(\gamma) = \phi(Z_i\gamma)/\Phi(Z_i\gamma)$ and $\lambda_i(\gamma) = -\phi(Z_i\gamma)/[1 - \Phi(Z_i\gamma)]$ for each project in the prefunding and non-prefunding group, respectively, where ϕ is the probability density function of the standard normal distribution, and Φ is the cumulative distribution function. Second, we augmented Model (3) by adding the inverse Mills ratio $\lambda_i(\gamma)$ as a regressor:

$$Total\ Funds_{it} = \alpha_i + \beta_1\lambda_i(\gamma) + \beta_2X_i + \beta_3X_{it} + \tau_t + u_{it} \quad (4)$$

In Model (4), project characteristics X_i is also augmented with variables based on prefunding discussions. We first included three variables aggregated at the project level (*Volume*, *Length*, and *Sentiment*) without distinguishing whether a discussion posting originated from founders or potential backers.

The results in Table 4, Column 1 show that all three factors drive the amount of funds significantly for projects with prefunding: the volume of prefunding discussions (total count of postings which indicates the amount of public interest), the average length (indicating the amount of information), and the average sentiment (indicating project's appeal to the crowd). Hence, the prefunding effect on increasing the amount of funds can be attributed to three specific categories of prefunding discussions. This finding sheds light on the underlying mechanism of how prefunding may serve as a channel of communications to reduce information asymmetry between founders and potential backers.

[Place Table 4 Here]

Additionally, the coefficient on the inverse Mills ratio is negative, suggesting that the prefunding effect would be underestimated without correcting the sample selection (bottom of Column 1, significant at the 1% level). The results for other regressors are consistent with the findings in Model (3).

Next, we dichotomized the volume, length, and sentiment of prefunding discussions respectively for founders and potential backers. We added each set of variables one at a time to Model (4) to avoid collinearity. The estimation results are reported in the last three columns of Table 4 where three major results stand out (standard error clustered at the project level).

First, a higher volume of discussions leads to a greater amount of funds (Column 2, positive coefficients of *Volume_Foudner* and *Volume_Backer*). Second, while the average length of discussions from founders (*Length_Founder*) is positively associated with more funds, the average length of discussions from potential backers (*Length_Backer*) has a negative relationship with it (Column 3). A plausible explanation is that objective descriptions in founders' discussions can be helpful for potential backers and thus attracts more funds. On the other hand, backers' discussions, after excluding comments with emotional sentiments, may tend to be interrogative questions or inquiries that can lead to defensive responses from founders, which in turn can signal potential issues about the project and reduce the attractiveness of funding it. Third, we find *Sentiment_Backer* contributes positively to the amount of funds (Column 4). Potential backers' sentiments, reflecting their interest and enthusiasm for the project, can serve as favorable signals of the project and may positively influence subsequent backers' perceptions, attitudes, and thus funding decisions. Conversely, a high sentiment score from founders can generate an adverse impact on funding outcomes, as shown by the negative coefficient of *Sentiment_Founder*. It is likely that founders' overly positive sentiments tend to be cautioned and discounted by backers in their assessments. Hence, while the sentiments of potential backers play an important role in shaping the perception and confidence of prospective backers which in turn attracts more funds, founders' overly sentimental statements can be interpreted as bravado intended to hype and oversell which can backfire in fundraising.

Together, the analyses of finer-grained information about prefunding discussions at the founder/backer level show that it is critical for founders to communicate informatively with potential backers during the prefunding period. Founders should focus on providing objective information, rather than raving about it with strong sentiments, to make communications with potential backers more informative and effective which can lead to greater funding.

5.5 Prefunding and Backers: Regular vs. Lottery

As the above findings show that prefunding is effective in raising more funds, a natural question then follows: "What type of backers does prefunding tend to attract: informed, regular backers or uninformed, lottery backers?" We tested our following hypotheses on the types of backers that prefunding information attracts and whether the prefunding effect is sequential across different backer groups.

