



Reward-Based Crowdfunding: The Role of Information Disclosure

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ABSTRACT

This article studies the role and value of information disclosure in a reward-based crowdfunding campaign for a new product development (NPD) project under quality uncertainty. The creator sets a funding target that is subject to a minimum capital requirement and prices for a leading backer and a following backer arriving in two sequential periods. The backers form a prior belief about the quality of the product and update their valuation according to their private signals before they decide whether to bid for the products. The leading backer's bid, if disclosed, may be used by the subsequent backer to infer the former's private signal. We identify two interacting effects that drive the bidding decisions and the profitability of the campaign: an observational learning effect driven by information disclosure and a targeting effect. When the target is relatively high, information disclosure can always benefit the creator. When the target is relatively low, information disclosure may hurt the creator. The optimal target level is always equal to the minimum capital requirement. We further extend the analysis to a setting with a forward-looking leading backer who may strategically wait and identify the conditions under which information disclosure can also increase the profitability of the campaign. Interestingly, to counteract the strategic delay, the optimal target can be set higher than the minimum capital requirement in the presence of information disclosure. [Submitted: June 11, 2019. Revised: July 19, 2020. Accepted: July 30, 2020.]

Subject Areas: *Advance selling, Crowdfunding, Funding target, and Information disclosure.*

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INTRODUCTION

A key challenge for the new product development (NPD) of small- and medium-sized enterprises (SMEs) is access to early-stage funding (Cosh, Cumming, & Hughes, 2009). Only one-third of SMEs are able to obtain the credit they need to finance their innovation from traditional financing sources, which is partly due to the high operational risk and low financial transparency that are naturally related to NPD (NFIB, 2012). In recent years, crowdfunding has emerged as an alternative financing method for NPD projects (The Economist, 2010; Schwienbacher & Larralde, 2012). Crowdfunding refers to the practice of funding a project by raising many small pledges from a large number of individual investors over the Internet to meet a specific capital target (Schwienbacher & Larralde, 2012). Crowdfunding platforms such as Kickstarter.com and Indiegogo.com allow fundraisers to upload their new product design concepts and raise funds online. For example, Pebble Time raised \$10.3 million (with a target of \$0.1 million) in 2012 and \$20.3 million (with a target of \$0.5 million) in 2015 from Kickstarter.com^{1,2} for the first two generations of their smartwatch project, respectively. Globally, crowdfunding has grown tremendously over the last decade, collecting \$34.4 billion in 2015 (Masolution, 2015), and is expected to exceed \$100 billion in 2022 (Statista, 2018).

A common crowdfunding campaign mechanism for NPD projects is *reward-based crowdfunding*, under which a fundraiser, also referred to as the *creator*, sets the unit price of the product developed by the funded project, subject to a funding target, and each backer (or contributor) decides whether to invest according to the price and will receive the product as a reward if the project succeeds (Bradford, 2012). Reward-based crowdfunding can be seen as an alternative advance selling mechanism that allows consumers to preorder a new product before it is released (Xie & Shugan, 2001; Shugan & Xie, 2004; Zhao & Stecke, 2010; Zhao, Pang, & Stecke, 2016; Pang, Zhao, & Xiao, 2019; Xu, Guo, Xiao, & Zhang, 2019). The backers, therefore, serve both as investors in the venture and consumers of the product.

A crowdfunding campaign is deemed successful if the funding target is met before a preset campaign time window. If the target is unmet by the end of the campaign, the campaign is deemed to be a failure, and the collected funds are all returned to the backers. This so-called all-or-nothing (AoN) *fixed funding* mechanism, which is commonly adopted in online crowdfunding, was popularized by Kickstarter. Both game-theoretic studies (e.g., Bagnoli & Lipman, 1989; Chemla & Katrin, 2016; Marx & Matthews, 2016) and experimental studies (e.g., Croson & Marks, 2002; List & Reiley, 2002) find that the introduction of the AoN mechanism generally increases investments.

An NPD project is often accompanied by a considerable number of uncertainties, including market uncertainties (e.g., market potential and consumer preference uncertainties), technological uncertainties (e.g., product specification uncertainties), process uncertainty (e.g., R&D and project management process uncertainties), and quality uncertainty of final products, which are typically driven

¹ <https://www.kickstarter.com/projects/getpebble/pebble-time-awesome-smartwatch-no-compromises>.

² <https://www.kickstarter.com/projects/getpebble/pebble-e-paper-watch-for-iphone-and-android>.

by the innovativeness of the underlying product concept, technological capabilities, and innovation experience of product developers (Stockstrom & Herstatt, 2008). Consumer valuation of the to-be-developed new product is naturally driven by these innovation uncertainties, particularly quality uncertainty, which can be further amplified by a lack of technological knowledge about the underlying new product, of confidence in the creators' capabilities, and of transparency in the development process. To resolve or partially resolve these uncertainties, consumers will search for relevant information over the Internet and social networks to learn about product concepts.

To enhance backers' confidence and reduce their valuation uncertainty of quality, many creators are willing to provide detailed product descriptions, although they often lack credibility for consumers. Some creators may tend to be overly optimistic or overconfident and hence overstate the quality and success rates of the products. Therefore, backers of the campaign have incentives to socially share knowledge and learn from each other. During the campaign, backers who arrive later may be interested in learning the bidding process status, such as accumulated funds and the number of backers who have invested, if such information is disclosed by the creator or the platform like Kickstarter, to infer the perceived quality. Such learning behavior can be seen as a type of *observational learning* (Banerjee, 1992; Zhang, Liu, & Chen, 2015). However, not all creators or crowdfunding platforms are willing to disclose the information about the bidding process due to the concern that a slow start may give future backers a negative impression that the public is bearish on the product. For example, artistshare.com, a popular crowdfunding platform among artists, does not provide information on the bidding process during campaigns.

Motivated by the above observations of reward-based crowdfunding, we ask the following research questions: What is the optimal pricing and targeting strategy for a crowdfunding campaign? What are the effects of funding targets and information disclosure on the backers' bidding strategy and the creator's optimal pricing strategy? Can the creator benefit from information disclosure?

To address these questions, we formulate a reward-based crowdfunding problem as a two-period pricing optimization problem under the AoN mechanism. Before the campaign starts, the creator announces the target and prices in the two periods and decides whether to disclose process information during the campaign. Two backers arrive sequentially in these two periods. Before arrival, the backers form their prior beliefs about the quality of the product based on their private information. Upon arrival, the first backer decides whether to invest according to his expected valuation of the prior belief and price, whereas the second backer, who can observe the first backer's investment decision if the process information is disclosed, updates her belief in a Bayesian fashion before deciding whether to invest. For simplicity, we assume that the first backer is myopic in the sense that he will either invest or leave according to his expected valuation immediately upon arrival in the first period. We first characterize the optimal pricing strategies with and without information disclosure. We then analyze the effects of target and information disclosure on the optimal pricing strategies and identify the conditions under which information disclosure may benefit or hurt the creator. We also characterize the optimal targeting strategy.

We further extend our analysis to the setting with a forward-looking leading backer who may have a motivation to strategically wait and bid at a lower price. We show that to induce the leading backer to bid earlier, the creator has to reduce the price in the first period, which reduces the profitability of the campaign. However, the creator may increase the expected profit by inducing the leading backer to strategically wait. We also analyze the value of information disclosure and the optimal targeting strategy.

The rest of this article is organized as follows. The first section reviews the literature. The following section introduces the problem formulation. The next two sections analyze the settings without and with information disclosure, respectively. Based on the former sections, the value of information disclosure and the optimal targeting decision are discussed. The penultimate section extends the analysis to address forward-looking backers. The last section concludes the article. Proofs and a table of notation are provided in the Appendix.

LITERATURE REVIEW

There are three streams of related literature: reward-based crowdfunding, observational learning, and advance selling.

The rise of crowdfunding has driven the rapid growth of crowdfunding literature; see Moritz and Block (2016) and Kuppuswamy and Bayus (2018) for detailed surveys of recent developments. Our article is closely related to several interesting papers that consider targeting and pricing strategies for reward-based crowdfunding campaigns.

Hu, Li, and Shi (2015) consider the optimal product and pricing strategy for a reward-based crowdfunding project in a two-period and two-backer setting where the product quality is known to both the creator and the backers. The investors are myopic but have heterogeneous tastes, which is modeled as a two-point distribution. Two types of pricing strategies are considered: a take-it-or-leave-it list-price strategy that specifies a price for each period and a menu strategy that provides a menu of prices from which each backer can choose. Instead of explicitly modeling the minimum capital requirement, they assume that the campaign succeeds if and only if both backers bid. They first characterize the optimal pricing strategy when quality is exogenously given and show that the menu strategy can be optimal for a certain degree of heterogeneity. They then extend the analysis to the optimal product-line decision and show that crowdfunding favors the product-line strategy over the single-product strategy, and the qualities are less differentiated under crowdfunding.

Our model differs from Hu et al. (2015) in two aspects. First, they assume that the product quality is known, while we assume that the product quality is unknown to the creator and backers; hence, the backers will be motivated to learn from their own or others' private quality signals. More specifically, we are interested in the strategic role and value of information disclosure in a crowdfunding campaign. Under the information disclosure mechanism, the following backer may infer the early backer's private quality signal from his bidding behavior and then update her belief about the product quality before she makes her own bidding decision—a typical observational learning behavior. Second, we explicitly take into account

the effect of the funding target and assume that the campaign succeeds as long as the target is met. When the target is relatively low, it may suffice to have one backer bidding for the success of the campaign, which implies that restricting the success of the campaign to the event that both backers bid may result in the underestimation of the success rate and, therefore, the profitability of the campaign. We identify two interacting effects on the optimal pricing strategy and the profitability of the campaign: the observational learning effect driven by information disclosure and the targeting effect that influences success. Moreover, we also extend our analysis to the setting with a forward-looking leading backer, who may strategically wait to bid in the second period if the price in that period is lower.

Chakraborty and Swinney (2019a) consider a reward-based crowdfunding campaign with asymmetric quality information: the product quality is known to the creator but unknown to the backers. Using a single-period setting and explicitly assuming that there is a fixed start-up cost for the project, they study how the creator can signal quality to backers via the design of the crowdfunding campaign, including the price of the reward and the funding target. Interestingly, they find that in the presence of information asymmetry, the creator should signal high quality by setting a higher target than the full-information optimal level that is always equal to the fixed cost.

Unlike Chakraborty and Swinney (2019a), who focus on the signaling mechanism and backer-adverse selection behavior under information asymmetry, we focus on observational learning behavior—a kind of social learning behavior—which allows us to analyze the role and value of information disclosure in the design of crowdfunding campaigns.

Chakraborty and Swinney (2019b) study how to design a reward-based crowdfunding campaign with a mixture of myopic and strategic (forward-looking) backers. They assume that the quality of the product is known and a random number of potential backers arrives in the first period but the strategic backers may choose to wait and decide whether to bid until they know the campaign is likely to succeed. Some strategic backers who decide to wait may be distracted and would not return. There exists a hassle cost if the backers bid in the first period regardless of whether the campaign succeeds. Waiting and deciding to bid later can avoid the hassle cost, although there is a waiting cost. They first consider a single-item menu consisting of a funding target and a fixed price and characterize the rational expectations equilibrium of the strategic backers' bidding behavior. They show that the strategic delay may hurt the creator if strategic backers are distracted. They propose a two-price menu strategy with a fixed number of units sold at a low price and show that such a strategy performs well compared to the theoretically optimal general menu strategy.

