

Article

Promotion Thresholds, Revenue Sharing, and Delivery Risk in Reward-Based Crowdfunding

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Abstract

This paper investigates two marketing strategies a reward-based crowdfunding platform employs to align its preferences with an entrepreneur's choice of pledge and target levels. These are (a) how to promote campaigns to potential backers, and (b) how to share campaign revenues with the entrepreneur. Kickstarter, for instance, promotes a set of campaigns by compiling a list of "recommended" projects. This research shows that the platform's choice of the promotion rule may expose entrepreneurs to the risk of not generating sufficient funds to start production, which can damage their and the platform's reputation. When the platform's reputational risk is not very high, it reduces the risk of non-delivery by increasing the revenue share of the entrepreneur. The platform's strategies are likely to ensure production when backers derive warm glow from pledging, when the entrepreneur's development cost is low, or when the entrepreneur has minimal reputational cost if production fails. However, low reputational costs motivate the entrepreneur to lower the target, thus increasing the likelihood of insufficient funds to start production. We propose strategies the platform can use, including customizing the revenue share based on the campaign characteristics, to rectify such misalignments.

Keywords: crowdfunding; platforms; promotion; recommendation system

1. Introduction

Crowdfunding (CF) platforms have gained prominence as viable channels of fund-raising for new projects, by early-stage entrepreneurs who have limited access to other funding channels. Participants on CF platforms consist of entrepreneurs seeking funds and investors (backers)¹ willing to contribute to campaigns. Unlike conventional investments, backers who are active on reward-based CF platforms do not anticipate growth in the value of an underlying asset. Instead, they expect consumption of a novel product in the future. In a reward-based CF campaign, the entrepreneur chooses a funding target that determines the minimum amount necessary for the campaign to be declared successful, and a pledge amount that backers need to contribute, to be entitled to the promised product if completed. The campaign is *commercially successful* if the aggregate pledge amount exceeds the target. In this case, the platform deducts its commission and remits the remaining amount to the entrepreneur. If the campaign does not reach the funding target, that is, when the campaign is not commercially successful, the platform returns the pledges to the backers.²

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When a campaign is commercially successful, and the entrepreneur receives the campaign funds, backers expect to receive the reward. However, the entrepreneur can initiate production only when their share of campaign proceeds covers the development cost of the product, that is, when the campaign achieves *production success*. Hence, a higher target increases the likelihood that a commercially successful campaign realizes production success and the entrepreneur delivers the promised product to backers. As a result, a higher target allows the entrepreneur to raise the pledge amount because the expected payoff of the backer increases. Setting a very high funding target, however, reduces the likelihood of reaching the target, in which case neither the entrepreneur nor the platform receives any proceeds from the campaign. When the funding target is set low in comparison to the development cost, backers face a greater risk of not receiving the promised product and losing their pledge. With non-delivery, both the entrepreneur and the platform face legal costs and reputational losses. Competition in the CF market forces each CF platform to pay close attention to preserving its reputation for trustworthiness. The reputational impact on the platform motivates its choice of the campaign promotion rule and the likelihood of promoted campaigns delivering the product. The interplay between the target, pledge amount, and reputational impact, however, is not straightforward.

Yet another complexity arises because the interests of the entrepreneur and the platform in setting the target level are not necessarily aligned. While the entrepreneur generates additional sales in the external market (i.e., post-campaign sales) if the product development is successful, the profits of the platform accrue only from its share of the revenues generated in the CF campaign. Moreover, in the case of product non-delivery, the reputational impact on the entrepreneur and the platform are mismatched. Early-stage entrepreneurs likely have limited resources that cap their liability cost, while a platform's reputational loss can be high when its trustworthiness is questioned, and its appeal to backers and new projects weakens.

While a substantial body of crowdfunding research has examined how entrepreneurs should design campaigns through their choice of funding targets, pledge levels, and signaling mechanisms, considerably less attention has been devoted to the strategic role played by the crowdfunding platform itself. Yet platforms actively govern their marketplaces through recommendation algorithms, campaign promotion policies, and commission structures, all of which influence entrepreneur incentives and ultimately determine whether commercially successful campaigns are able to fulfill their promises. This paper develops a game-theoretic framework that explicitly models the platform as a strategic decision maker. We show how the platform can jointly use a fractional-threshold promotion rule and a corresponding revenue-sharing policy to align entrepreneur incentives with platform objectives, reduce the risk of delivery failure, and protect its reputation. In doing so, the paper contributes to the emerging literature on platform governance by demonstrating that recommendation policy formulation and commission structure design should be viewed as complementary governance instruments rather than as independent operational decisions.

Specifically, we investigate how reward-based CF platform can design strategies to motivate entrepreneurs to choose their pledge and target levels that are consistent with the platform's interests. We consider two instruments that the platform can employ: (i) the rule to promote campaigns to potential backers, and (ii) the share of (that is, commission from) campaign revenues. Platforms promote a select set of campaigns by compiling a list of recommended projects. Because some backers find it difficult to differentiate among the many campaigns active on a CF platform, the entrepreneur benefits greatly from being included in the "recommended list".³ The revenue sharing rule is also an important instrument at the platform's disposal. When the platform awards a larger share of campaign revenues, the entrepreneur is more likely to have sufficient funds to deliver

the product, thus lowering the risk of reputational damage to both the entrepreneur and platform for not meeting their obligations.