First, we examined whether projects with prefunding attract a larger number of informed, regular backers (H3) in the following model:

$$Regular\ Backers_{it} = \alpha_i + \beta_1 Prefunding_i + \beta_2 Lottery\ Backers_{i,t-1} \tag{5}$$

$$+\beta_3 Regular\ Backers_{i,t-1} + \beta_4 X_i + \beta_5 X_{it} + \tau_t + v_{it}$$

where variables of X_i and X_{it} are defined the same as in Model (3). To investigate the potential mediation effect of lottery backers on regular backers, we added the lagged number of lottery backers from the last period as another explanatory variable. In addition, as the number of regular backers increases over time, we control for it from the previous funding day. Table 5, Column 1 shows the estimation results of the baseline Model (5) without any lagged effects ($\beta_2 = \beta_3 = 0$), where the positive coefficient of prefunding is significant (at the 1% level). This result provides evidence for H3: prefunding attracts more regular backers. When the lagged number of lottery backers is included (Column 2), the coefficient of prefunding remains highly significant (at the 1% level) while that of lagged lottery backers is insignificant.

[Place Table 5 Here]

Second, following studies on financial markets, we earlier hypothesized that uninformed, lottery backers may not be driven directly by prefunding; rather, they naively follow the informed, regular backers, leading to herding (H4). In other words, lottery backers and prefunding are independent, conditional on regular backers. To test the conditional unconfoundedness between prefunding and lottery backers (who are influenced by the size of regular backers, rather than prefunding), we regressed the number of lottery backers on prefunding and the number of regular backers in the previous funding day, while controlling for the lagged lottery backers:

$$Lottery\ Backers_{it} = \alpha_i + \beta_1 Prefunding_i + \beta_2 Regular\ Backers_{i,t-1} + \beta_3 Lottery\ Backers_{i,t-1} + \beta_4 X_i + \beta_5 X_{it} + \tau_t + \theta_{it} \quad (6)$$

We first estimated the direct effect of prefunding by imposing $\beta_2 = \beta_3 = 0$. We then included the meditation effect of regular backers without this restriction; if the coefficient on prefunding (β_1) is statistically *insignificant*, then it provides evidence to support H4. Column 3 in Table 5 shows the direct effect of prefunding on lottery backers; the positive coefficient on prefunding is highly significant (at the 1% level). However, Column 4 shows that when we introduced the number of regular backers as a mediator, the coefficient of prefunding becomes insignificant while that of the regular backers remains significantly positive (at the 1% level). Therefore, we infer that prefunding affects regular backers directly, who in turn influence lottery backers, demonstrating the mediation effect of regular backers on lottery backers. As a result, the prefunding effect on lottery backers is indirect and second-order; herding occurs where lottery backers are attracted primarily due to regular backers and their funding decisions, rather than prefunding. Together, these findings support H4: the number of regular backers mediates the relationship between prefunding and the number of lottery backers. For robustness checks, we performed a parallel analysis for the amount of funds, using regular funds and lottery funds as dependent variables for Models (5) and (6), respectively. We found consistent, corroborative evidence for H3 and H4.

Exploring deeper, we conducted text analyses of prefunding discussions (Online Appendix A, Table A3). The effects of volume, length, and the sentiment of prefunding discussions on regular backers and regular funds are like those on the total amount of funds in Section 5.4. In contrast, in support of the hypothesized rationality of herding for lottery backers, we did not find significant results in any of the above three dimensions for lottery backers/funds. These results provide further evidence that lottery backers tend to ignore prefunding information and simply follow the funding decisions of regular backers who are rational in learning, discerning, and inferring information from prefunding discussions to inform their funding decisions. It is possible that prefunding initiates a cascade of project information before and during the funding period. Informed, regular backers tend to utilize this information, whereas uninformed, lottery backers follow the conspicuous accretion of funds from regular backers. Hence, we infer that prefunding information generates a first-order effect on regular backers, followed by a second-order effect on lottery backers. As such, prefunding creates a primary and a secondary stream of funding.

5.6 Counterfactual Decomposition

The effects we have identified thus far are the average effects of prefunding across all projects. Our next step is to test H5(A/B) and delve into the differential effects of prefunding among projects with varying amounts of funding. This direction of investigation is motivated by the skewed distribution of our data.

We examined the distributions of *Total Funds* at the end of the funding period for all projects, prefunding projects, and non-prefunding projects (Online Appendix A, Table A4, Panel A). The distribution of the full sample is highly skewed to the right, with a positive skewness of 9.060 as well as the mean and the median being ¥263,775 CNY and ¥63,192 CNY, respectively. The distributions of prefunding and non-prefunding projects are also positively skewed (with the skewness being 8.197 and 12.112, respectively). In the lower range of the distributions, 60% of non-prefunding projects, in contrast to 34% of prefunding projects, raised less than ¥50,000 CNY. On the higher end, about 53% of the prefunding projects raised over ¥100,000 CNY, compared with only 26% of non-prefunding projects.