We also extend our analysis to the setting with strategic backers. Unlike the study of Chakraborty and Swinney (2019b), in which the strategic waiting is induced by the hassle and waiting costs, in our model, the skimming strategy naturally drives the strategic leading backer's waiting motive. The presence of quality uncertainty and learning behavior (self-learning with one's own private signals and observational learning with other backers' bid information) further enriches the model, enabling us to analyze the role and value of the information disclosure strategy. We show that the presence of strategic backers may not necessarily hurt

the creator when the funding target is relatively low and information disclosure may be more likely to benefit a creator who has strategic backers.

With the presence of quality uncertainty and behavior information disclosure, our article is naturally related to the vast body of literature on observational learning. This literature has primarily focused on the role of observational learning in quality inference (e.g., Banerjee, 1992; Bikhchandani, Hirshleifer, & Welch, 1992; Acemoglu & Ozdaglar, 2011; Zhang et al., 2015). A common analytical modeling framework in this literature is to assume that individuals make decisions sequentially and that they observe independent private signals and the actions of others and update their beliefs according to Bayes' rule. Our model adopts a similar analytical framework to formulate the backers' learning mechanism in a reward-based crowdfunding campaign, which allows us to investigate the role and value of information disclosure in crowdfunding.

Reward-based crowdfunding could be seen as an alternative model of advance selling, which has been widely studied in both marketing and operations management literature. In marketing literature, the related research focuses on characterizing the optimal pricing strategy under advance selling in the presence of forward-looking consumers under consumer valuation uncertainty (e.g., Shugan & Xie, 2000, 2004, 2005; Xie & Shugan, 2001). In operations management literature, researchers focus on its effect on reducing the demand uncertainty for the retailer (Tang, Rajaram, Alptekinoglu, & Ou, 2004; Zhao & Steckle, 2010; Li & Zhang, 2013; Zhao, Pang, & Steckle, 2016; Ma, Li, Sethi, & Zhao, 2019; Peng et al., 2019). However, none of the aforementioned papers considers the budget constraint and, therefore, the role of advance selling in financing NPD. Our work contributes to this literature by considering a new model of advance selling with financial budget constraint that integrates the role of information disclosure under observational learning.

PROBLEM FORMULATION

We consider an NPD fundraiser (the creator) who launches a crowdfunding campaign over a time window of two periods with funding target T , indexed by $n = 1, 2$. At the beginning of the campaign, the creator announces the funding target T and prices p_1, p_2 for periods 1 and 2, respectively, as well as an information mechanism (whether to disclose campaign process information) for the campaign with the objective of maximizing the expected total investment (profit) collected from backers during the campaign. Two representative investors (backers) arrive sequentially in each of the two periods and decide whether to pledge/bid at the given prices. For convenience, we call them the leading backer and following backer, respectively. Under reward-based funding, each backer receives a unit of the finished product as a reward, which implies that p_n can also be viewed as the preorder price paid to the creator. At the end of the period 2, the crowdfunding campaign is deemed a success if the funding target is met. If the funding target is not met, the pledged fund will be fully returned to the backers (e.g., AoN mechanism).

A typical NPD project often requires a substantial capital investment to cover the costs of R&D and production facilities. Chakraborty and Swinney (2019a) argue that these projects typically incur fixed startup costs in the process of moving

from the design and prototyping phase to full-scale production. They further assume that once the fixed cost has been invested, the creator can fulfill all demands of the backers without incurring additional variable costs. They justify such an assumption with two reasons. First, fixed costs are a key element of fixed-funding reward-based crowdfunding. Second, variable costs have minimal impacts on the creator's pricing and targeting decisions. Following Chakraborty and Swinney (2019a, 2019b), we assume that the creator requires a minimum capital budget of B to be financed through the crowdfunding campaign, which implies that the targeting decision cannot be lower than B , and there are no other variable costs.

The two backers arrive sequentially in periods 1 and 2. Before their arrival, they form a common prior belief about the value of the product's quality. Upon arrival, each backer receives a private signal and updates his or her belief and then makes his or her bidding decision by accepting or rejecting the offer at the corresponding price option. Such a pricing mechanism is also called list-price strategy. In particular, if the bid of the leading backer is disclosed, the following backer will take it into account when updating her belief.

The Learning and Bidding Behavior of Backers

Following the social learning literature (Bikhchandani et al., 1992; Acemoglu & Ozdaglar, 2011; Zhang et al., 2015), we assume that the quality of the NPD product is either high or low with the respective values $V = 1$ and $V = 0$. The prior probabilities are $Pr\{V = 1\} = \theta$ and $Pr\{V = 0\} = 1 - \theta$, respectively. Although it is common in the social learning literature to assume $\theta = \frac{1}{2}$ (i.e., backers have no knowledge about the quality level) for simplicity (Smith & Sørensen, 2000; Zhang et al., 2015), our model allows a general value of the prior in $[0, 1]$.

Each backer independently receives a private quality signal regarding the quality of the product, denoted by S_n for the n th backer. This private quality signal is determined by each backer's private information and, therefore, is independent across different individuals. As argued by Zhang et al. (2015), in real-world situations, the private quality signal could come from various sources, such as online product reviews or third-party expert opinions. It is common in the social learning literature to assume that individuals receive independent private signals, which are then used to update the belief about the quality of the product (e.g., Bikhchandani et al., 1992; Acemoglu & Ozdaglar, 2011; Zhang et al., 2015, and references therein). Following the common treatment in this literature, we assume that S_n follows a Bernoulli distribution, with the values s_h and s_l , respectively, representing a high-quality signal and a low-quality signal, and that the backers' private signals are independent of each other.

The distribution of the signal S_n depends on the true quality of the product. The accuracy of the quality signal is defined as the probability $q = Pr\{S_n = s_h|V = 1\} = Pr\{S_n = s_l|V = 0\}$. Assume $q \in (1/2, 1]$, which implies that the backers have a higher probability of observing high (low) signals when the true quality is high (low) than when the quality is low (high). The greater the value of q , the more accurate the quality inference provided by the private signal. Based on his or her prior belief, the probability of receiving a high signal for each backer can be denoted by $\lambda = Pr\{S_n = s_h\} = q\theta + (1 - q)(1 - \theta) = (2q - 1)\theta + 1 - q$. Clearly,

$1 - q \leq \lambda \leq q$, and the higher the value of the prior belief of high-quality θ , the higher the predictive probability λ . However, λ is increasing (decreasing) in q if and only if $\theta \geq 1/2$ ($\theta \leq 1/2$). Following the social learning literature (e.g., Bikhchandani et al., 1992; Acemoglu & Ozdaglar, 2011; Zhang et al., 2015), we assume that the prior and the accuracy of the private signal is common knowledge for the creator and backers, which implies that the backers are *ex ante* homogenous and the creator knows the backers' learning behavior well. Such an assumption makes sense when the backers have a similar experience and they can learn from their past experience about the accuracy of the private quality signals, and the creator can learn their beliefs through extensive data analysis. Although there may exist significant information asymmetry in the real world, this treatment from the literature provides better analytical tractability while capturing the key feature of social learning.

For convenience, we detail the joint probabilities of the signals received by both backers:

$$\begin{aligned} Pr\{S_1 = s_h, S_2 = s_h\} &= q^2\theta + (1 - q)^2(1 - \theta) = (2q - 1)\theta + (1 - q)^2 \\ &= \lambda - q(1 - q), \end{aligned} \quad (1)$$

$$Pr\{S_1 = s_h, S_2 = s_l\} = Pr\{S_1 = s_l, S_2 = s_h\} = q(1 - q), \quad (2)$$

$$Pr\{S_1 = s_l, S_2 = s_l\} = (1 - 2q)\theta + q^2. \quad (3)$$

Without information disclosure, the creator reveals no fundraising process information to the backers such that everyone in the market makes their decision independently (i.e., as if they had arrived simultaneously). Then, the information sets of the two backers, denoted by I_n , both contain only their private signals, namely, $I_n = \{S_n\}$. Given their information set I_n , the backers update their beliefs according to Bayes' rule:

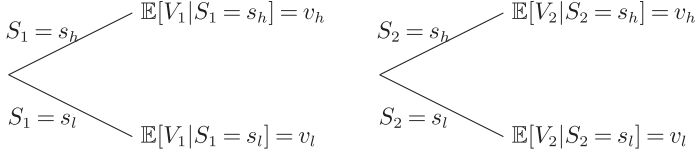
$$Pr(V|I_n) = \frac{Pr(I_n|V)Pr(V)}{Pr(I_n|V = 1)Pr(V = 1) + Pr(I_n|V = 0)Pr(V = 0)}. \quad (4)$$

Then, the expected valuations under private signals (high or low) can be derived as follows:

$$v_h = \mathbb{E}[V_n|I_n = \{s_h\}] = Pr(V = 1|S_n = s_h) = \frac{q\theta}{q\theta + (1 - q)(1 - \theta)} = \frac{q}{\lambda}\theta, \quad (5)$$

$$v_l = \mathbb{E}[V_n|I_n = \{s_l\}] = Pr(V = 1|S_n = s_l) = \frac{(1 - q)\theta}{(1 - q)\theta + q(1 - \theta)} = \frac{1 - q}{1 - \lambda}\theta. \quad (6)$$

Observe that $v_l \leq v_h$ and both v_h and v_l are increasing in θ for any given q , which implies that a greater prior probability of high quality leads to greater posterior expected valuations. For a given $\theta \in (0, 1)$, v_h is increasing in q while v_l is decreasing in q , which implies that a higher degree of accuracy of private signals favors (reduces) the posterior expected valuation upon receiving a high (low) signal. We assume that both backers are myopic in the sense that they are willing to

Figure 1: Expected valuation updates without information disclosure.

bid if and only if $\mathbb{E}[V_n|I_n]$ is greater than p_n , $n = 1, 2$. The strategic backers with forward-looking behavior will be addressed in the extension.

Figure 1 illustrates how backers update their beliefs without information disclosure. Let a_n denote backer n 's decision, with $a_n = 1$ and $a_n = 0$ representing "bids" and "does not bid," respectively. Upon receiving a high (low) signal, backer n would bid if and only if $v_h \geq p_n$ ($v_l \geq p_n$). This implies that if $p_n \leq v_l$, both backers bid; by contrast, if $v_l < p_n \leq v_h$, backer n bids if and only if $S_n = s_h$; otherwise, no one bids. That is, the data on backers' decisions are informative if and only if $v_h \geq p_n > v_l$, which drives the value of information disclosure.

With information disclosure, although the leading backer still updates his belief based exclusively on the private signal, the following backer may learn from the bidding decision of the leading backer through *observational learning*. The follower's information set is then $I_2 = \{a_1, S_2\}$.