Since the platform has very limited verifiable information about the quality of the project when it is launched, it is unclear what the platform's strategy should be for compiling its recommended list. One rule that seems to be utilized by Kickstarter in choosing its recommended list is the early success of a campaign in raising a substantial share of its declared funding target. The CF platform's share of the campaign revenues is conditional on and grows in proportion to a campaign's success. Hence, the most obvious threshold in which the platform has a vested interest is the funding target. While it is difficult to ascertain the exact threshold that the platform uses to promote campaigns, prior studies (Dehdashti et al., 2022; G. Li & Wang, 2019) have shown that backer traffic increases during certain periods of a campaign when specific thresholds are reached. In Kickstarter, backers discover campaigns through sorting filters such as "Projects We Love", "Trending", and "Recommended". Many campaigns appear across multiple filters, expanding discoverability beyond a single category. Most top-ranked campaigns exhibit one consistent theme across all sorting filters; a high percentage of its target raised. In Figure 1, we plot the proportion of the 120 top-ranked campaigns that have raised a specific percentage of their set target, across the three sorting filters of "Recommended", "Projects We Love", and "Trending." Raising a substantial share of the target indicates that many backers are interested in the project. If early backers tend to be those who are better informed about the project, a large number of early contributions can serve as a signal of a higher quality project to less informed potential backers.⁴ Moreover, using the early success of the campaign in raising funds as a basis for promoting the campaign is also consistent with results reported in the herding and information cascades literature (see Banerjee, 1992; Bikhchandani et al., 1992; and Chamley & Scaglione, 2013, for instance). This literature has demonstrated that the convergence of beliefs among individuals about an uncertain environmental parameter leads to information cascades, where individuals start disregarding their own private signals after observing overwhelming agreement by others.

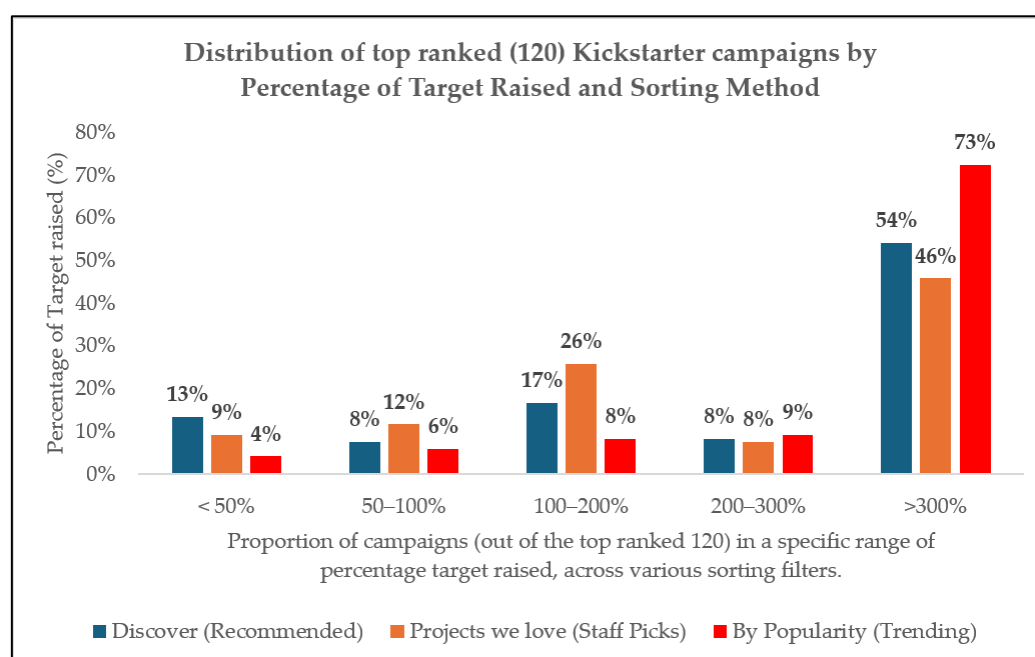


Figure 1. Distribution of top-ranked (120) Kickstarter campaigns by the Percentage of Target Raised and Sorting Method (as on 14 July 2026).⁵ A campaign's rank depends on the specific filter used to discover projects. The overwhelming majority of campaigns, across all search categories, have raised more than three times (>300%) their stated targets.

By setting a demanding threshold for promoting campaigns, measured by the proportion of the target raised, the platform can guarantee that the promoted campaign raises enough funds not only to meet its target but also to cover the development cost to start production. Thus, setting a high threshold reduces the risk of delivery failure by the entrepreneur, minimizing possible loss of reputation for both the platform and the entrepreneur. However, setting a very demanding threshold level for promotion implies that fewer campaigns are eligible for promotion. This reduces the visibility of campaigns and number of potential backers, thus adversely affecting the platform's profits.

The sharing rule for campaign revenues has similar counteracting effects on the platform's profits. While a larger share awarded to the entrepreneur increases the odds of successful product delivery, it also reduces the platform's share of the campaign revenues, and thus, its expected profits. Our analysis suggests that when backers derive lower consumption or warm glow benefits, when there are fewer informed backers who can evaluate the product characteristics, when entrepreneurs incur significant reputational losses if they cannot deliver the product, and when the product development cost is high, the platform finds it optimal to lower its share of the campaign revenues. Moreover, if warm glow plays a role in the decision of backers to fund the campaign and the platform's reputational cost is low, having a uniform revenue share (entrepreneur's share of campaign revenues) that is the same across all campaigns has a drawback. Indeed, a uniform revenue share rule does not prevent the participation of some entrepreneurs who are projected, with certainty, to not deliver the promised product. It is noteworthy that most reward-based CF platforms use a uniform revenue share across all campaigns (about 8–10% for Kickstarter).⁶ Furthermore, investors are indeed driven by altruistic⁷ motives to help creators of new ideas (Burtch et al., 2013). Hence, there is a definite possibility of campaigns, with low reputational cost, participating in CF platforms simply to get as much money as possible from the campaign, without any intention of delivering the product. We show that reward-based platforms can eliminate this risk by customizing the revenue share to the heterogeneous product development cost of the campaigns.