We also analyzed detailed distribution statistics of the log-transformed total funds, ln(*Total Funds*), for both the full sample and prefunding/non-prefunding samples (Online Appendix A, Table A4, Panel B). The statistics include the mean, the standard deviation, the 10th, 25th, 50th, 75th, and 90th quantiles, and the inter-quartile range (IQR, measuring the 75th–25th dispersion). First, we observed that the prefunding projects top the non-prefunding projects across all quantiles of the funding outcome. Second, the gaps between the prefunding and non-prefunding projects at the lower tail (10th, 25th, and 50th) are wider than those at the upper tail of the distributions (75th and 90th). This pattern is echoed by the greater IQR spread in the non-prefunding sample. In summary, the distributions of the funding outcome variable are skewed and differ between prefunding vs. non-prefunding projects. This evidence corroborates our application of quantile regressions to uncover differential effects of prefunding across projects.

We then employed the counterfactual decomposition technique to address the selection of prefunding and tease out the prefunding effect (Liu et al. 2014, Melly 2005). We decomposed the differences in funding outcomes of prefunding and non-prefunding projects into two parts (see Online Appendix B.1 for technical details). The first is the characteristics effect, arising from different inherent characteristics of prefunding vs. non-prefunding projects. The second is the prefunding effect, the difference in funding outcomes that prefunding projects can incrementally derive over non-prefunding projects from the same characteristics. Our primary interest is the second, the prefunding effect.

We applied Melly's method (2005) and created decompositions at different quantiles of the total funds' distribution. The counterfactual decomposition applies the returns on the project characteristics of one group (prefunding vs. non-prefunding) to the distributions of the project characteristics endowed to the *other* group. By replacing the characteristics of non-prefunding projects with those of prefunding projects (and *vice versa*), we obtained the counterfactual distribution of the quantiles that we would have observed if the non-prefunding projects had the characteristics of prefunding projects. As a result, our counterfactual decomposition consists of quantile regressions (Koenker and Bassett 1978)[16] in a two-step Heckman (1979) framework to estimate the quantile treatment effect. The first step is the prefunding selection model that produces a correction term (a function of the inverse Mills ratio). In the second step, we incorporate the selection-correction into the conditional quantile regression for each quantile.

Specifically, in the first step, we estimated Model (1), calculated the inverse Mills ratio, and specified the conditional θth quantile of the error term in Model (3) as

$$Quantile_{\theta}[u_{it}|X_i, X_{it}, Total\ Funds_{it}] = \sum_{m=1}^{M} \delta_m^{\theta} \lambda_i^{(m)}(\gamma) \tag{7}$$

[16] In a quantile regression, the conditional θth quantile of the dependent variable (e.g., the cumulative funds in a project greater than θ*100 percentage of the projects in the sample) is expressed as a linear function of project characteristics. The coefficients of the θth quantile are estimated by minimizing the weighted sum of the absolute residuals, where positive residuals receive a weight of θ and negative residuals receive a weight of (1-θ). For quantiles below the median, the number of positive residuals is greater, and these positive residuals receive higher weights than negative residuals. *Vice versa* for quantiles above the median.

We allowed for possible curvilinearity in the prefunding selection bias by including a quadratic term of the inverse Mills ratio ($M = 2$).

In the second step, we constructed the terms in (7) with the estimated first-stage parameters and added (7) into Model (3), which then became:

$$Total\ Funds_{it} = \alpha_i + \beta_1^{\theta} X_i + \beta_2^{\theta} X_{it} + \sum_{m=1}^{M} \delta_m^{\theta} \lambda_i^{(m)}(\gamma) + \tau_t + u_{it} \tag{8}$$

To capture the heterogeneity in the distribution of dependent variables, we estimated (8) for 99 quantiles from 0.01 to 0.99 for each funding day.