In particular, if $v_l < p_1 \leq v_h$, the following backer knows that $S_1 = s_h$ if $a_1 = 1$ and that $S_1 = s_l$ if $a_1 = 0$, which implies that the leading backer's bidding decision, if observable, can indicate his private signal. Correspondingly, the updated valuations are

$$\begin{aligned} v_{hh} &= \mathbb{E}[V_2|I_2 = \{a_1 = 1, S_2 = s_h\}] = \mathbb{E}[V_2|S_1 = s_h, S_2 = s_h] \\ &= \frac{q^2\theta}{q^2\theta + (1-q)^2(1-\theta)}, \end{aligned} \quad (7)$$

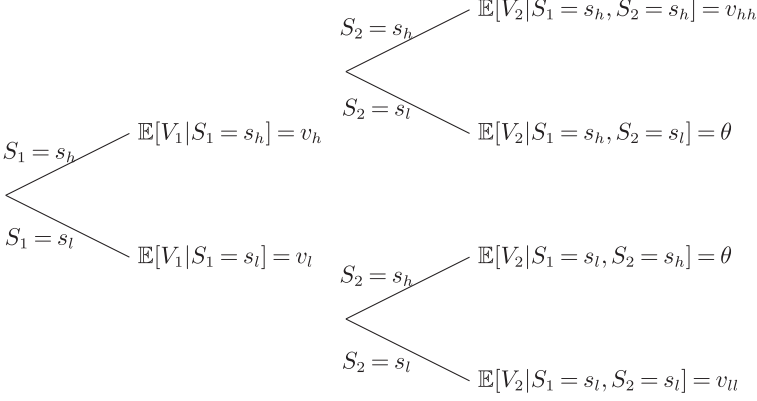
$$\begin{aligned} v_{ll} &= \mathbb{E}[V_2|I_2 = \{a_1 = 0, S_2 = s_l\}] = \mathbb{E}[V_2|S_1 = s_l, S_2 = s_l] \\ &= \frac{(1-q)^2\theta}{(1-q)^2\theta + q^2(1-\theta)}, \end{aligned} \quad (8)$$

$$v_{hl} = \mathbb{E}[V_2|I_2 = \{a_1 = 1, S_2 = s_l\}] = \mathbb{E}[V_2|S_1 = s_h, S_2 = s_l] = \theta, \quad (9)$$

$$v_{lh} = \mathbb{E}[V_2|I_2 = \{a_1 = 0, S_2 = s_h\}] = \mathbb{E}[V_2|S_1 = s_l, S_2 = s_h] = \theta. \quad (10)$$

Note that $0 \leq v_{ll} \leq v_l \leq \theta \leq v_h \leq v_{hh} \leq 1$ and that all these updated valuations are increasing in the prior probability of high-quality θ . For any given $\theta \in (0, 1)$, v_{hh} is increasing in the degree of accuracy of private signals q while v_{ll} is decreasing in q . Figure 2 illustrates how backers update their expected valuation with information disclosure when $v_l < p_1 \leq v_h$.

Figure 2: Expected valuation updates with information disclosure when $v_l < p_1 \leq v_h$.



The Creator's Pricing and Information Disclosure Strategies

The preceding analysis shows that in response to the price pair (p_1, p_2) set by the creator, backer n would bid if and only if his or her posterior expectation of the valuation $\mathbb{E}[V_n|I_n]$ is no less than p_n . In particular, backer 2's expected valuation may be dependent on backer 1's decision, a_1 , which implies that the distribution of I_2 may depend on p_1 . Suppose that the prior distributions of the valuation (quality) of the backers' private signals are common knowledge. To maximize the expected investment raised by the campaign, the creator needs to take into account how the backers respond to its prices and how they learn from each other.

Given the prices (p_1, p_2) and the information sets (I_1, I_2) , the total potential investment is $\sum_{i=1}^2 p_i \mathbf{1}_{\{\mathbb{E}[V_i|I_i] \geq p_i\}}$. Given any target level T , the campaign succeeds if and only if $\sum_{i=1}^2 p_i \mathbf{1}_{\{\mathbb{E}[V_i|I_i] \geq p_i\}} \geq T$. For any given $T > 0$, the creator's objective function can be expressed as

$$\begin{aligned}
 \Pi(p_1, p_2) &= \mathbb{E}_{I_1, I_2} \left[\left(\sum_{i=1}^2 p_i \mathbf{1}_{\{\mathbb{E}[V_i|I_i] \geq p_i\}} \right) \mathbf{1}_{\{\sum_{i=1}^2 p_i \mathbf{1}_{\{\mathbb{E}[V_i|I_i] \geq p_i\}} \geq T\}} \right] \\
 &= p_1 \mathbb{E}_{I_1, I_2} [\mathbf{1}_{\{\mathbb{E}[V_1|I_1] \geq p_1, \mathbb{E}[V_2|I_2] < p_2, p_1 \geq T\}}] \\
 &\quad + p_2 \mathbb{E}_{I_1, I_2} [\mathbf{1}_{\{\mathbb{E}[V_1|I_1] < p_1, \mathbb{E}[V_2|I_2] \geq p_2, p_2 \geq T\}}] \\
 &\quad + (p_1 + p_2) \mathbb{E}_{I_1, I_2} [\mathbf{1}_{\{\mathbb{E}[V_1|I_1] \geq p_1, \mathbb{E}[V_2|I_2] \geq p_2, p_1 + p_2 \geq T\}}]. \quad (11)
 \end{aligned}$$

In what follows, we first analyze the creator's optimal pricing strategies with-out and with information disclosure and the value of information disclosure under a given funding target. We then analyze the optimal targeting decision.

OPTIMAL PRICING STRATEGIES WITHOUT INFORMATION DISCLOSURE

Without information disclosure, backers update their beliefs independently based on their private signals, that is, $I_n = S_n$ for $n = 1, 2$. Backer n is willing to bid if and only if $\mathbb{E}[V_n|S_n] \geq p_n$. Note that $\mathbb{E}[V_n|S_n = s_l] = v_l$ and $\mathbb{E}[V_n|S_n = s_h] = s_h$ for $n = 1, 2$. Clearly, the expected profit $\Pi(p_1, p_2)$ is piecewise linearly increasing in p_1 and p_2 , respectively, which implies that it suffices to choose p_1 and p_2 in $\{v_l, v_h\}$. For ease of interpretation, we define the four possible price pairs as follows:

- Economy strategy (v_l, v_l) . Set low prices in both periods to secure the minimum investments from both early and following backers. The success rate is 100% if $T \leq 2v_l$ and 0 if $T > 2v_l$.
- Penetration strategy (v_l, v_h) . Set a low price for the early backer to secure the minimum early bid then a high price to target the follower with a high signal. The success rate is 100% if $T \leq v_l$, λ if $v_l < T \leq v_l + v_h$, and 0 if $T > v_l + v_h$.
- Skimming strategy (v_h, v_l) . Set a high price to target the early backer receiving the high signal and then a low price to assure the bid from the follower. The success rate is 100% if $T \leq v_l$, λ if $v_l < T \leq v_l + v_h$, and 0 if $T > v_l + v_h$.
- Premium strategy (v_h, v_h) . Set high prices to target high-signal receivers. The success rate is $\lambda + q(1 - q)$ if $T \leq v_h$, $\lambda - q(1 - q)$ if $v_h < T \leq 2v_h$, and 0 if $T > 2v_h$.

The profit functions under different pricing strategies depend on the target value T . By the definitions of v_l and v_h , we can readily verify that $v_h < 2v_l$ if and only if $\theta \geq \theta^*(q)$ (or equivalently, $\lambda > \frac{q}{2-q}$) for any $q > 1/2$, where $\theta^*(q) = \frac{2-(2-q)^2}{(2-q)(2q-1)}$. The expected profits under different pricing strategies and target levels are summarized in Table 1. The trivial case with $T > 2v_h$ is excluded.

The following proposition characterizes the optimal pricing strategy without information disclosure under different target values.

Proposition 1 (Optimal Pricing without Information Disclosure): *Suppose there is no information disclosure.*

- (a) For $0 < T \leq \min(2v_l, v_h)$, there are two subcases. Define $\tilde{\theta}(q) := \frac{(q^2+q-1)^+}{q(2q-1)}$.
- (a.1) If $0 \leq \theta \leq \tilde{\theta}(q)$, then the premium strategy is optimal.
- (a.2) If $\tilde{\theta}(q) < \theta \leq 1$, then the economy strategy is optimal.
- (b) For $\min(2v_l, v_h) < T \leq \max(2v_l, v_h)$, there are two subcases:
- (b.1) For $0 \leq \theta \leq \theta^*(q)$, the premium strategy is optimal.
- (b.2) For $\theta^*(q) < \theta \leq 1$, if (i) $\frac{1}{2} < q \leq \hat{q}$ or (ii) $\hat{q} < q \leq 1$ and $\hat{\theta}(q) < \theta \leq 1$, then the economy strategy is optimal. If, otherwise, $\hat{q} < q \leq 1$ and $\theta^*(q) < \theta \leq \hat{\theta}(q)$, the premium strategy is optimal, where $\hat{q} \approx 0.7966$ is the unique solution to the equality $2q^3 - 6q^2 + q + 2 = 0$ and

$$\hat{\theta}(q) = \frac{1}{2q-1}$$

Table 1: Expected profits without information disclosure.

Expected Profits for $2v_l \leq v_h$ ($0 \leq \theta \leq \theta^*(q)$)					
Strategy	$0 < T \leq v_l$	$v_l < T \leq 2v_l$	$2v_l < T \leq v_h$	$v_h < T \leq v_l + v_h$	$v_l + v_h < T \leq 2v_h$
Economy strategy	$2v_l$	$2v_l$	0	0	0
Penetration strategy	$v_l + \lambda v_h$	$\lambda(v_l + v_h)$	$\lambda(v_l + v_h)$	$\lambda(v_l + v_h)$	0
Skimming strategy	$v_l + \lambda v_h$	$\lambda(v_l + v_h)$	$\lambda(v_l + v_h)$	$\lambda(v_l + v_h)$	0
Premium strategy	$2\lambda v_h$	$2\lambda v_h$	$2\lambda v_h$	$2[\lambda - q(1 - q)]v_h$	$2[\lambda - q(1 - q)]v_h$
Expected Profits for $2v_l > v_h$ ($\theta^*(q) < \theta \leq 1$)					
Strategy	$0 < T \leq v_l$	$v_l < T \leq v_h$	$v_h < T \leq 2v_l$	$2v_l < T \leq v_l + v_h$	$v_l + v_h < T \leq 2v_h$
Economy strategy	$2v_l$	$2v_l$	0	0	0
Penetration strategy	$v_l + \lambda v_h$	$\lambda(v_l + v_h)$	$\lambda(v_l + v_h)$	$\lambda(v_l + v_h)$	0
Skimming strategy	$v_l + \lambda v_h$	$\lambda(v_l + v_h)$	$\lambda(v_l + v_h)$	$\lambda(v_l + v_h)$	0
Premium strategy	$2\lambda v_h$	$2\lambda v_h$	$2[\lambda - q(1 - q)]v_h$	$2[\lambda - q(1 - q)]v_h$	$2[\lambda - q(1 - q)]v_h$

$$\times \left[\frac{3q^2 - q^3 - 1}{2q} + \sqrt{\frac{1}{4}(2 - 1/q + q(1 - q))^2 - q(1 - q)} \right].$$

(c) For $\max(v_h, 2v_l) < T \leq v_l + v_h$, if (i) $1/2 < q \leq \bar{q}$, or (ii) $\bar{q} < q \leq 1$ and $\theta \in [0, \underline{\theta}(q)] \cup [\bar{\theta}(q), 1]$, then both the skimming strategy and the penetration strategy are optimal. If, otherwise, $\bar{q} < q \leq 1$ and $\underline{\theta}(q) < \theta < \bar{\theta}(q)$, then the premium strategy is optimal, where $\bar{q} \approx 0.7712$ is the unique solution to the equality $4q^4 - 8q^3 + 12q - 7 = 0$ and