We consider an entrepreneur who has access to only CF as a source of funding and assume that potential backers of the campaign derive both consumption benefits from the product and altruistic benefits from helping entrepreneurs. There are two types of backers in our model: informed and uninformed. Informed backers know about the campaign when it is launched and can evaluate its quality. The number of informed backers who fund the campaign is a random variable, and the platform may choose to promote a campaign based upon the realization of this random variable, given that it does not have any access to information about the quality of the product beforehand. Therefore, in formulating the platform's promotion strategy, we assume that the platform includes campaigns on its recommended list that are successful in raising a prespecified share of their declared target. We refer to this promotion rule as the Fractional Threshold (FT) rule. After the platform promotes the campaign, uninformed potential backers become aware of the campaign and can also observe the level of contributions thus far in the campaign. When a larger number of informed backers have already contributed, more uninformed backers are willing to contribute to the campaign. Hence, the uninformed use the number of informed backers as a signal of the quality of the project.

When backers are altruistic, we find that the entrepreneur sets a funding target that exposes backers to the risk of not receiving the product because the campaign may not achieve production success even though it is commercially successful. Thus, warm glow causes entrepreneurs to intentionally increase the risk of forgoing future profits (from external sales) in favor of short-term proceeds from the campaign. We also find that the FT level chosen by the platform may not ensure that the entrepreneur generates sufficient funds to start production. Hence, the platform may choose a threshold that does not elim-

inate the risk induced by the target setting behavior of the entrepreneur. We show that, unlike current practice, the platform can set customized sharing rules that depend on campaign characteristics to lower this risk when the warm-glow benefit is high. To our knowledge, while reward based crowdfunding platforms use a single commission (share) across all types of products and campaigns, many digital platforms in other settings use a heterogeneous fee schedule. For example, most ride sharing platforms offer the driver a varying revenue share based on location, traffic congestion, ongoing customer acquisition campaigns, etc. All these metrics are unique to a ride and result in tailor-made commission shared with the driver. Other platforms such as (Apple) App Store and Amazon Seller Central also charge different commissions or referral fees based on the developer or seller characteristics. Thus, there is an opportunity for such custom strategies to be used by the CF platforms—an observation we share in our propositions.

To the best of our knowledge, this study is among the very few (Strausz, 2017) that focuses on strategies that a CF platform can use to enhance its profitability. Earlier theoretical work on CF has focused on strategies entrepreneurs should adopt to ensure success in raising funds or to facilitate learning about the potential demand for their products. Belavina et al. (2020) emphasize designing mechanisms to eliminate deliberate malicious intent and to alleviate the problem of performance opacity of entrepreneurs. We consider an environment where the inability of entrepreneurs to deliver their promised products is not the result of malicious intent. Instead, entrepreneurs may fail to fulfill their promises because they are unable to raise sufficient funds or because they encounter technical difficulties.

Our paper shows how a platform's choice of the screening mechanism to recommend campaigns and the revenue-sharing strategy affect product delivery in a CF campaign. We also show that, unlike current practice, platforms should customize the revenue-sharing rule (that is, commission) to product characteristics. We establish the following managerial insights:

- i. The optimal choice of promotion and revenue-sharing rules ensure that promoted campaigns raise enough funds to start production only when the platform's reputational cost, in case the entrepreneur is unable to deliver the product, is sufficiently high.
- ii. The optimal revenue-sharing rule chosen by the platform may result in some campaigns definitely failing to deliver their promised products, thereby adversely affecting the platform's reputation. We demonstrate that customizing the revenue share to product development cost, instead of utilizing an identical rule for all projects, eliminates this risk when backers are altruistic.
- iii. Customizing the revenue sharing rule to the attributes of a product, including its development cost, enhances the platform's profits. When customization is tied to the development cost of the project, the platform should award a larger revenue share to projects with higher development costs.
- iv. If the platform customizes the revenue share, the FT promotion rule and the revenue sharing rule act as substitutes in aligning the objectives of the platform and the entrepreneur. In particular, when the production success is not guaranteed, the platform should increase the revenue share of the entrepreneur to compensate for a higher risk of non-delivery.

In Section 2, we position the paper in the context of the literature, followed by a description of the model assumptions. We then derive the equilibrium implied by the FT promotion rule when the revenue sharing fraction is fixed. In Section 4, we derive the optimal revenue-sharing rule chosen by the platform to maximize its profits. We discuss the main takeaways for crowdfunding platforms and entrepreneurs in Section 5 and then conclude the paper. We present the technical results related to this paper in two Appendices A and B. Appendix A discusses two extensions of our model. Appendix B contains our empirical analysis on real

data that suggests the FT rule: we find a strong correlation between campaigns promoted on the recommended pages and a high percentage of target raised, and Appendix C has a simple numerical example to easily relate to the notions of commercial and production success.

2. Literature Review

Although most early studies on CF are empirical (see, for instance, Ordanini et al., 2011; Agrawal et al., 2014; Mollick, 2014; Ahlers et al., 2015; Burtch et al., 2013, 2015; Colombo et al., 2015; Mollick & Nanda, 2016), there are a growing number of theoretical studies of late. Belleflamme et al. (2014) compare reward-based campaigns, where funders are consumers who pre-order the product, with equity-based campaigns, where funders invest in exchange for a share of future profits. These studies address various aspects of CF campaigns, mostly with a focus on the entrepreneur's behavior. One important theme in this stream is how entrepreneurs use CF campaigns as vehicles for learning about the future demand of the product. For instance, Roma et al. (2018) demonstrate how market demand information from a campaign can help entrepreneurs convince venture capitalists (VCs) to invest in the company. Babich et al. (2021) study learning via CF campaigns when VC and/or bank financing can supplement funds raised in the campaign. Drawing from the real option literature, Chemla and Tinn (2020) investigate how the outcome of a CF campaign can guide entrepreneurs in deciding whether to initiate production. This option to abandon production is especially valuable when demand uncertainty is high. Our study does not address issues related to entrepreneurs using CF as a vehicle for learning. Rather, in our case, uninformed backers learn from the pledging behavior of informed backers, and this learning affects their decision on whether to fund the campaign.