In Table 6, we report the results of the counterfactual decomposition of the difference in *Total Funds* on the last funding day for nine quantiles (0.1–0.9 quantiles for brevity). For each quantile, the total difference between prefunding and non-prefunding projects (first row) is the sum of the project characteristics effect (second row) and the prefunding return (third row). The percentage of the prefunding effect out of the total difference is reported in the last column.

[Place Table 6 here]

We observed three patterns. First, the estimated gaps (total difference) in total funds for prefunding and non-prefunding are positive and highly significant (at the 1% level) across the entire distribution, which implies that the total funds for prefunding projects are higher than that of non-prefunding projects at all quantiles. Second, the prefunding vs. non-prefunding gap in total funds is wider for projects at the bottom quantiles, and the difference declines as the projects move up the quantiles. Third, and most interestingly, the prefunding effect declines as quantiles increase while project characteristics continue to play an important role in the differential outcomes between prefunding and non-prefunding projects. Specifically, in Table 6, as the quantile increases (projects with greater total funds), the coefficient of prefunding decreases in both magnitude and statistical significance while that of project characteristics remains stable (Column 3). The contribution of prefunding to the total differences is 64.2% at the 10th quantile, declining to 16.2% at the 90th quantile (last column). The remaining difference is contributed by project characteristics.

Prefunding changes the distributions of funding outcomes of projects treated by prefunding vs. their counterfactual counterparts not treated by prefunding. The difference between these two distributions is more pronounced on the left tail than on the right tail, thus lending support to H5B: for projects in lower quantiles that would have raised relatively fewer funds without prefunding, prefunding would elevate them more, compared with projects in upper quantiles that would have raised relatively more funds without prefunding. Figure 1 visualizes the decomposition for all 99 quantiles (the green dash line shows the prefunding effect; the red dotted line indicates the project characteristics effect) and confirms this trend. We repeated the counterfactual decomposition analysis for the other funding days and found similar results.

[Place Figure 1 here]

Moreover, the prefunding effect declines over time for any given quantile. When singling out the 25th, 50th, and 75th quantiles and visualized the prefunding effects, the declining trend is prominent (Online Appendix, Figure A3). We graphed the coefficients of the prefunding effect in 3-dimensional space by quantiles and funding days in Figure 2. The visual evidence in both Figures further corroborates H2: prefunding increases the total funds raised and its effect decreases over time.

[Place Figure 2 here]

Together, the results of this counterfactual decomposition show that for top-ranked projects in fundraising, the characteristics effect dominates the incremental prefunding return on funds. These projects raise more funds primarily due to their inherent project characteristics (e.g., well-known founders), rather than prefunding. In contrast, for lower-ranked projects, prefunding plays a more critical role in raising funds. As prefunding can boost the funding outcomes of these projects with disadvantaged endowments but with strong potential (e.g., avant-garde concepts, unknown founders), an implication follows that prefunding can be a valuable operational design to democratize funding outcomes on crowdfunding platforms.

6. Robustness Checks

As an alternative method to address the endogeneity of prefunding, we used a residual-based instrumental variable (IV) method (Dobbie et al. 2018).[17] The approach is to calculate the residual from the prefunding selection function for each project of the same founder, then derive the average residual after excluding the focal project. This "leave-one-out average residual" contains the idiosyncratic features of other projects by the same founder, and it is unlikely to correlate with the prefunding decision of the focal project after controlling for project-specific characteristics and founder fixed effects (for details see Online Appendix B2.1). The result of this robustness check echoes our main findings on the positive effect of prefunding on crowdfunding outcomes (Online Appendix A, Table A5). We also used this IV to perform text analyses and hypothesis testing as in Sections 5.4–5.6; all the results and qualitative interpretations remain consistent.

As an alternative to the CEM matched sample, we applied the traditional Propensity Score Matching (PSM) to generate a sample of prefunding and non-prefunding projects matched on project characteristics (goal, duration, video, pictures, product categories) and founder experience (launching and backing). All the prior analyses performed on this sample led to similar findings. A major limitation of the PSM is that the matching over observable characteristics can lead to estimation biases (Pearl 2009). To mitigate this limitation, we employed a matching technique from the recent IS literature called Look-Ahead Propensity Score Matching (LA-PSM) (Bapna et al. 2018) (see Online Appendix B2.2). We focused on founders who launched both non-prefunding and prefunding projects and accounted for the unobserved time-invariant characteristics which can drive the founder's intrinsic propensity to adopt prefunding. With LA-PSM, the prefunding effects on funds raised and funding success remain highly significant.