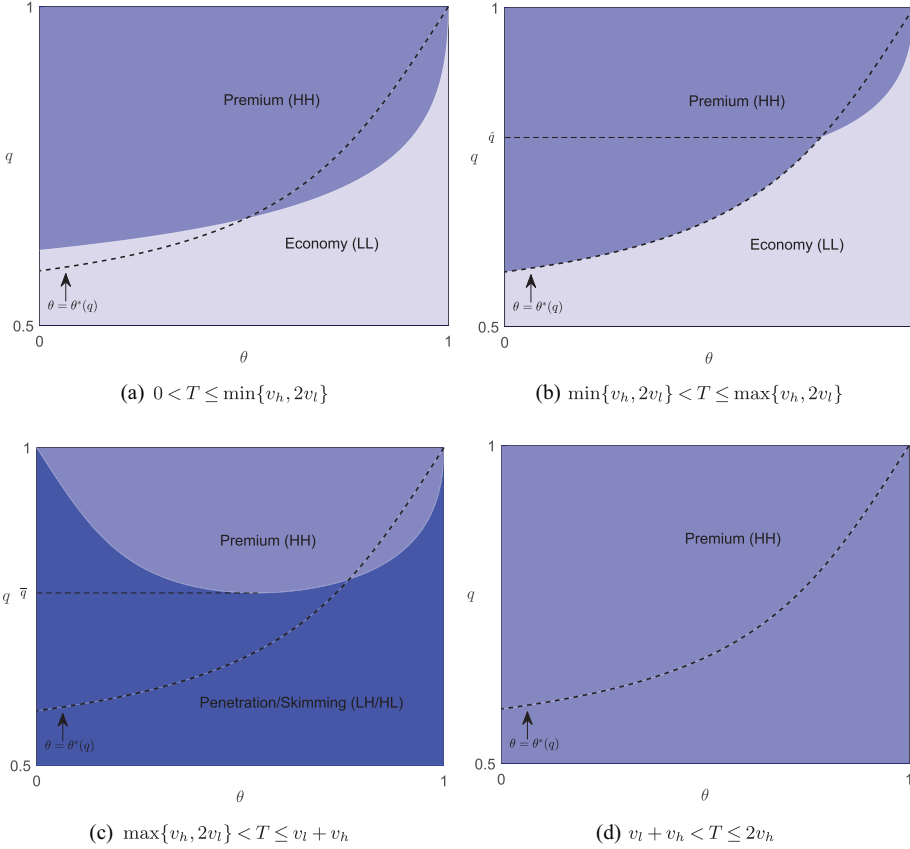
$$\begin{aligned} \underline{\theta}(q) &= \frac{1}{2q - 1} \\ &\times \left[\frac{2q^2(1 - q) + 3q - 2}{2} - \sqrt{\frac{(2q(1 - q) + 1)^2 q^2}{4} - 2q^2(1 - q)} \right], \end{aligned} \quad (12)$$

$$\begin{aligned} \bar{\theta}(q) &= \frac{1}{2q - 1} \\ &\times \left[\frac{2q^2(1 - q) + 3q - 2}{2} + \sqrt{\frac{(2q(1 - q) + 1)^2 q^2}{4} - 2q^2(1 - q)} \right]. \end{aligned} \quad (13)$$

(d) For $v_l + v_h < T \leq 2v_h$, the premium strategy is optimal.

Proposition 1 shows that the optimal pricing strategy is driven by the target level T , the prior probability in quality θ , and the accuracy of private signals q . Recall that a greater prior probability increases the updated valuations under both signals, while a higher degree of accuracy of private signals only favors v_h . Moreover, a higher funding target reduces the success rate. According to the target levels, we can classify the cases into four categories: (i) low targets ($T \leq \min(2v_l, v_h)$), (ii) medium–low targets ($\min(2v_l, v_h) < T \leq \max(2v_l, v_h)$), (iii) medium–high targets ($\max(2v_l, v_h) < T \leq v_l + v_h$), and (iv) high targets ($v_l + v_h < T \leq 2v_h$). Figure 3 provides the corresponding descriptive figures for the optimal policies under these target categories.

When the targets are low ($T \leq \min(v_h, 2v_l)$), it is optimal to choose either the premium strategy or the economy strategy. As shown in Figure 3(a), for a given prior belief θ , the creator tends to choose the premium strategy for more accurate private signals. This is because the updated valuation upon receiving high signals and the probability of receiving high signals are strictly increasing in the accuracy of the signal. However, for any given accuracy level q , the creator tends to choose the economy strategy (premium strategy) for a higher (lower) prior belief in high quality, which reveals the trade-off between a greater premium and a higher success rate. On the one hand, although a higher prior belief in high quality leads to a higher posterior expected valuation upon receiving a high signal, v_h , the lower success rate under the premium strategy restricts the increase in the expected investment of

Figure 3: Pricing strategies without information disclosure.

each backer ($\lambda v_h = q\theta$). On the other hand, a higher prior belief in high quality also leads to higher posterior expected valuation even upon receiving a low signal, $v_l = \frac{1-q}{1-\lambda}\theta$, while having a 100% success rate under the economy strategy. Clearly, $\frac{v_l}{\lambda v_h} = \frac{1-q}{q(1-\lambda)}$, which is an increasing function of θ . That is, the marginal benefit of a higher prior belief under the economy strategy is greater than that under the premium strategy. In the trade-off between the premium and the success rate, the higher prior belief is more favorable to the creator via the success rate. In addition, the penetration strategy and the skimming strategy are dominated by the economy or premium strategy, which is due to the lower success rate compared to the economy strategy and the lower premium compared to the premium strategy. Hence, the creator can only focus on either the high success rate or the high premium, and the intention to reconcile the success rate and the premium may not be optimal when the target is not so high.

When the targets are medium–low ($\min(v_h, 2v_l) < T \leq \max(v_h, 2v_l)$), the optimal pricing strategies are also either the premium strategy or the economy

strategy. Figure 3(b) shows that, similar to the case with low targets, for a given accuracy level q , the creator tends to choose the economy strategy for a higher prior belief of high quality, whereas for a given prior belief θ , the creator tends to choose the premium strategy for more accurate private signals. Note that $2v_l < v_h$ for the medium blue area above the curve indicated by $\theta^*(q)$. In this area, the medium–low target that satisfies $2v_l < T \leq v_h$ has prevented the creator from choosing the economy strategy. For the area below the curve indicated by $\theta^*(q)$, the trade-off between the premium and the success rate still exists, resulting in a similar policy structure as that under low targets. However, the success rate under the premium strategy becomes lower, that is, $\lambda - q(1 - q)$, as it requires that both backers receive high signals when $v_h < T \leq 2v_l$. As a result, compared to the case with low targets, the creator is more likely to choose the economy strategy under medium–low targets when $\theta > \theta^*(q)$. Indeed, as shown in Figure 3(b), the area of the economy strategy is greater than that in Figure 3(a) when $\theta > \theta^*(q)$.

When the targets are medium–high ($\max(v_h, 2v_l) < T \leq v_l + v_h$), the optimal pricing strategy is either the premium strategy or the skimming/penetration strategy since a successful campaign requires the creator to set at least one price at v_h (which excludes the economy strategy). Clearly, the success rate under the skimming strategy or the penetration strategy is greater than that under the premium strategy. As described by Figure 3(c), if the accuracy level q is sufficiently low (below \bar{q}), only the skimming or penetration strategy is optimal for any θ . When the accuracy level is sufficiently high (above \bar{q}), the premium strategy can be optimal only when the prior belief is neither too low nor too high. This indicates the complexity of the interaction between the success rate and the premium in determining the optimal pricing strategies under the medium–high targets.

When the targets are high ($v_l + v_h < T \leq 2v_h$), as indicated by Figure 3(d), only the premium strategy may lead to the total investment that meets the target.

In the special case with $q = 1$, that is, the private quality signal is 100%, parts (b) and (d) together indicate that the premium strategy is optimal for all θ . Note that $v_l = 0$ and $v_h = 1$ for $q = 1$. Then, the backers will purchase if and only if they receive high signals, which explains the optimality of the premium strategy for $q = 1$. In another special case with $\theta = 0$ or $\theta = 1$, that is, the prior probability of high quality is 100%, we have $v_l = v_h = 0$ or $v_l = v_h = 1$, which implies that there is no difference among the four pricing strategies.

Last but not least, comparing the four subfigures of Figure 3, we can observe that as the funding target increases, although the premium strategy tends to outperform the economy strategy, the skimming or penetration strategy may be more favorable when the target is medium–high.

OPTIMAL PRICING STRATEGIES WITH INFORMATION DISCLOSURE

When the bidding information is disclosed, the following backer can infer the leading backer's private signal from his bidding decision when the first price is sufficiently large. The piecewise linear structure of the objective function implies that p_1 is either v_l or v_h . If $p_1 = v_l$, the disclosed bidding information cannot signal the

leading backer's private information; hence, p_2 can only be v_l or v_h . If $p_1 = v_h$, the disclosed bidding information can signal the leading backer's private information; hence, p_2 can be chosen from the updated valuation values $\{v_{ll}, \theta, v_{hh}\}$.

For ease of interpretation, the possible pricing strategies can be described as follows.

- Economy strategy (v_l, v_l) . Similar to the case without information disclosure, the economy strategy maximizes the success rate. The disclosed bid of the leading backer does not have a signaling role. The success rate is 100% if $T \leq 2v_l$ and 0 if $T > 2v_l$. Correspondingly, the total expected profit is $2v_l$ if $T \leq 2v_l$ and 0 otherwise.
- Penetration strategy (v_l, v_h) . Similar to the economy strategy, the disclosed bid of the leading backer does not have a signaling role. Under the penetration strategy, the success rate is 100% if $T \leq v_l$, λ if $v_l < T \leq v_l + v_h$, and 0 if $T > v_l + v_h$. Correspondingly, the total expected investment is $v_l + \lambda v_h$ if $T \leq v_l$, $\lambda(v_l + v_h)$ if $v_l < T \leq v_l + v_h$, and 0 otherwise.
- Skimming strategy (v_h, θ) . Under the skimming strategy, the leading backer's bid can signal his private signal information. Under this strategy, if the leading backer bids, which implies a high signal s_h , then the following backer updates her valuation to v_{hh} for a high signal or θ for a low signal. If, otherwise, the leading backer does not bid, which implies a low signal, then the following backer updates her valuation to θ for a high signal and v_{ll} for a low signal. That is, it allows the creator to secure the investment from at least one backer as long as at least one backer receives a high signal. The success rate is $\lambda + q(1 - q)$ if $T \leq \theta$, λ if $\theta < T \leq \theta + v_h$, and 0 if $T > \theta + v_h$. Correspondingly, the expected total investment is $\lambda(v_h + \theta) + q(1 - q)\theta$ if $T \leq \theta$, $\lambda(v_h + \theta)$ if $\theta < T < \theta + v_h$, and 0 otherwise.

Note that it is also possible to set $(p_1, p_2) = (v_h, v_{ll})$ to receive a minimum investment of v_{ll} even if both backers receive low signals. Under this pricing strategy, the success rate is 100% if $T \leq v_{ll}$, λ if $v_{ll} < T \leq v_{ll} + v_h$, and 0 if $T > v_{ll} + v_h$. Correspondingly, the expected total investment is $\lambda v_h + v_{ll}$ if $T \leq v_{ll}$, $\lambda(v_h + v_{ll})$ if $v_{ll} < T \leq v_{ll} + v_h$, and 0 otherwise. Note that for $T \leq v_{ll}$, the penetration strategy leads to an expected investment of $\lambda v_h + v_l$, which is strictly greater than $\lambda v_h + v_{ll}$. Hence, this pricing strategy is strictly dominated by the penetration strategy. For $T > v_{ll}$, $\lambda(v_h + v_{ll}) < \lambda(v_h + \theta)$, which implies that it is strictly dominated by the skimming strategy with (v_h, θ) . Therefore, it suffices to omit this strategy in the following analysis.

- Premium strategy (v_h, v_{hh}) . Setting the prices to the highest updated valuations allows the creator to target only the high-signal receivers. Under the premium strategy, the success rate is λ if $T \leq v_h$, $\lambda - q(1 - q)$ if $v_h < T \leq v_h + v_{hh}$, and 0 if $T > v_h + v_{hh}$. Correspondingly, the expected total investment is $(\lambda - q(1 - q))(v_h + v_{hh}) + q(1 - q)v_h = \lambda v_h + q^2\theta$ if $T \leq v_h$, $(\lambda - q(1 - q))(v_h + v_{hh}) = (\lambda - q(q - q))v_h + q^2\theta$ if $v_h < T \leq v_h + v_{hh}$, and 0 otherwise.