CF can also use a price discrimination strategy when consumers have heterogeneous product valuations. Hu et al. (2015) examine how a project creator offers a menu of product options in a CF campaign to facilitate price discrimination. Bender et al. (2019) show that allowing consumers to pledge can lead to more successful extraction of consumer surplus when consumers have different valuations and when the cost of gaining access to external funding is not prohibitive. Since all consumers in our model have the same valuation for the product, price discrimination is not relevant in our study.

Extant literature has also addressed whether signaling can resolve problems related to the incomplete information of backers regarding the quality of crowdfunded projects. Chakraborty and Swinney (2021) and Sayedi and Baghaie (2017), for instance, investigate how an entrepreneur can select instruments of the campaign (funding target and pledge) to signal project quality. Although we do not formally model the type of incomplete information facing potential backers, in our model, uninformed backers use the behavior of early backers in assessing the prospects of the project.

The question of “why investors invest” has received extensive attention. Besides capital appreciation, extant studies show that altruistic motives also influence investment behavior. Andreoni (1989, 1990) distinguishes between pure altruism and impure altruism. Consider a setting of charitable giving. Individuals who are purely altruistic derive utility *only* from the impact their donations have. The impurely altruistic individuals derive both purely altruistic utility and warm-glow utility (Ottoni-Wilhelm et al., 2017). Here, warm-glow utility is the utility derived from simply the act of donating rather than the impact of the donation (Bonnefon et al., 2025). Thus, warm glow reflects the psychological satisfaction from the act of giving that may not necessarily benefit the recipient, or any others, materially. We use the term altruism in this sense of impure altruism. Chen et al. (2026) and Strahilevitz and Myers (1998) use the notion of ‘warm glow altruism’ as a collective. Taking a similar approach, we use the term ‘warm-glow altruism’ to indicate the act of pledging with the intent of helping the entrepreneur. For simplicity, we use simply warm glow or altruistic to refer to ‘warm-glow altruism.’

Burtch et al. (2013) confirmed that backers in a CF Platform have altruistic motives for online journalism projects. In a controlled experiment, Gneezy et al. (2012) find that people are willing to incur an expense to validate their self-perceived social image. In the CF context, the desire for self-image confirmation, rather than purely utilitarian motives, may drive ‘serial backers’ to pledge. Ellman and Hurkens (2019) note that warm glow is a relevant motive in signaling and reward design, informing design choices in reward tiers and presentation that marketers can leverage. We demonstrate that when backers have such non-economic motives, entrepreneurs may choose a funding target lower than that necessary to accomplish production, and the platform’s share of campaign revenue may attract entrepreneurs who, with certainty, will never deliver the product to backers.

All the above studies focus on entrepreneur behavior and not on platform strategies for governing campaigns. Gal-Or et al. (2019) consider equity-based CF, where the investor and entrepreneur segments differ by their risk profiles, and ask whether competing platforms can appeal to different entrepreneur populations. Our research is based on the finding that the percentage of target raised affects promotion in the first pages of a reward-based CF campaign. To motivate our analysis, we conduct an empirical analysis (refer the Appendix B) and observe that Kickstarter tends to include campaigns on its recommended list based upon their success in raising a substantial share of their declared target during the early period of the campaign.⁸ Long and Liu (2024) have studied the motivation of an online market place to manipulate ranking of sellers to convey better quality to consumers. In our paper, a crowdfunding platform’s motivation to promote a campaign comes from the desire to earn a higher revenue share. Z. Li et al. (2020) find evidence of time varying thresholds in reaching a certain percentage of the target amount and their corresponding effect in funding success. In this paper, we treat the threshold as a static invariant for simplicity, but the principle remains the same. Du et al. (2022) find the providing a stimulus, such as update about the product development in the middle of the campaign brings the greatest benefit in ensuring meeting the target amount. Bollinger and Yao (2018) find that a profit maximizing online microfinance platform transfers risk to the lenders which manifests in higher interest rates. The high interest rates do not serve as a restraining mechanism on the lender’s lending behavior. We address the platform’s role in lowering the risk backers face in case of product non-delivery. The model captures the reputational cost that entrepreneurs and platforms incur when the entrepreneur reneges on delivering the reward. Our main contribution to the literature stems from the focus on strategies a CF platform can deploy to enhance its profitability. To better present our contributions we have divided the literature in broad topic areas, highlighted the contribution of each, and positioned our paper among these topics in Table 1.

Table 1. Paper positioning in extant literature.