Prefunding offers an additional period of exposure before fundraising which may lead to increased backer awareness. To tease out the information effect from the potential awareness effect, we incorporated the *exposure duration* of each project, calculated as the sum totals of funding and prefunding days (if any). We used this exposure duration as a matching variable (to replace the funding duration) in our CEM

[17] We would like to thank an anonymous reviewer for suggesting this method.

matching and then repeated the analyses in Section 5.4. We found that after controlling for the awareness effect, prefunding projects still outperform non-prefunding ones and the prefunding information drives this funding premium (Online Appendix, Table A6).

In the text analysis of prefunding discussions, we measured the length of discussions with three alternative measures: the word count, the number of characters, and the number of non-sentiment words. None of them yielded significant results compared with our original measure of normalized length (the percentage of non-sentiment words). Hence, we infer that it is not the absolute length of a typical discussion, but rather the percentage of informativeness contained within that would affect the amount of funds.

Among regular backers, the distributions of backers and funds in prefunding projects are likely different from those of non-prefunding projects. We separated four quartiles of regular backing choices based on the backing prices in each project and examined whether prefunding affects the number (percentage) of regular backers and the amount (percentage) of regular funds in each quartile (Online Appendix B2.3). We found that prefunding projects tend to attract regular backers toward higher-priced backing options, driving them to outperform non-prefunding projects. In addition, we selected the lowest- and the highest-priced regular backing choices; while prefunding attracts more backers and more funds for both types of backing options, it elevates a higher percentage of funds to the most expensive backing choices.

7. Conclusions and Discussion

Unregulated reward-based crowdfunding platforms require minimal information disclosures from founders to potential backers. Such a laissez-faire approach can aggravate information asymmetry between founders and backers and lead to market inefficiencies or failures. In response to this challenge, JD Crowdfunding introduced prefunding, an elective feature that permits founders to share additional information with potential backers.

To evaluate the effectiveness of this feature, we compiled and analyzed daily project-level data from the platform. We found that projects with prefunding on average raised considerably more funds and were more likely to succeed in reaching their funding goals. To probe deeper, we used text analyses on the communication between founders and backers, revealing that prefunding discussions, measured by volume, length, and sentiment, have strong explanatory power for funds raised. Taken together, we concluded that prefunding provided an additional communication channel, and the different types of information that flowed through this channel were the mechanisms for funding. Our analyses also showed that informed (regular) backers acted on the prefunding information to make their funding decisions which were then emulated by uninformed (lottery) backers, thereby creating primary and secondary streams of funds for prefunding projects. Finally, using counterfactual decomposition analysis to estimate the quantile treatment effects of prefunding, we found that prefunding drives success unevenly across projects. Specifically, the prefunding effect appears to be greater for projects in the lower quantiles. These projects that raised the lowest amount of funds were the least endowed with favorable characteristics; they could benefit the most from utilizing the prefunding feature.

Our research contributes to the literature in the following ways. First and foremost, we extend the core research at the OM-IS interface on the operational designs of digital platforms. Our research was motivated by the vital need to design features for digital platforms where minimal mandated information disclosures exacerbate information asymmetry. We demonstrated that prefunding was effective in improving information flow and increasing backers' willingness to fund products. Second, unlike static models that draw inferences from only the first and last days, our insights were based on the empirical modeling and analyses of daily data throughout the prefunding and funding periods. This dynamic framework extends modeling techniques in OM-IS literature and enabled us to discover that prefunding creates long-lasting funding effects. Third, by using text analysis to analyze different categories of information and their effects on fundraising, our study provided managerial implications for communication strategies in crowdfunding. We found that objective information is valuable to potential backers. Thus, founders should focus on providing objective, tangible information, rather than hyped sales efforts and overselling which appear to backfire in fundraising. Fourth, we show how prefunding triggers herding and how such herding can generate a secondary source of funding. Prefunding first catalyzes information that cascades before funding begins. Informed backers act on this increased information by providing additional funds, and this conspicuous accretion of funding induces uninformed lottery backers to follow. These insights into herding are novel and extend the literature of OM-IS and information economics. Fifth, to the best of our knowledge, our paper is the first to apply counterfactual decomposition analysis in the OM literature. This application reveals that prefunding assists projects with an inherent lower likelihood of success, which may help democratize funding outcomes on crowdfunding platforms. Lastly, to the benefit of all stakeholders in the rewards-based crowdfunding ecosystem—founders, backers, crowdfunding platforms, policymakers, and the general public—we offer insights into the overall operational design features that improve funding success for early-stage ventures in an online environment plagued by information asymmetry but with minimal oversight and regulations.