The profit functions under different pricing strategies depend on the target value T . Note that $2v_l > \theta$ if and only if $\lambda \geq 2q - 1$, or equivalently, $\theta \geq \theta^{**}(q) := \frac{(3q-2)^+}{2q-1}$. Then, according to the relative magnitudes of $2v_l$, θ , and v_h ,

the profits under different pricing strategies and target levels can be summarized as follows in Table 2. Note that the trivial case with $T > v_h + v_{hh}$ is excluded.

Define $\theta_L(q) = \frac{(q^2+q-1)^+}{2q-1}$, $\theta_M(q) = \frac{(q^3+q^2+2q-2)^+}{q(1+q)(2q-1)}$, and $\theta_H(q) = \frac{(\sqrt{((1-q)^2+4(3q-2)^+)-(1-q)^+}}{2(2q-1)}$. The following proposition characterizes the optimal pricing strategy with information disclosure.

Proposition 2 (Optimal Pricing with Information Disclosure): Suppose there is information disclosure.

- (a) For $0 < T \leq \min(2v_l, \theta)$, there are three cases.
- (a.1) If $0 \leq q \leq \frac{(2q^2-1)^+}{2q-1}$, then the premium strategy is optimal.
- (a.2) If $\frac{(2q^2-1)^+}{2q-1} < \theta \leq \frac{(\sqrt{(1-q)^4+4q-q^2-2-(1-q^2)^+}}{4q-2}$, then the skimming strategy is optimal.
- (a.3) Otherwise, then the economy strategy is optimal.
- (b) For $\min\{\theta, 2v_l\} < T \leq \min\{\max\{\theta, 2v_l\}, v_h\}$, there are five cases. Let q_m be the unique solution to $q^3 + 2q^2 + q - 2 = 0$ with $q_m \approx 0.6956$.
- (b.1) If $0 \leq \theta \leq \frac{(2q^2-1)^+}{1-q}$, then the premium strategy is optimal.
- (b.2) If $\frac{(2q^2-1)^+}{1-q} < \theta \leq \theta^{**}(q)$, then the skimming strategy is optimal.
- (b.3) If $\theta^{**}(q) < \theta \leq \theta_M(q)$ for $\frac{1}{2} < q \leq q_m$ or $\theta^{**}(q) < \theta \leq \theta_L(q)$ for $q_m < q \leq 1$, then the premium strategy is optimal.
- (b.4) If $\theta_L(q) < \theta \leq \theta_H(q)$ for $q_m < q \leq 1$, then the skimming strategy is optimal.
- (b.5) Otherwise, then the economy strategy is optimal.
- (c) For $\min\{\max\{\theta, 2v_l\}, v_h\} < T \leq \max\{v_h, 2v_l\}$, there are three cases.
- (c.1) If $0 \leq \theta \leq \theta_L(q)$, then the premium strategy is optimal.
- (c.2) If $\theta_L(q) < \theta \leq \theta^*(q)$ for $\frac{1}{2} < q \leq \frac{7-\sqrt{17}}{4}$ or $\theta_L(q) < \theta \leq \theta_H(q)$ for $\frac{7-\sqrt{17}}{4} < q \leq 1$, then the skimming strategy is optimal.
- (c.3) Otherwise, then the economy strategy is optimal.
- (d) For $\max\{v_h, 2v_l\} < T \leq \theta + v_h$, there are two cases.
- (d.1) If $\frac{1}{2} < q \leq 2\sqrt{2} - 2$, then the skimming strategy is optimal.
- (d.2) If $2\sqrt{2} - 2 < q \leq 1$, then the premium strategy is optimal for $\frac{q^2 - \sqrt{\frac{q^4}{4} - q^2(1-q) - (1-q)}}{2q-1} \leq \theta \leq \frac{q^2 + \sqrt{\frac{q^4}{4} - q^2(1-q) - (1-q)}}{2q-1}$, and the skimming strategy is optimal otherwise.
- (e) For $\theta + v_h < T \leq v_h + v_{hh}$, the premium strategy is optimal.

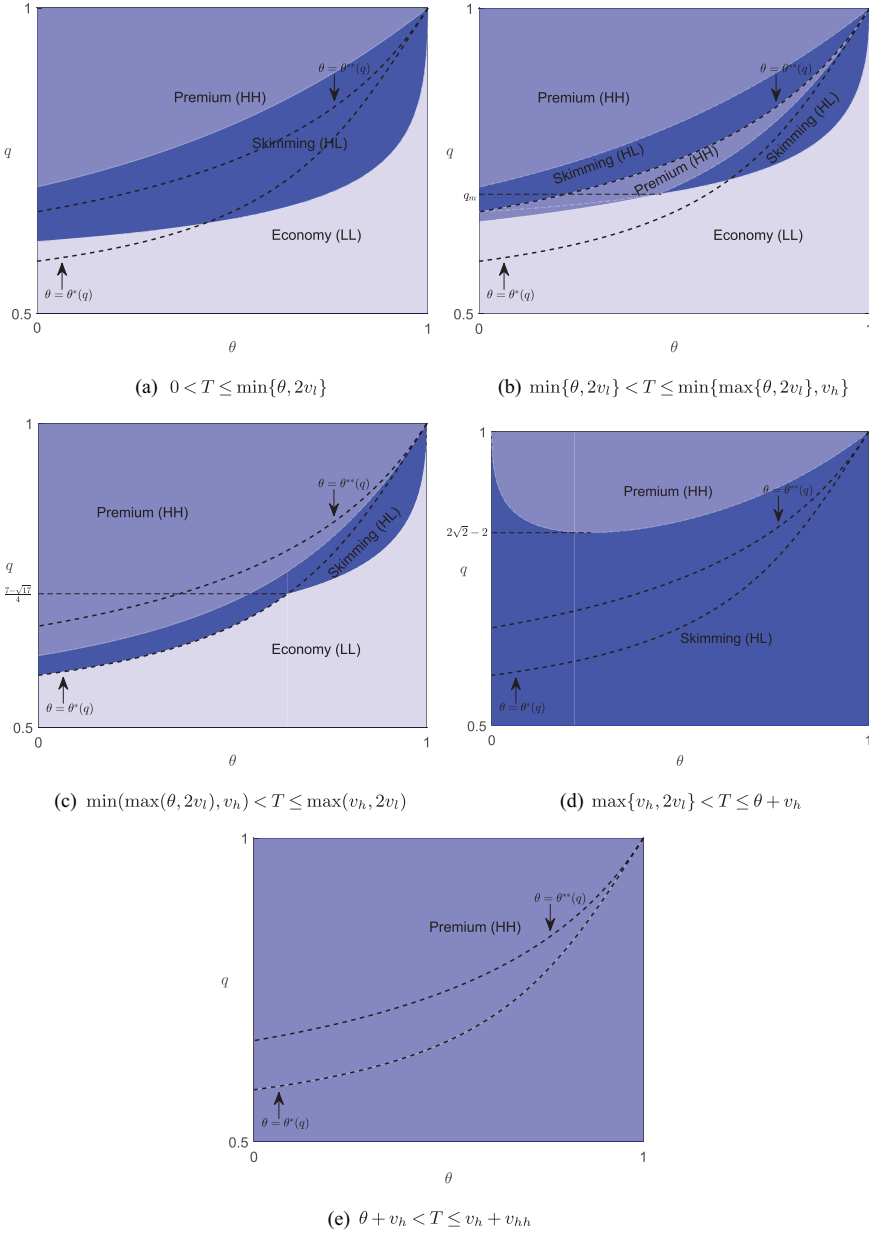
According to the target level T , we can classify the cases into five categories: (a) very low targets ($0 < T \leq \min(2v_l, \theta)$), (b) low targets ($\min(\theta, 2v_l) < T \leq \min(\max(\theta, 2v_l), v_h)$), (c) medium-low targets ($\min(\max(\theta, 2v_l), v_h) < T \leq \max(v_h, 2v_l)$), (d) medium-high targets ($\max(v_h, 2v_l) < T \leq \theta + v_h$), and (e) high targets ($\theta + v_h < T \leq v_h + v_{hh}$). Figure 4 provides the corresponding descriptive figures for the optimal policies under these target categories.

As described by Figure 4(a), when the targets are very low ($0 < T \leq \min(2v_l, \theta)$), the optimal strategy changes from the premium strategy to the skimming strategy and then to the economy strategy as the prior belief in high-quality θ

Table 2: Expected profits with information disclosure.

Expected Profits for $2v_l \leq \theta \leq \theta \leq \theta^{**}(q)$							
Strategy	$T \in (0, v_l]$	$T \in (v_l, 2v_l]$	$T \in (2v_l, \theta]$	$T \in (\theta, v_h]$	$T \in (v_h, v_l + v_h]$	$T \in (v_l + v_h, \theta + v_h]$	$T \in (v_m + v_h, v_h + v_{hh}]$
Economy strategy	$2v_l$	$2v_l$	0	0	0	0	0
Penetration strategy	$v_l + \lambda v_h$	$\lambda(v_l + v_h)$	$\lambda(v_l + v_h)$	$\lambda(v_l + v_h)$	$\lambda(v_l + v_h)$	0	0
Skimming strategy	$\lambda(v_h + \theta) + q(1 - q)\theta$	$\lambda(v_h + \theta) + q(1 - q)\theta$	$\lambda(v_h + \theta) + q(1 - q)\theta$	$\lambda(\theta + v_h)$	$\lambda(\theta + v_h)$	$\lambda(\theta + v_h)$	0
Premium strategy	$\lambda v_h + q^2\theta$	$\lambda v_h + q^2\theta$	$\lambda v_h + q^2\theta$	$\lambda v_h + q^2\theta$	$(\lambda - q(1 - q)) \cdot (v_h + v_{hh})$	$(\lambda - q(1 - q)) \cdot (v_h + v_{hh})$	$(\lambda - q(1 - q)) \cdot (v_h + v_{hh})$
Expected Profits for $\theta < 2v_l \leq v_h$ ($\theta^{**}(q) < \theta \leq \theta^*(q)$)							
Strategy	$T \in (0, v_l]$	$T \in (v_l, \theta]$	$T \in (\theta, 2v_l]$	$T \in (2v_l, v_h]$	$T \in (v_h, v_l + v_h]$	$T \in (v_l + v_h, \theta + v_h]$	$T \in (\theta + v_h, v_h + v_{hh}]$
Economy strategy	$2v_l$	$2v_l$	$2v_l$	0	0	0	0
Penetration strategy	$v_l + \lambda v_h$	$\lambda(v_l + v_h)$	$\lambda(v_l + v_h)$	$\lambda(v_l + v_h)$	$\lambda(v_l + v_h)$	0	0
Skimming strategy	$\lambda(v_h + \theta) + q(1 - q)\theta$	$\lambda(v_h + \theta) + q(1 - q)\theta$	$\lambda(v_h + \theta) + q(1 - q)\theta$	$\lambda(\theta + v_h)$	$\lambda(\theta + v_h)$	$\lambda(\theta + v_h)$	0
Premium strategy	$\lambda v_h + q^2\theta$	$\lambda v_h + q^2\theta$	$\lambda v_h + q^2\theta$	$\lambda v_h + q^2\theta$	$(\lambda - q(1 - q)) \cdot (v_h + v_{hh})$	$(\lambda - q(1 - q)) \cdot (v_h + v_{hh})$	$(\lambda - q(1 - q)) \cdot (v_h + v_{hh})$
Expected profits for $2v_l > v_h$ ($\theta^*(q) < \theta \leq 1$)							
Strategy	$T \in (0, v_l]$	$T \in (v_l, \theta]$	$T \in (\theta, v_h]$	$T \in (v_h, 2v_l]$	$T \in (2v_l, v_l + v_h]$	$T \in (v_l + v_h, \theta + v_h]$	$T \in (\theta + v_h, v_h + v_{hh}]$
Economy strategy	$2v_l$	$2v_l$	$2v_l$	$2v_l$	0	0	0
Penetration strategy	$v_l + \lambda v_h$	$\lambda(v_l + v_h)$	$\lambda(v_l + v_h)$	$\lambda(v_l + v_h)$	$\lambda(v_l + v_h)$	0	0
Skimming strategy	$\lambda(v_h + \theta) + q(1 - q)\theta$	$\lambda(v_h + \theta) + q(1 - q)\theta$	$\lambda(v_h + \theta) + q(1 - q)\theta$	$\lambda(\theta + v_h)$	$\lambda(\theta + v_h)$	$\lambda(\theta + v_h)$	0
Premium strategy	$\lambda v_h + q^2\theta$	$\lambda v_h + q^2\theta$	$\lambda v_h + q^2\theta$	$\lambda v_h + q^2\theta$	$(\lambda - q(1 - q)) \cdot (v_h + v_{hh})$	$(\lambda - q(1 - q)) \cdot (v_h + v_{hh})$	$(\lambda - q(1 - q)) \cdot (v_h + v_{hh})$

Figure 4: Pricing strategies with information disclosure.



becomes larger or the accuracy level q becomes lower. Compared to the low-target case without information disclosure (Figure 3(a)) where the optimal strategy is either the economy or the premium strategy, the skimming strategy is optimal for moderate q and θ in the presence of information disclosure. This implies that information disclosure allows the creator to use the skimming strategy to elicit a

greater premium from the backer in the second period ($\theta > v_l$) without reducing the success rate ($\lambda + q(1 - q)$), which increases the profitability of the skimming strategy.