Author(s) (Year)	TOPIC AREAS				
	Entrepreneur Strategy	Backer Behavior	Platform Governance	Promotion & Visibility	Revenue Sharing
Belleflamme et al. (2014)	✓				
Mollick (2014)	✓	✓			
Ahlers et al. (2015)	✓	✓			
Hu et al. (2015)	✓				
Roma et al. (2018)	✓				
Babich et al. (2021)	✓				
Chemla and Tinn (2020)	✓				✓
Sayed and Baghaie (2017)	✓	✓			
Chakraborty and Swinney (2021)	✓	✓			
Strausz (2017)			✓		✓

Gal-Or et al. (2019)			✓		✓
Belavina et al. (2020)		✓	✓		✓
Long and Liu (2024)			✓	✓	
Bollinger and Yao (2018)			✓		✓
Z. Li et al. (2020)	✓	✓		✓	
Du et al. (2022)	✓	✓		✓	
<i>This Paper</i>	✓	✓	✓	✓	✓

3. Model

We consider a situation where entrepreneurs raise funds on a CF platform from two types of backers, informed and uninformed. Informed backers know about the campaign when it is launched and can evaluate its characteristics. Uninformed backers, on the other hand, are unaware of the campaign and consider backing it only if the platform promotes the campaign in its recommended list. When the campaign is promoted, the uninformed backers can also observe how many informed backers have funded the campaign. They interpret a larger number of informed backers as a signal of a higher quality project. Hence, the number of uninformed backers who fund the campaign increases with the number of informed backers that the campaign attracted before promotion. The use of the terms “informed” and “uninformed” is common in the quantitative marketing literature (Godes, 2017), especially in the context of word of mouth or viral growth in consumer demand. The finance and economics literature has also used the concept of uninformed individuals following the informed to explain decision making as in the literature on herd behavior (e.g., Banerjee, 1992), information cascades literature (e.g., Bikhchandani et al., 1992), rational expectations literature (e.g., Grossman & Stiglitz, 1980), and pricing of stocks (e.g., Avery & Zemsky, 1998), among others.

The platform promotes a campaign if it meets a specified fraction, $\alpha \in \mathbb{R}_+$, of its declared funding target.⁹ We refer to this rule as the Fractional Threshold (FT) rule. When promoted, the number of uninformed backers attracted to the campaign is determined as a non-negative multiple, δ of the number of informed backers. The size of the informed backer population is uncertain. We designate by N the random size of the informed backer population and assume this size to be distributed uniformly¹⁰ over the support $[0, \bar{N}]$. Thus, if n is the realized number of informed backers, the total size of the backer population becomes $n(1 + \delta)$, conditional on the campaign’s promotion. Intuitively, uninformed backers use the realization of the number of informed backers as a proxy for the probability of project success.¹¹ That is, if $\bar{N}$ informed backers can evaluate a project, and only n of them choose to back it, uninformed backers infer that the probability of project success is $\frac{n}{\bar{N}}$. If the total size of the uninformed backer population on the platform is Z , then promoting the project will attract $\frac{nZ}{\bar{N}}$ uninformed backers. Hence, defining δ to be $\frac{Z}{\bar{N}}$, we obtain an expansion of $n\delta$ in the number of backers.¹² We note that δ captures a reduced-form effect of the expansion in the total backer population resulting from the campaign promotion.

The entrepreneur chooses two instruments when launching a campaign: a target T and a pledge p . The target determines the minimum amount necessary for the campaign to be successful. Only when the campaign revenues reach the selected target, can the entrepreneur collect its share of the revenues. Paying the pledge amount, p entitles the backers to receive the product when it is successfully developed. We assume that the only source of funding available to the entrepreneur is the CF campaign. This assumption is consistent with the reality that early-stage entrepreneurs have very limited access to conventional funding sources such as banks or equity markets. Therefore, to initiate production, the entrepreneur needs to raise the development cost, M , from the campaign. Even

if enough funds to cover this cost are raised, technical difficulties may prevent the entrepreneur from delivering the product as promised. We designate the probability of technical success by k . If the entrepreneur raises sufficient funds to reach the target but is unable to deliver the promised product to backers, both the entrepreneur and the platform suffer reputational loss and legal costs of settling lawsuits because backers, in this case, lose their pledges. We designate the reputational cost incurred by the entrepreneur (platform) as R_e (R_p). Given that the entrepreneur has no financial sources except CF, to cover the development cost M , it is unlikely that an amount higher than M would be given as compensation to disappointed backers. Therefore, we assume that $R_e < M$. Strausz (2017) accommodates the possibility for the entrepreneur to keep a certain portion of the raised amount. In our model, the reputational penalty to an entrepreneur, R_e , is incurred only when the total amount raised meets the target level but entrepreneurs fail to deliver the product. We assume that the development cost, M , is observable by the platform until Section 3. Observe that M could be a parameter inferred from disclosed information such as creator profile, prototype review, budget disclosures, historical performance of the entrepreneur, and audits. We relax the assumption of a fixed development cost in Section 4, where we allow for the platform to set their revenue share between a possible realized development cost from a known distribution. The entrepreneur receives additional profits π from selling the product in the external market, if the product is delivered successfully to CF backers.

We assume that informed backers are rational decision makers and incorporate the risk of product non-delivery in their decision on whether to submit the required pledge p . Backers have the same willingness to pay, g , for the consumption of the product if it is delivered as promised. This *consumption* willingness to pay decreases to $v \equiv kg$ when backers incorporate the possibility that the product might not be successfully produced even when the development cost is collected from the campaign. Backers also derive warm-glow (altruistic) utility, s , with $s < v$, from backing new entrepreneurs regardless of whether they receive the reward or not, or even whether the pledge results in an actual payment by the backer. Thus, s can be seen as the warm-glow utility obtained when a backer pledges an amount with the intent of supporting the campaign. Receiving this utility is not conditional on the campaign's commercial or production success.¹³ The existence of warm glow among contributors to CF campaigns has been discussed in Burtch et al. (2013). We assume that the size of the informed backer population is not large enough to cover the development cost M by itself. Recall that promoting the campaign has the potential to expand the population of backers by attracting more backers who were initially unaware of the project. Table 2 summarizes our notation.

Table 2. Variable and parameter definitions.