Our study has the following limitations which provide opportunities for future research. First, to focus on product crowdfunding, we excluded charity projects because the motivation of their contributors might deviate from the economic rationality of backers seeking tangible product rewards. Yet, it can be intriguing to examine whether and how prefunding leads to different outcomes in donation-based crowdfunding. Second, in our text mining, we distinguished between sentiment words (emotions) and non-sentiment words (objectivity). It may be interesting to use other content analyses and machine learning to probe deeper into different categories of information (words, videos, and pictures) to generate further insights into optimal communication strategies. Third, while we showed that improved funding outcomes are attributed to increased information, it requires future research to quantify the relative informational advantages brought by prefunding or other design features on crowdfunding platforms.

In conclusion, our study validates prefunding as a valuable feature in the operational designs of crowdfunding platforms in online environments with minimal oversight and regulations. Our implications on mechanism design can be extended to other types of crowdfunding such as equity-based crowdfunding, where information asymmetries between entrepreneurs and investors are ubiquitous. We hope our study stimulates more research in these interesting and important areas.

Table 1. Variable Descriptions and Summary Statistics

Variable	Description	Mean	S.D.	Min	Max
Total Funds	Cumulative amount of funds raised	170,200	536,735	0	12,400,000
Ratio	Ratio between total funds raised to the funding goal	3.066	15.493	0	853.417
Success	Binary indicator of whether the project reaches the funding goal	0.761	0.426	0	1
Backers	Total number of regular and lottery backers	1,415	6,789	0	374,823
Regular Backers	Number of backers for regular backing options	375	5,969	0	374,764
Lottery Backers	Number of backers for lottery backing options	1,071	3,190	0	97,974
Regular Funds	Cumulative amount of funds raised from regular bakers	164,507	519,561	0	11,500,000
Lottery Funds	Cumulative amount of funds raised from lottery bakers	5,469	125,038	0	9,294,088
Goal	Target amount of funds to raise	100,264	150,627	1,000	2,000,000
Duration	Number of days of the funding period (excluding prefunding days)	38.673	11.072	7	60
Options	Number of backing options available	7.801	1.783	1	17
Value	Median price of regular backing options	2,092	7,050	1	151,499
Pictures	Number of pictures within the product description	9.459	6.807	0	47
Video	Binary indicator of whether the project description includes a video	0.374	0.484	0	1
Delivery Lag	Days to deliver the product after the funding period is over	26.529	11.147	1	90
Expn_Launch	Number of prior projects backed by the founder	0.127	0.817	0	19
Expn_Back	Number of prior projects launched by the founder	0.125	0.797	0	24
Expn_Launch_Pref	Number of prior prefunding projects launched by the founder	0.072	0.368	0	8
Expn_Back_Pref	Number of prior prefunding projects backed by the founder	0.081	0.665	0	21
Others_Pref	Number of other prefunding projects on the platform the founder did not involve	1,217	723	0	2,658
Volume	Total number of prefunding discussions of a project	30.195	47.979	1	475
Length	Average normalized proportion of non-sentiment words in a prefunding discussion	0.860	0.115	0	59
Sentiment	Average sentiment score in the prefunding discussions of a project	0.075	0.124	-1	1
Likes	Number of likes from the crowd during the funding period	1,722	5,864	0	344,746
Updates	Number of updates from founders during the funding period	2.59	5.143	0	64
Q&A	Number of questions and answers during the funding period	0.947	3.019	0	70
Discussions	Number of discussions during the funding period	74.463	279.457	0	16,785

Notes: All funds are measured in Chinese Yuan (CNY). During the sample period, the exchange rate fluctuated around $1 USD = ¥6.20 CNY.