When the targets are low ($\min(2v_l, \theta) < T \leq \min(\max(\theta, 2v_l), v_h)$), there are two subcases. As indicated by Figure 4(b), for any given value of q , if $\theta \leq \theta^{**}(q)$, then the condition becomes $2v_l < T \leq \theta$, under which the optimal strategy changes from the premium strategy to the skimming strategy as the prior belief in high-quality θ increases. When the prior belief in high quality becomes greater and satisfies $\theta > \theta^{**}(q)$, then the condition becomes $\theta < T \leq \min(2v_l, v_h)$, under which the optimal strategy again changes from the premium strategy to the skimming strategy and then to the economy strategy as θ increases. Observe in Table 2 that as θ crosses over $\theta^{**}(q)$, the success rate under the skimming strategy falls while that under the premium strategy remains unchanged, which explains the change of the optimal strategy.

As described by Figure 4(c), when the targets are medium–low ($\min(\max(\theta, 2v_l), v_h) < \theta \leq \max(v_h, 2v_l)$), the optimal policy has a similar pattern to that for very low targets: the optimal strategy changes from the premium strategy to the skimming strategy and then to the economy strategy as the prior belief in high-quality θ becomes larger or the accuracy level q becomes lower. Similarly, compared to the low-target case without information disclosure (Figure 3(b)), the skimming strategy becomes more profitable in the presence of information disclosure.

As described by Figure 4(d), when the targets are medium–high ($\max(v_h, 2v_l) < \theta \leq v_h + \theta$), if the information accuracy level q is sufficiently high and the prior belief in high-quality θ is neither too high nor too low, the premium strategy is optimal; otherwise, the skimming strategy is optimal, which is similar to the case without information disclosure (Figure 3(c)).

In particular, when $q = 1$, we have $v_{ll} = 0$, $v_{lh} = v_{hl} = \theta$, and $v_{hh} = 1$. It follows from Proposition 2 that the premium strategy is optimal. When $\theta = 0$ or 1, we have $v_{ll} = v_{lh} = v_{hl} = v_{hh} = 0$ or 1, which implies no difference among the four pricing strategies.

Parts (b) and (d) together indicate that the premium strategy is optimal for all θ . Note that $v_l = 0$ and $v_h = 1$ for $q = 1$. Then, the backers will purchase if and only if they receive high signals, which explains the optimality of the premium strategy for $q = 1$. In another special case with $\theta = 0$ or $\theta = 1$, that is, the prior probability of high quality is 100%, we have $v_l = v_h = 0$ or $v_l = v_h = 1$, which implies that there is no difference among the four pricing strategies.

In summary, Proposition 2 reveals the complex interaction between the observational learning effect and the targeting effect. Under the information disclosure strategy, to induce the following backer to learn, the creator needs to set a higher price for the leading backer, which may result in a lower success rate. The skimming strategy allows the creator to better balance the success rate and premiums; therefore, it is more favorable under information disclosure when the target is not too high.

THE VALUE OF INFORMATION DISCLOSURE

In this section, we address the question of when information disclosure is valuable by comparing the expected profits (investments) with and without information disclosure.

For convenience, let Π^{NID} and Π^{ID} denote the expected profits with and without information disclosure, respectively. Let p_n^{NID} and p_n^{ID} , $n = 1, 2$, be the corresponding pricing decisions. Recall that $\theta_L(q) = \frac{(q^2+q-1)^+}{2q-1}$, $\theta_M(q) = \frac{(q^3+q^2+2q-2)^+}{q(1+q)(2q-1)}$, and $\theta_H(q) = \frac{(\sqrt{((1-q)^2+4(3q-2))^+}-(1-q))^+}{2(2q-1)}$. The next proposition identifies the conditions under which information disclosure can increase or reduce the profitability of the crowdfunding campaign.

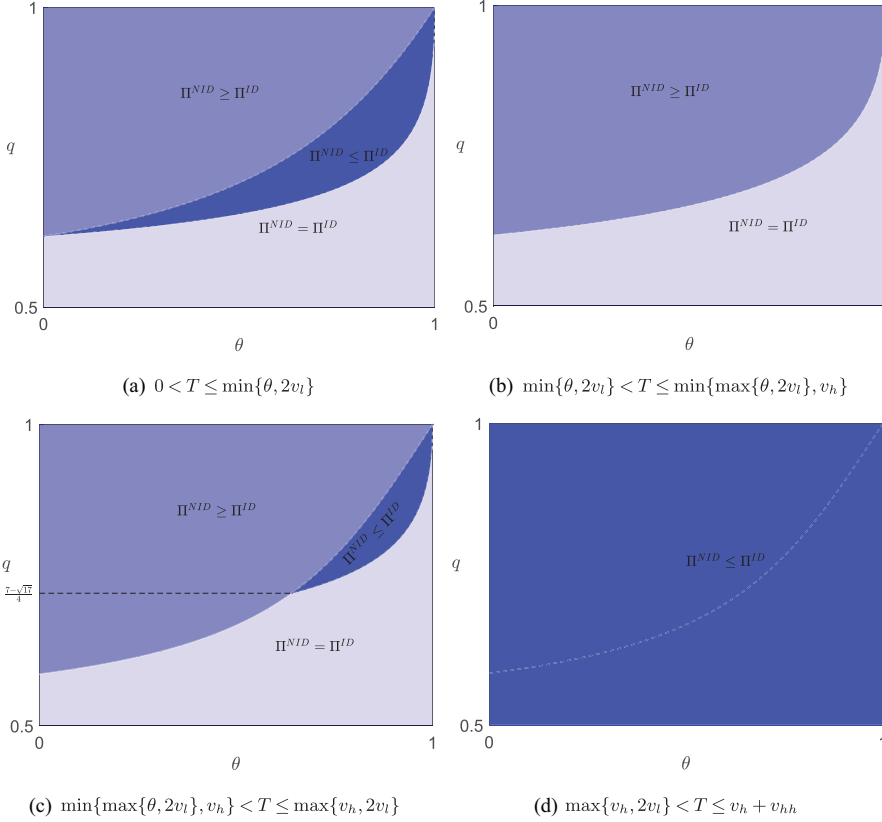
Proposition 3 (The Value of Information Disclosure): *Comparing the expected profits with and without information disclosure, we have four cases.*

- (a) For $0 < T \leq \min\{\theta, 2v_l\}$, there are three subcases:
 - (a.1) If $0 \leq \theta \leq \theta_L(q)$, then $\Pi^{NID} \geq \Pi^{ID}$ with $(p_1^{NID}, p_2^{NID}) = (v_h, v_h)$.
 - (a.2) If $\theta_L(q) < \theta \leq \frac{(\sqrt{(1-q)^4+4(4q-q^2-2)}-(1-q^2))^+}{2(2q-1)}$, then $\Pi^{NID} \leq \Pi^{ID}$ with $(p_1^{ID}, p_2^{ID}) = (v_h, \theta)$.
 - (a.3) Otherwise, $\Pi^{NID} = \Pi^{ID}$.
- (b) For $\min\{\theta, 2v_l\} < T \leq \min\{\max\{2v_l, \theta\}, v_h\}$, there are two subcases:
 - (b.1) If $\theta \leq \tilde{\theta}(q)$, then $\Pi^{NID} \geq \Pi^{ID}$ with $(p_1^{NID}, p_2^{NID}) = (v_h, v_h)$.
 - (b.2) Otherwise, $\Pi^{NID} = \Pi^{ID}$.
- (c) For $\min\{\max\{\theta, 2v_l\}, v_h\} < T \leq \max\{v_h, 2v_l\}$, there are three subcases:
 - (c.1) If $\theta < \theta^*(q)$, then $\Pi^{NID} \geq \Pi^{ID}$ with $(p_1^{NID}, p_2^{NID}) = (v_h, v_h)$.
 - (c.2) If $\theta^*(q) < \theta \leq \theta_H(q)$, then $\Pi^{NID} \leq \Pi^{ID}$ with $(p_1^{ID}, p_2^{ID}) = (v_h, \theta)$.
 - (c.2) Otherwise, $\Pi^{NID} = \Pi^{ID}$.
- (d) For $\max\{v_h, 2v_l\} < T \leq v_h + v_{hh}$, $\Pi^{NID} \leq \Pi^{ID}$.

Proposition 3 identifies the conditions under which information disclosure can be more or less valuable. The value of information disclosure is determined by the interactions among the target T , the prior probability of high-quality θ , and the accuracy of the private quality signal q : a higher target reduces the success rate, a very high or very low prior probability of high quality restricts the effect of learning, and a higher accuracy of the quality signal increases the dependence on the private signal.

More specifically, according to the target level T , we can classify the cases into four major categories: (a) very low targets ($0 < T \leq \min(2v_l, \theta)$), (b) low targets ($\min(\theta, 2v_l) < T \leq \min(\max(\theta, 2v_l), v_h)$), (c) medium–low targets ($\min(\max(\theta, 2v_l), v_h) < T \leq \max(v_h, 2v_l)$), and (d) high targets ($\max(v_h, 2v_l) < T \leq v_h + v_{hh}$). Figure 5 provides the corresponding illustrative figures for the four categories.

In particular, parts (a)–(c) of Proposition 3 show that, as indicated by sub-figures 5(a)–(c), when the target is relatively low ($T \leq \max(v_h, 2v_l)$), information disclosure may increase the profitability of the crowdfunding campaign if the prior

Figure 5: The value of information disclosure.

probability of high-quality θ and the accuracy of the quality signal q are sufficiently high (but not too high). According to parts (a)–(c) of Proposition 2, for the area where information disclosure dominates no information disclosure when the target is relatively low, the skimming strategy is optimal in the presence of information disclosure. This is because the skimming strategy with the price pair (v_h, θ) can induce the following backer to infer the quality from the leading backer’s bid and ensure that the valuation of the second backer is at least θ as long as one of the backers receives a high signal. Meanwhile, the success rate increases (compared to that without information disclosure) due to the relatively low target, which drives information disclosure to be more profitable.