Parameters	
v	Valuation of the product
s	Backer's warm-glow utility from supporting a campaign
M	Development cost of the product
N	Random variable, with realization n , indicating the number of informed backers in the campaign
$\bar{N}$	Total size of informed backers in the population
Z	Total size of uninformed backers in the population
k	Probability of technical success
δ	Expansion factor of backer population conditional on campaign promotion
R_e	Reputation cost incurred by entrepreneur on failing to deliver the product to backers

R_p	Reputation cost incurred by the platform if the entrepreneur fails to deliver the product
Decision variables, indices and payoffs	
p	Pledge level that backers pay to the campaign—chosen by entrepreneur
T	Target amount for the campaign—chosen by entrepreneur
γ	Entrepreneur's share of campaign revenue—chosen by platform (platform's share, or <i>commission</i> , is $1 - \gamma$). $\gamma(M)$ denotes the customized value of the entrepreneur's share for a specific value of the development cost M .
α	Threshold percentage of target that entitles campaigns for promotion—chosen by platform
π	Profit in the external market, post campaign, if product is successfully produced
u, c	Uniform sharing rule and customized sharing rule respectively.
j	L, I, H , corresponding to low, intermediate and high fractional threshold value cases.
Π_b^j	Payoff of Backers for $j = L, I, H$
Π_e^j	Payoff of Entrepreneur for $j = L, I, H$
Π_p^j	Payoff of Platform for $j = L, I, H$
T_e^{j*}	Optimum target that maximizes payoff to the Entrepreneur for $j = L, I, H$
T_p^{j*}	Optimum target that maximizes payoff to the Platform for $j = L, I, H$

The game proceeds in the following stages (see Figure 2). In the first stage, the platform chooses the fractional threshold α when implementing the FT promotion rule and the entrepreneur's share, $\gamma \in (0, 1)$, of the funds raised. In the second stage, the entrepreneur chooses the target level, T , and pledge amount, p , while being aware of the platform's stage-one decisions. In the third stage, informed backers submit their pledges after observing the selection of the entrepreneur.

Following the stages of the game, the platform executes its choice of α by implementing the FT rule. If the campaign is promoted by the platform, the uninformed backers become aware of and invest in the project. When the combined revenue from informed and uninformed backers exceeds the target, T , the campaign is declared commercially successful. In this case, the platform shares a fraction γ of the campaign proceeds with the entrepreneur and retains the fraction $1 - \gamma$ as commission from the campaign. Next, production takes place if the entrepreneur's share of revenues covers the development cost M . If the production stage is technically successful (with probability k), the entrepreneur delivers the promised product to the backers and receives the additional profit π from selling the product in the external market. If the entrepreneur is unable to deliver the product to backers either because of insufficient funds to cover the development cost or because of technical difficulties, backers lose their investment, and both the entrepreneur and platform incur reputational and legal costs, R_e and R_p , respectively. Note that for production to occur, the campaign revenues raised in the campaign should exceed M/γ . We refer to a campaign as a *commercial success* if the revenues raised are at least as high as the target T set by the entrepreneur, and as a *production success* if the revenues raised in the campaign suffice to start product development, that is, revenues exceed M/γ . For the campaign to be viable, the highest possible revenue shared with the entrepreneur for a given p must exceed the development cost, that is, $\gamma p(1 + \delta)\bar{N} > M$. We relax this assumption in Section 4.3. In Appendix C, we provide an example to illustrate this process and help clarify the notions of commercial and production success.

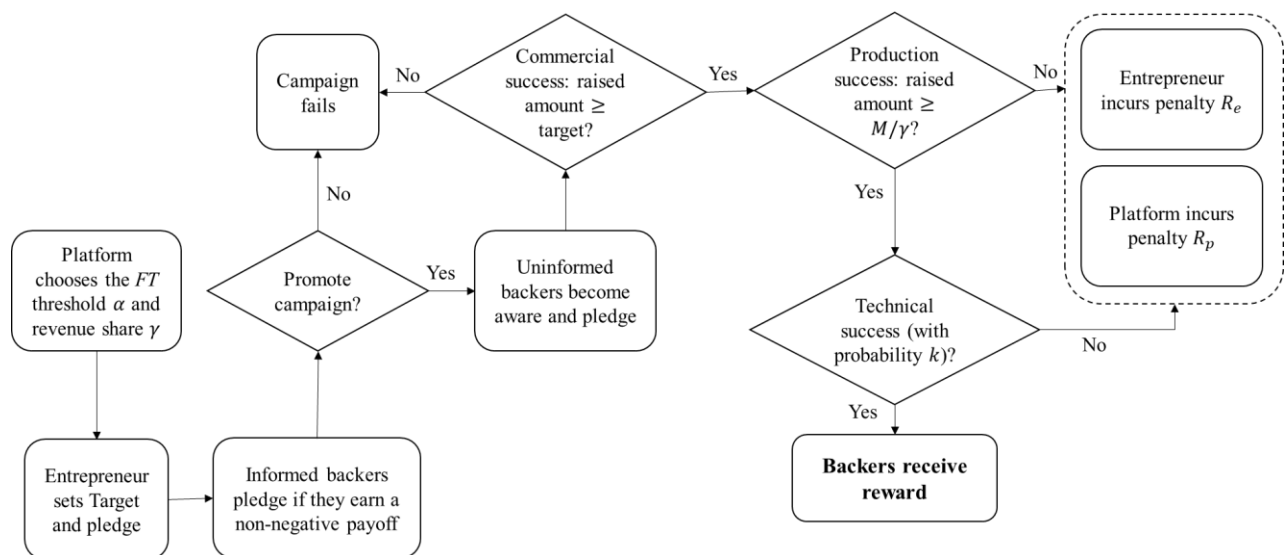


Figure 2. Evolution of the game.