Table 2. The Effect of Prefunding on Funding Success

	Success
Prefunding	0.669***
	(0.043)
Goal	0.585***
	(0.143)
Duration	-0.527***
	(0.184)
Video	0.177*
	(0.095)
Pictures	0.215***
	(0.062)
Options	0.826***
	(0.260)
Delivery Lag	-0.197*
	(0.101)
Expn_Launch	0.349*
	(0.189)
Expn_Back	0.590***
	(0.164)
Constant	5.155
	(3.217)
Prefunding	
Goal	0.190***
	(0.022)
Duration	0.059
	(0.085)
Expn_Launch_Pref	0.266**
	(0.131)
Expn_Back_Pref	0.101***
	(0.025)
Others_Pref	0.072***
	(0.025)
Constant	-1.880***
	(0.413)
N	3,159

Notes: All non-categorical variables are log-transformed. Seven product categories also are included in the prefunding selection equation; results are not reported. Clustered robust standard errors are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 3. The Effect of Prefunding on Total Funds Raised

	(1)	(2)	(3)
	Total Funds	Total Funds	Total Funds
Prefunding	5.485***	8.856***	5.658***
	(0.242)	(0.315)	(0.238)
Prefunding × Duration		-0.835***	
		(0.044)	
Prefunding × Funding Day			-0.010***
			(0.001)
Prefunding			
Goal	0.184***	0.184***	0.184***
	(0.004)	(0.004)	(0.004)
Duration	-0.235***	-0.591***	-0.215***
	(0.015)	(0.094)	(0.017)
Expn_Launch_Pref	0.188***	0.187***	0.188***
	(0.023)	(0.023)	(0.023)
Expn_Back_Pref	0.086***	0.086***	0.086***
	(0.021)	(0.021)	(0.021)
Others_Pref	0.059***	0.250***	0.056***
	(0.004)	(0.050)	(0.004)
Inverse Mills Ratio	-2.880***	-3.070***	-2.877***
	(0.145)	(0.150)	(0.141)
N	100,474	100,474	100,474

Notes: Dependent variable is ln(*Total Funds*) in all columns. All non-categorical variables are log-transformed. Clustered robust standard errors are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Control variables of project and founder characteristics, monthly dummies, and founder fixed effects are not reported for brevity.

Table 4. The Effect of Prefunding on Total Funds Raised: Further Analysis

	(1)	(2)	(3)	(4)
	Total Funds	Total Funds	Total Funds	Total Funds
Volume	0.444***			
	(0.009)			
Length	1.785***			
	(0.154)			
Sentiment	0.450***			
	(0.086)			
Volume_Founder		0.030***		
		(0.009)		
Volume_Backer		0.475***		
		(0.011)		
Length_Founder			4.148***	
			(0.166)	
Length_Backer			-0.712***	
			(0.180)	
Sentiment_Founder				-2.472***
				(0.103)
Sentiment_Backer				0.174*
				(0.100)
N	65,874	65,944	55,605	55,605

Notes: Dependent variable is ln(*Total Funds*) in all columns. All non-categorical variables are log-transformed. Clustered robust standard errors are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Control variables of project and founder characteristics, monthly dummies, and founder fixed effects, as well as the prefunding selection results are not reported for brevity.

Table 5. The Effect of Prefunding on Regular vs. Lottery Backers

	(1)	(2)	(3)	(4)
	Regular Backers	Regular Backers	Lottery Backers	Lottery Backers
Prefunding	3.098***	0.188***	6.129***	0.127
	(0.179)	(0.024)	(0.267)	(0.084)
Lag Regular Backers		0.972***		0.017***
		(0.000)		(0.000)
Lag Lottery Backers		-0.021		0.964***
		(0.011)		(0.011)
Prefunding Selection				
Goal	0.184***	0.173***	0.174***	0.173***
	(0.004)	(0.004)	(0.004)	(0.004)
Duration	-0.235***	-0.210***	-0.217***	-0.210***
	(0.015)	(0.016)	(0.015)	(0.016)
Expn_Launch_Pref	0.185***	0.159***	0.157***	0.159***
	(0.023)	(0.024)	(0.023)	(0.024)
Expn_Back_Pref	0.058***	0.036*	0.030	0.036*
	(0.020)	(0.021)	(0.020)	(0.021)
Others_Pref	0.059***	0.053***	0.056***	0.053***
	(0.004)	(0.004)	(0.004)	(0.004)
Inverse Mills Ratio	-1.645***	-0.113***	-3.476***	-0.133***
	(0.107)	(0.014)	(0.159)	(0.014)
N	100,474	90,540	97,024	90,536

Notes: All non-categorical variables are log-transformed. Robust standard errors are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Control variables of project and founder characteristics, monthly dummies, and founder fixed effects are not reported for brevity.