When the prior probability of high quality is relatively small and the accuracy of the quality signal is relatively high, disclosing information reduces the profitability. Note that under information disclosure, a low signal for the leading backer reduces the valuation of the following one. As a result, the premium strategy without information disclosure (v_h, v_h) tends to be more profitable than the skimming strategy (v_h, θ) or the premium strategy (v_h, v_{hh}) under information disclosure. Hence, information disclosure may hurt the profitability of the campaign.

If otherwise, the prior probability of high quality is relatively large and the accuracy of the private quality signal is relatively low, the creator tends to maximize the success rate through the economy strategy under both information mechanisms; hence, information disclosure does not benefit or hurt the profitability of the campaign.

Part (d) of Proposition 3 shows that, as indicated by Figure 5(d), when the target is relatively high ($\max(v_h, 2v_l) < T \leq v_h + v_l$), information disclosure can always increase the profitability of the campaign. According to part (d) of Proposition 2, when the target is relatively high, under both information mechanisms, either the skimming or the premium strategy is optimal. Clearly, in the presence of information disclosure, the creator can induce the following backer to learn from the leading backer's investment decision, which results in a posterior expected valuation of θ , if one of the creators receives a high signal, or v_{hh} , if both receive high signals, under both the skimming and the premium strategies. Hence, information disclosure is more profitable. When the target is very high ($T > v_h + v_l$), the campaign may succeed only under the premium strategy. Similarly, information disclosure leads to a greater posterior expected valuation under the premium strategy and is, therefore, more profitable.

Finally, for $q = 1$, we have $v_l = v_{ll} = 0$, $v_h = v_{hh} = 1$, and that the premium strategy is optimal under both information mechanisms, leading to the same expected profit. For $\theta = 0$ or 1 , we have $v_l = v_h = v_{ll} = v_{hh} = 0$ or $v_l = v_h = v_{ll} = v_{hh} = 1$, which results in the same optimal strategy and therefore the same expected profit under both information mechanisms.

In summary, information disclosure as an information mechanism of the crowdfunding platform is a double-edged sword: it may benefit or hurt the profitability of a crowdfunding campaign, which is driven by the interactions among the funding target, the prior probability of high quality, and the accuracy of private quality signals. The design of crowdfunding campaigns should take into account the characteristics of underlying products, especially the degree of quality uncertainty that is inherent in the development of new products.

OPTIMAL CROWDFUNDING TARGET

The preceding analysis focuses on the optimal pricing strategies and the effect and value of information disclosure for the crowdfunding campaign with a given funding target T . The funding target T can also be endogenously determined by the creator (e.g., Hu et al., 2015; Chakraborty & Swinney, 2019a, 2019b). We next address the optimal targeting problem.

Specifically, given any minimum capital requirement for the project to be funded, B , the creator's optimal targeting and pricing decision problem can be expressed as

$$\max_{T \geq B, p_1, p_2 \geq 0} \mathbb{E}_{I_1, J_2} \left[\left(\sum_{i=1}^2 p_i \mathbb{1}_{\{\mathbb{E}[V_i | I_i] \geq p_i\}} \right) \mathbb{1}_{\{\sum_{i=1}^2 p_i \mathbb{1}_{\{\mathbb{E}[V_i | I_i] \geq p_i\}} \geq T\}} \right]. \quad (14)$$

The following proposition characterizes the optimal targeting decision.

Proposition 4 (Optimal Funding Target): *For campaigns with or without information disclosure, the optimal funding target is $T^* = B$.*

Proposition 4 shows that it is always optimal for the creator to set the lowest possible funding target to meet the minimum capital requirement. The rationale is that the lower target level leads to a greater success rate without influencing the posterior expected valuation for any pair of fixed prices; therefore, higher expected profitability also results. Substituting the target T in Propositions 1–3 with the budget requirement B , we can alternatively characterize the optimal pricing strategy and the value of information disclosure with B .

In a single-period setting, Chakraborty and Swinney (2019a) also show that the optimal target level is always equal to the minimum capital requirement when the backers are informed of the quality information of the creator (i.e., symmetric information). They show that the creator has the motive to set a higher target level to signal the quality when the quality information is asymmetric. Our model focuses on the role of information disclosure, and the targeting decision does not directly influence the following backer’s learning behavior.

It is notable Hu et al. (2015) impose the restriction that the campaign succeeds only when both backers bid by enforcing $T = p_1 + p_2$ for all possible price levels without specifying a minimum budget requirement. Such a strategy, which requires both backers to bid and the target is essentially the total investment from both backers, ignores the impact of the targeting decision on the success rate and the possibility of having only one backer to bid; therefore, it may result in an underestimation of the success rate and the profitability of the crowdfunding campaign. For example, in the absence of information disclosure, for $(p_1, p_2) = (v_h, v_h)$, setting $T = 2v_h$ will lead to an expected profit of $2(\lambda - q(1 - q))v_h$, while setting $T = v_h$ will lead to an expected profit of $2\lambda v_h > 2(\lambda - q(1 - q))v_h$. Hence, their targeting and pricing strategy can be viewed as a heuristic strategy for our model. The optimal choice of the target and the optimal pricing strategy need to carefully balance the success rate and premiums.

EXTENSION: CROWDFUNDING WITH STRATEGIC BACKERS

The preceding analysis is based on the assumption that both the leading and following backers are myopic, and they are willing to bid as long as their expected valuations are higher than the corresponding prices. In the real world, backers, especially the leading backer, may be strategic in the sense that he may have a motive to wait if the expected surplus of bidding in the second period is higher. Such forward-looking behavior is commonly seen in the advance-selling literature (e.g., Shugan & Xie, 2000, 2004, 2005; Xie & Shugan, 2001; Zhao & Stecke, 2010; Zhao et al., 2016; Pang et al., 2019). We follow this literature to analyze the strategic leading backer’s bidding decision.

More recently, Chakraborty and Swinney (2019b) analyze the optimal design of reward-based crowdfunding campaigns in the presence of a mixture of myopic and strategic backers. In their model, the strategic waiting motive is driven by hassle costs incurred in bidding. Unlike in Chakraborty and Swinney (2019b), in our

model, the strategic waiting behavior of the leading backer is driven by the pricing strategy, the target level, and the information mechanism.

In the absence of information disclosure, backers can only make decisions based on their own signals, and the leading backer is indifferent to earlier or later purchase. In the presence of information disclosure, if $p_1 \leq p_2$ (the economy, premium, or penetration strategy), it is always worse for the leading backer to wait due to the lower success rate and net surplus if he bids in the second period at a higher price. Hence, if $p_1 \leq p_2$, both backers make decisions as if they were myopic. However, under the skimming strategy, that is, $p_1 > p_2$, the leading backer may be willing to wait if it may lead to a greater expected surplus. Under the skimming strategy with $p_1 > v_l$, the leading backer may bid in the first period if and only if he receives a high signal, which implies that the following bidder can infer a high signal from when the leading backer bids or a low signal from when he does not. Otherwise, it is optimal for the leading backer to bid in the second period; in this case, the following backer can only update her valuation based on her own signal.

It is notable that the funding target also moderates the leading backer's strategic bidding behavior as he can bid in the first or the second period only if the bid leads to the success of the campaign by meeting the target. Similar to the menu strategy studied in Hu et al. (2015), which allows both backers to choose any price in the menu and therefore interact with each other to meet the target, the forward-looking backer can also choose either the first or the second price to strategically influence the following backer's learning process and bidding decision.

The next proposition characterizes the optimal pricing strategy with information disclosure with a forward-looking leading backer. For simplicity, we focus on the case with $2v_l > v_h$.

Proposition 5 (Optimal Pricing with Strategic Backers): *Suppose $2v_l > v_h$ (i.e., $\theta > \theta^*(q)$). In the presence of information disclosure and forward-looking backers, the optimal pricing strategy can be characterized as follows:*

- (a) For $0 < T \leq \theta$, there are three subcases:
- (a.1) If (i) $\theta^*(q) < \theta \leq \tilde{\theta}(q)$ for $\frac{2}{3} < q \leq \sqrt{3} - 1$ or (ii) $\theta^*(q) < \theta \leq \frac{(q^2+3q-2)^+}{2(2q-1)}$ for $q > \sqrt{3} - 1$, then the skimming strategy $(v_h + \epsilon, v_h)$, which induces the leading backer to wait, is optimal, resulting in an expected profit of $2\lambda v_h$, where ϵ can be any arbitrarily small positive real value.
- (a.2) If $\frac{(q^2+3q-2)^+}{2(2q-1)} < \theta \leq \frac{q^2+3q-2+\sqrt{8(q-2)(1-q)+(2-q(1-q))^2}}{4(2q-1)}$ for $q > \sqrt{3} - 1$, then the skimming strategy (θ, θ) is optimal, resulting in an expected profit of $[2\lambda + q(1 - q)]\theta$.
- (a.3) Otherwise, the economy strategy (v_l, v_l) is optimal, resulting in an expected profit of $2v_l$.
- (b) For $\theta < T \leq v_h$, there are two subcases:
- (b.1) If $\theta^*(q) < \theta \leq \tilde{\theta}(q)$ for $q > \frac{2}{3}$, then the skimming strategy $(v_h + \epsilon, v_h)$ is optimal, resulting an expected profit of $2\lambda v_h$.
- (b.2) Otherwise, the economy strategy (v_l, v_l) is optimal, resulting in an expected profit of $2v_l$.

- (c) For $v_h < T \leq 2v_l$, define $\theta_s(q) = \inf\{\theta \geq \theta^* | h((2q-1)\theta + 1 - q) \geq 0\}$ with $h(\lambda) = \lambda^3 - \lambda^2q + (2q-1)\lambda + 2 - 3q$.
- (c.1) If $\theta^*(q) < \theta \leq \theta_s$, the *skimming strategy* $((1-\lambda)v_h + \lambda\theta, \theta)$ is optimal, resulting in an expected profit of $\lambda[(1-\lambda)v_h + (1+\lambda)\theta]$.
- (c.2) Otherwise, the *economy strategy* (v_l, v_l) is optimal, resulting in an expected profit of $2v_l$.
- (d) For $2v_l < T \leq 2\theta$, there are two subcases:
- (d.1) If $T \leq 2(1-q+\lambda)\theta$, the *skimming strategy* $((1-\lambda)v_h + \lambda\theta, \theta)$ is optimal, resulting in an expected profit of $\lambda[(1-\lambda)v_h + (1+\lambda)\theta]$.
- (d.2) If, otherwise, $2(1-q+\lambda)\theta < T \leq 2\theta$, the *skimming strategy* $(v_h, T/2 - \epsilon)$ is optimal, resulting in an expected profit of $\lambda(v_h + T/2 - \epsilon)$.
- (e) For $2\theta < T \leq \theta + v_h$, the *skimming strategy* (v_h, θ) is optimal, resulting in an expected profit of $\lambda(\theta + v_h)$.
- (f) For $\theta + v_h < T \leq v_h + v_{hh}$, the *premium strategy* (v_h, v_{hh}) is optimal, resulting in an expected profit of $[\lambda - q(1-q)](v_h + v_{hh})$.

The strategic waiting motive of the forward-looking leading backer may reduce the profitability of the campaign by incentivizing the leading backer to bid in the first period; to address this issue, the creator may need to reduce the first-period price. Proposition 5 shows that the optimal pricing strategy in the presence of information disclosure and strategic backers is also driven by the funding target T , the prior probability of high-quality θ , and the accuracy of the signal q . We next discuss the optimal pricing strategies in different target regions and compare them to those in the setting without forward-looking backers, as described in Proposition 2.

When the target is very low ($T \leq \theta$), for a fixed q , the optimal pricing strategy tends to change from the *skimming strategy* $(v_h + \epsilon, v_h)$ to (θ, θ) and then to the *economy strategy* (v_l, v_l) , that is, the prices decline when θ increases. In particular, when θ is relatively small and q is sufficiently high, it is optimal to adopt the *skimming strategy* $(v_h + \epsilon, v_h)$, which will induce both backers to bid in the second period at v_h upon receiving high signals.