We solve this three-stage game (described above) using backward induction. We first determine the informed backer's decision of whether to participate, given the strategies of the entrepreneur and the platform. We next determine the target level (T) and the pledge (p), chosen by the entrepreneur in the second stage, as a function of the platform's choice of the fractional threshold (α) and the revenue sharing percentage (γ) selected in the first stage. The entrepreneur's strategies are chosen to ensure that the backer is willing to participate. Finally, we find the platform's best strategy in the first stage, as expressed through the choice of the fractional threshold (α) and the revenue sharing percentage (γ). All decisions are selected as a function of the model parameters.

3.1. Equilibrium Analysis for an Exogenous, Fixed Sharing Rule

When using the FT rule, the platform promotes a campaign if the amount raised from the informed backers exceeds a fraction α of the target T , i.e., if $pn \geq \alpha T$. Appropriately selected values of the threshold α can guarantee the commercial and production success of the campaign. For instance, if $\alpha \geq \frac{1}{1+\delta}$, the commercial success of the campaign is assured. Promotion implies that $np \geq \alpha T$ and the commercial success of the campaign implies that $(1+\delta)np \geq T$. The former inequality imposes a more demanding constraint on the realization of the random variable N when $\alpha \geq \frac{1}{1+\delta}$, implying that when the campaign is promoted, it will definitely raise enough funds to meet the target. Similarly, when $\alpha \geq \frac{M}{\gamma T(1+\delta)}$, it is guaranteed that the aggregate funds raised in the campaign are sufficient to start production. Promotion implies that $np \geq \alpha T$, and production success of the campaign implies that $(1+\delta)np \geq \frac{M}{\gamma}$. The former inequality imposes a more demanding constraint on n when $\alpha \geq \frac{M}{\gamma T(1+\delta)}$. These observations lead to three cases depending on the value of α :

Case 1. $\alpha < \frac{1}{1+\delta}$. In this case (which we refer to as the Low fractional threshold case), neither the commercial nor the production success of the campaign can be guaranteed.

Case 2. $\frac{1}{1+\delta} \leq \alpha < \frac{M}{\gamma T(1+\delta)}$. In this case (referred to as Intermediate fractional threshold case), commercial success can be guaranteed but not production success.

Case 3. $\alpha \geq \frac{M}{\gamma T(1+\delta)}$. In this case (referred to as High fractional threshold case), both commercial and production success can be guaranteed.

We denote the low, intermediate, and high cases by indices L, I , and H , respectively. In all three cases, we assume that the entrepreneur sets the instruments of the campaign to ensure that informed backers are not exposed to the risk of losing their pledges when the campaign is not selected for promotion. Specifically, the entrepreneur sets a large enough target to prevent collection of pledges from informed backers when $pn < \alpha T$. We impose conditions on the parameters that guarantee this to be the case at equilibrium.¹⁴ If $\alpha \leq 1$, the additional risk is definitely removed because when a campaign is not promoted $pn < \alpha T \leq T$, and the aggregate pledges of the informed backers are insufficient to meet the target when a campaign is not promoted.¹⁵

3.1.1. Case 1: Low Fractional Threshold (i.e., $\alpha < \frac{1}{1+\delta}$)

Since the promotion of the campaign cannot guarantee either commercial or production success in this case, the expected payoff of the informed backer can be expressed as

$$\mathbb{E}(\Pi_b^L) = s + \left[v \left[1 - \frac{M}{\gamma(1+\delta)p\bar{N}} \right] - p \left[1 - \frac{T}{(1+\delta)p\bar{N}} \right] \right] \quad (1)$$

where $\mathbb{E}(\Pi_b^L)$ denotes the expected payoff of an informed backer for the low fractional threshold case. We note that, in Equation (1), the backer receives the utility s regardless of whether the campaign is a commercial or production success. Despite their ability to evaluate project quality at the time of submitting the pledge, informed backers face several uncertainties. They are uncertain about how many other informed backers will back the project. Thus, they are uncertain whether the platform will promote the campaign and whether production will materialize even if the platform promotes the campaign. If the platform promotes the project, informed backers derive the expected benefit¹⁶ v from consuming the product if production is successful, namely if the proceeds of the campaign are sufficient to cover the development cost (if $\gamma p(1+\delta)n \geq M$). They must pay the pledge whenever the campaign is commercially successful (when $p(1+\delta)n \geq T$). Note that in all cases, even if the platform does not promote the project, informed backers derive the additional altruistic benefits from supporting new entrepreneurs. This benefit is added to the payoff regardless of whether backers get to consume the product.¹⁷ The payoff function of the backer changes when the product development cost, M , exceeds the maximum possible revenue from the CF campaign, namely $\gamma p(1+\delta)\bar{N}$. We analyze this case in Section 4.3.

Since for Case 1, the conditions $\gamma p(1+\delta)n \geq M/\gamma$ and $p(1+\delta)n \geq T$ are more binding than the condition necessary for promotion, $pn \geq \alpha T$, the prior probabilities of production and commercial success do not depend on the threshold level α selected by the platform. Recall that informed backers are concerned about prior probabilities because at the time they submit the pledge, they are uncertain about whether the campaign will be promoted and whether there are sufficiently many informed backers to support commercial success or the start of production. The instruments selected by the entrepreneur must ensure that informed backers derive nonnegative expected utility. From (1), therefore, we can solve for the highest pledge level that the entrepreneur can choose as a function of the target level. We express this highest level, $p^L(T)$, as follows:

$$p^L(T) = \begin{cases} \frac{[(1+\delta)(v+s)\bar{N}+T] + \sqrt{[(v+s)((1+\delta)\bar{N})-T]^2 - 4[(1+\delta)\bar{N}][\frac{M}{\gamma} - (v+s)T]}}{2[(1+\delta)\bar{N}]} & \text{if } T < \frac{Mv}{\gamma(v+s)}, \\ v + s & \text{if } T \geq \frac{Mv}{\gamma(v+s)}. \end{cases} \quad (2)$$

From expression (2), we observe that the pledge level is strictly increasing with the target for $T < \frac{Mv}{\gamma(v+s)}$. Moreover, the entrepreneur can extract the entire willingness to pay of the informed backers, $v + s$, when setting a target at least at $\frac{Mv}{\gamma(v+s)}$. Interestingly, when $s > 0$, the expression $\frac{Mv}{\gamma(v+s)}$ is strictly smaller than the campaign revenues of M/γ

needed to start production. Hence, when backers derive some altruistic benefits from participating in the campaign, the entrepreneur can expose them to the risk of production failure and still extract their full willingness to pay for participating in the campaign.