Table 6. Counterfactual Decomposition of Prefunding Effects on Total Funds Raised

Quantiles	Effect Sources	Coefficients	Std. Err.	Prefunding Effect %
0.1	Total Difference	1.707***	0.083	
	Project Characteristics	0.611***	0.174	
	Prefunding	1.096***	0.144	64.2%
0.2	Total Difference	1.482***	0.062	
	Project Characteristics	0.678***	0.122	
	Prefunding	0.804***	0.099	54.2%
0.3	Total Difference	1.351***	0.053	
	Project Characteristics	0.703***	0.103	
	Prefunding	0.648***	0.077	47.9%
0.4	Total Difference	1.286***	0.049	
	Project Characteristics	0.724***	0.091	
	Prefunding	0.562***	0.069	43.7%
0.5	Total Difference	1.220***	0.044	
	Project Characteristics	0.723***	0.086	
	Prefunding	0.497***	0.067	40.7%
0.6	Total Difference	1.171***	0.043	
	Project Characteristics	0.743***	0.084	
	Prefunding	0.428***	0.065	36.6%
0.7	Total Difference	1.121***	0.042	
	Project Characteristics	0.768***	0.086	
	Prefunding	0.353***	0.065	31.5%
0.8	Total Difference	1.042***	0.044	
	Project Characteristics	0.761***	0.093	
	Prefunding	0.281***	0.077	27.0%
0.9	Total Difference	0.950***	0.056	
	Project Characteristics	0.796***	0.120	
	Prefunding	0.154	0.101	16.2%

Notes: Dependent variable is ln(*Total Funds*) on the last funding day. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Figure 1. Counterfactual Decomposition of Prefunding Effects on Funds Raised

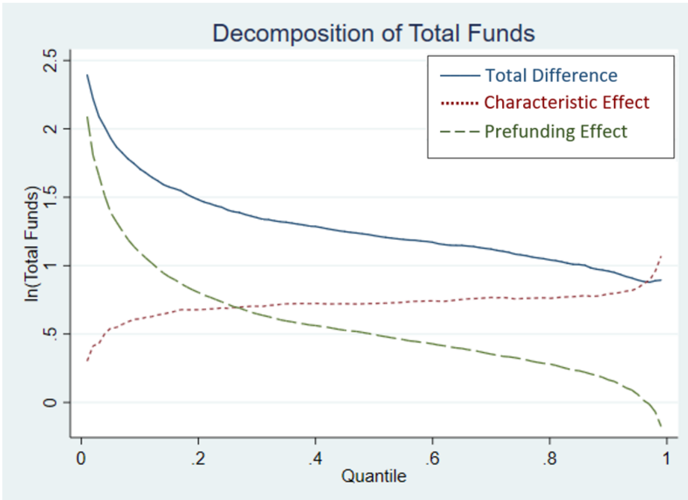
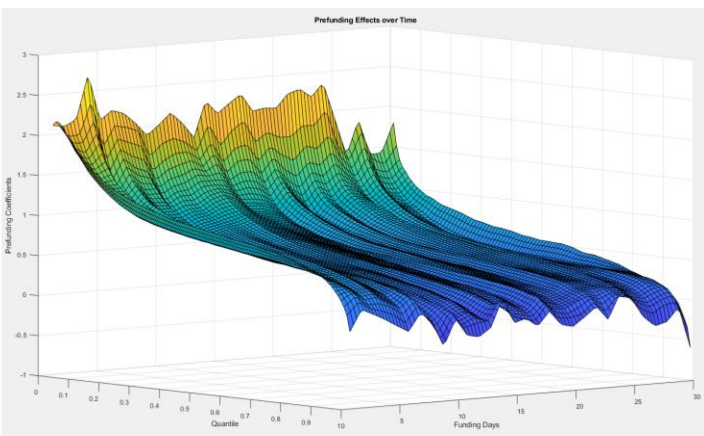


Figure 2. Counterfactual Decomposition of Prefunding Effects across Quantiles over Time



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