Recall that in the setting without forward-looking behavior, the *skimming strategy* (v_h, θ) is optimal when θ is relatively small, resulting in an expected profit of $\lambda(v_h + \theta) + q(1-q)\theta$. In the presence of forward-looking backers, the waiting motive of the leading backer drives the creator to adopt the price $(v_h + \epsilon, v_h)$ to induce strategic waiting, resulting in an expected profit of $2\lambda v_h$. Comparing the expected profits in the two settings, we have $\lambda(v_h + \theta) + q(1-q)\theta - 2\lambda v_h = (\lambda - q^2)\theta > 0$ if and only if $\lambda > q^2$. Note that $\frac{q}{2-q} \geq q^2$, which implies that $\lambda(v_h + \theta) + q(1-q)\theta \geq 2\lambda v_h$ for all $\lambda > \frac{q}{2-q}$, that is, the forward-looking behavior may indeed reduce the profitability of the campaign.

When the target is low ($\theta < T \leq v_h$), the optimal strategy changes from the *skimming strategy* $(v_h + \epsilon, v_h)$ to the *economy strategy* when θ increases. Similarly, such a *skimming strategy* induces the leading backer to strategically wait. However, compared to the expected profit under the *skimming strategy*

(v_h, θ) without forward-looking behavior, $\lambda(v_h + \theta)$, inducing the leading backer to bid in the second period at v_h , in fact, increases the profitability as $2\lambda v_h \geq \lambda(v_h + \theta)$.

When the target is medium-low ($v_h < T \leq 2v_l$), the optimal skimming strategy becomes $((1 - \lambda)v_h + \lambda\theta, \theta)$, under which the leading backer, receiving a high signal, will bid in the first period. Compared to the optimal skimming strategy (v_h, θ) in the setting without forward-looking behavior, to induce the leading backer to bid, the creator has to reduce the first-period price from v_h to $(1 - \lambda)v_h + \lambda\theta$, which reduces the premium without increasing the success rate and therefore reduces the profitability of the campaign.

When the target is medium-high ($2v_l < T \leq 2\theta$), the optimal skimming strategy is $((1 - \lambda)v_h + \lambda\theta, \theta)$ or $(v_h, T/2 - \epsilon)$, which also indicates that to induce the leading backer to bid, the creator has to reduce the first-period price from v_h to $(1 - \lambda)v_h + \lambda\theta$ or reduce the second-period price from θ to $T/2 - \epsilon$ without increasing the success rate, which reduces the profitability of the campaign.

When the target is high ($2\theta < T \leq v_h + v_{hh}$), the optimal strategy is the same as that in the setting without forward-looking backers.

Finally, we identify the value of information disclosure in the presence of strategic backers.

Proposition 6 (Value of Information Disclosure with Strategic Backers): Suppose $2v_l > v_h$. Consider the setting with information disclosure and forward-looking backers.

- (a) For $0 < T \leq \theta$, $\Pi^{ID} \geq \Pi^{NID}$.
- (b) For $\theta < T \leq v_h$, $\Pi^{ID} = \Pi^{NID}$.
- (c) For $v_h < T \leq v_h + v_{hh}$, $\Pi^{ID} \geq \Pi^{NID}$.

Proposition 6 shows that in the presence of forward-looking backers, information disclosure can improve the profitability of the campaign, especially when $2v_l > v_h$ and the target is relatively low ($T \leq \theta$) or sufficiently high ($T > v_h$). Recall that in the setting without forward-looking behavior, information may hurt profitability when the target is medium-low, that is, $\theta < T \leq v_h$ (see Proposition 3). By contrast, the presence of forward-looking backers allows the creator to set the skimming price $(v_h + \epsilon, v_h)$ to induce the leading backer to bid in the second period, resulting in a higher expected profit, as discussed above. As we show in this proposition, the increase of the profitability is sufficient for the creator to benefit from information disclosure.

Finally, we characterize the optimal funding targeting policy in the presence of strategic backers.

Proposition 7 (Optimal Funding Target with Strategic Backers): Suppose $v_h < 2v_l$. In the presence of strategic backers, the optimal funding targeting policy can be characterized as follows:

- (a) For $B \leq v_h$, $T^* = B$.
- (b) For $v_h < B \leq 2v_l$, $T^* = B$ if $\theta > \theta_H(q)$ and $T^* = v_h + \theta$ if $\theta^*(q) < \theta \leq \theta_H(q)$.

- (c) For $2v_l < B \leq 2\theta$, $T^* = v_h + \theta$.
 (d) For $2\theta < B \leq v_h + v_{hh}$, $T^* = B$.

Proposition 7 shows that in the presence of strategic backers, the optimal target may not always be the minimum capital requirement B . In particular, as shown in cases (b) and (c), when the minimum capital requirement B is sufficiently high, it may be optimal to set the target to $v_h + \theta$, under which the skimming strategy (v_h, θ) is optimal. Note that under the target $v_h + \theta$ and the skimming pricing strategy (v_h, θ) , the leading backer receiving a high signal does not have the motive to wait, which is due to the fact that the target will not be met if the leading backer waits and bids with the following backer at the price of θ while $2\theta < v_h + \theta$. That is, it is optimal to use a higher target to counteract strategic waiting when the minimum budget requirement is relatively high. It is notable that when the minimum capital requirement is relatively high (e.g., $B > 2v_l$), the success rate cannot be greater than λ for $T^* \geq B$. That is, the benefit of using a higher target to counteract strategic waiting may exceed the benefit of higher success rates under a relatively lower target. When the minimum capital requirement is sufficiently small, it is still optimal for the creator to set the target as low as possible to increase the success rate.

CONCLUDING REMARKS

Crowdfunding provides an alternative financing model for NPD projects with quality uncertainty for small- and medium-size entrepreneurial firms. Reward-based crowdfunding, as one of the most popular crowdfunding mechanisms, combines the roles of advance selling and financing. This study investigates the role and value of information disclosure in reward-based crowdfunding campaigns to meet the funding target of an NPD project.

We consider a two-period setting where the creator announces the funding target and the prices of the two periods at the beginning of the campaign with two representative backers (a leading backer and a following backer) arriving sequentially in each of the two periods. The true quality of the product is unknown by the creator and the backers, and each backer will receive a private quality signal, which can be used to update their belief about the quality. For simplicity, we assume that the leading backer will not strategically wait. We first consider the settings without and with information disclosure and characterize the optimal pricing strategies. Without information disclosure, the backers can only infer the quality with their own private signals and bid at the corresponding prices if and only if their valuations are greater than the prices. With information disclosure, under the skimming or premium strategy, the leading backer's bidding behavior can be used by the following backer to infer his private signal (an observational learning behavior).

We show that information disclosure may increase or reduce the profitability of the campaign. We identify two interacting effects: an observational learning effect due to information disclosure and the targeting effect. Disclosing the bid of the leading backer under the premium or skimming strategy allows the following backer to use the leading backer's and her own signals to update her belief. A higher target will reduce the success rate. When the target is relatively low,

information disclosure may hurt (benefit) the creator when the prior probability is low (moderate) and the accuracy of the private signal is relatively high. When the target is relatively high, information disclosure is always profitable.

We then analyze the optimal targeting decision. We show that the optimal target is always equal to its minimum capital requirement for the success of the campaign. The implication is that a higher target tends to reduce the success rate without influencing the valuations of the backers. As a result, the expected profit is always decreasing in the target.

We further extend our analysis to a setting with forward-looking backers. The forward-looking leading backer makes a trade-off between bidding in the first period and in the second period, whichever leads to a higher expected net surplus. In particular, under the skimming strategy, the leading backer has the motivation to strategically wait as the price in the second period is lower. We follow an analysis framework from the advance selling literature (e.g., Zhao & Stecke, 2010; Zhao et al., 2016; and Pang et al., 2019) to characterize the strategic decision of the forward-looking leading backer. We show that to induce the leading backer to bid in the first period, the creator has to reduce the price in the first period, which reduces the premiums without increasing the success rate and therefore reduces the profitability of the campaign. Interestingly, we find that, when the target is not very low, instead of inducing the leading backer to bid in the first period, the creator can also deliberately design the skimming scheme to induce the leading backer to wait, which allows the creator to set a higher price in the second period to target backers with high signals without reducing the success rate, thereby increasing the profitability of the campaign. Moreover, compared to the setting with myopic backers, information disclosure is more likely to benefit the creator in the presence of strategic backers. Interestingly, in the presence of forward-looking backers, the optimal target level may be higher than the minimum capital requirement when that is sufficiently high.

Our findings have important practical implications for the design of reward-based crowdfunding campaigns for new products. Quality uncertainty is an inherent feature of NPD, which drives the valuation uncertainty and learning behavior of creators and backers (consumers). The optimal design of the crowdfunding campaign needs to take into account not only the targeting and pricing strategies but also the information mechanism. Our results show that disclosing bid process information to backers may not always benefit the creator due to the observational learning behavior of the backers. The creator or the crowdfunding funding platform should investigate how their targeting and pricing strategies interact with the information strategy and its effect on the profitability of the campaign.

Finally, we outline some limitations of our model, which leads to interesting research avenues.

First, our analysis is restricted to a setting with two representative backers arriving in two consecutive periods. It would be interesting to explore dynamic bidding/pledging behavior in a multiperiod setting where herding and information cascade may arise under certain conditions (Bikhchandani et al., 1992). For example, when the price is fixed at p such that $v_l < p \leq \theta$, our analysis shows that the first backer will bid if and only if he receives a high signal, and the second backer can infer the first backer's private signal from his bidding behavior. If

the first backer bids, then the second backer will update her valuation to either θ or v_h upon receiving a low or high signal and will certainly bid at p . Similarly, all the subsequent backers will bid, regardless of what signals they receive. If otherwise, the first backer does not bid, then the second backer will bid if and only if she receives a high signal, which implies that the first two backers' bidding behavior can be used to infer their private signals. According to the Bayes' rule, $\mathbb{E}[V_3|S_1 = s_l, S_2 = s_l, S_3 = s_l] < \mathbb{E}[V_3|S_1 = s_l, S_2 = s_l, S_3 = s_h] = v_l < p$, $\mathbb{E}[V_3|S_1 = s_l, S_2 = s_h, S_3 = s_l] = v_l$ and $\mathbb{E}[V_3|S_1 = s_l, S_2 = s_h, S_3 = s_h] = v_h$. Hence, if the first two backers do not bid, then none of the subsequent backers will bid, regardless of their private signals. If, otherwise, the first backer bids, but the second backer does not, then the third backer will update their valuation as if they did not observe the first two backers' bidding behavior. Summarizing these situations, we can conclude that herding occurs after two consecutive backers both bid or both do not bid when the price is fixed at θ . However, to examine the optimal pricing and targeting strategy, we need to have a more thorough analysis.

Second, also for tractability, we restrict our analysis to the pricing and targeting strategy under which the target and prices are announced at the beginning of the campaign. It would be interesting to extend the analysis to dynamic sequential pricing strategies under which prices are announced sequentially over the campaign.

Third, our analysis focuses on the AoN funding mechanism, which is required by platforms like Kickstarter. It would be interesting to investigate other possible funding mechanisms, such as keep-it-all, which may also be available on platforms like Indiegogo.

Last but not least, another interesting topic would be to investigate the pay-as-you-wish pricing mechanism in crowdfunding, which only specifies the minimum price of each bid while allowing a backer to pay any amount above the ask price to increase the success rate of the campaign. To formulate the pricing decision under such a mechanism, one would have to model the backer's bidding decision as a continuous variable bounded below by the ask price.

SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of the article.

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