It also follows from (2) that the pledge level increases when the consumption or altruistic benefits (v or s) are higher, when the target level (T) or entrepreneur's share (γ) of the campaign revenues is larger, and when the development cost (M) is lower. While the effect of changes in v and s on the pledge level are to be expected, the effect of changes in the other variables require additional explanation. To understand the effect of the target level, note that the entrepreneur's decision to set a higher target reduces the likelihood that the campaign is commercially successful, but the product is not delivered to backers. This is also the case when γ is higher or when M is lower.

Next, we express the expected profits of the entrepreneur for the low fractional threshold case, $\mathbb{E}(\Pi_e^L)$, as a function of the pledge and target levels as follows:

$$\mathbb{E}(\Pi_e^L) = \left\{ \frac{\gamma p(1+\delta)\bar{N}}{2} \left[1 - \left(\frac{T}{(1+\delta)p\bar{N}} \right)^2 \right] + [k\pi - (1-k)R_e - M] \left[1 - \frac{M}{\gamma(1+\delta)p\bar{N}} \right] - R_e \left[\frac{M/\gamma - T}{(1+\delta)p\bar{N}} \right] \right\} \quad (3)$$

When $T \leq \frac{M}{\gamma}$ and p are expressed in terms of T as in (2), the first term in (3) is the entrepreneur's expected revenues from the campaign. We focus on projects that have a positive expected payoff from the external market, that is, $k\pi - (1-k)R_e > M$, implying that the expected profit from external sale of the completed product net of the entrepreneur's expected reputational loss is positive. The last term corresponds to the entrepreneur's reputational cost if the campaign is a commercial but not a production success. When $T > M/\gamma$, the last term of (3) goes away because production success is guaranteed in that case. Furthermore, in this region of target levels, it follows from (2) that the pledge level is equal to $v + s$. As a result, the entrepreneur's expected payoff is a strictly decreasing function of the target level when $T > M/\gamma$, implying that the entrepreneur will never set a target level in this region. We summarize this result in Lemma 1 and note that it holds for all three cases.

Lemma 1. *The entrepreneur never sets the target at a level higher than M/γ . That is, the entrepreneur sets the target so that the amount received from the campaign does not exceed the development cost, M .*

Optimizing the entrepreneur's expected profits, $\mathbb{E}(\Pi_e^L)$, with respect to the target level yields the optimal target level, T_e^{L*} reported in Lemma 2.

Lemma 2.

$$\begin{aligned} \text{If } R_e < \frac{Mv}{v+s}, T_e^{L*} &= \frac{Mv}{\gamma(v+s)}, \text{ and} \\ \text{If } R_e \geq \frac{Mv}{v+s}, T_e^{L*} &= \frac{R_e}{\gamma}. \end{aligned}$$

Proof of Lemma 2. Differentiating the expected payoff expression (3), with respect to T , we obtain: $\frac{\partial \mathbb{E}(\Pi_e^L)}{\partial T} = \frac{[R_e - \gamma T]}{(1+\delta)p\bar{N}} + \frac{\partial p}{\partial T} \left[\frac{\gamma(1+\delta)\bar{N}}{2} + \frac{T^2\gamma}{2(1+\delta)p^2\bar{N}} + \frac{[k\pi - (1-k)R_e - M]M + R_e(M - \gamma T)}{\gamma(1+\delta)p^2\bar{N}} \right]$, where

$$\begin{aligned} \frac{\partial p}{\partial T} &= \frac{[(1+\delta)(v+s)\bar{N} + T] + \sqrt{[(v+s)((1+\delta)\bar{N}) - T]^2 - 4[(1+\delta)\bar{N}][\frac{M}{\gamma} - (v+s)T]}}{2(1+\delta)\bar{N} \sqrt{[(v+s)((1+\delta)\bar{N}) - T]^2 - 4[(1+\delta)\bar{N}][\frac{M}{\gamma} - (v+s)T]}} = \\ &= \frac{p}{\sqrt{[(v+s)((1+\delta)\bar{N}) - T]^2 - 4[(1+\delta)\bar{N}][\frac{M}{\gamma} - (v+s)T]}}. \end{aligned}$$

The expression for $\frac{\partial p}{\partial T}$ is obtained from (2). When $T = \frac{Mv}{\gamma(v+s)}$, the biggest value consistent with the region $T \leq \frac{Mv}{\gamma(v+s)}$, $p = v + s$ and $\frac{\partial p}{\partial T} = \frac{v+s}{[(1+\delta)(v+s)\bar{N} - \frac{vM}{\gamma(v+s)}]}$. Evaluating

$\frac{\partial \mathbb{E}(\Pi_e^L)}{\partial T}$ at the biggest value of $T = \frac{Mv}{\gamma(v+s)}$ for the region, yields that $\frac{\partial \mathbb{E}(\Pi_e^L)}{\partial T} > 0$. Given the concavity of the payoff function, it follows, therefore, that the highest payoff for the region is obtained when the target is $\frac{Mv}{\gamma(v+s)}$.

Next, we consider the possibility that $T > \frac{Mv}{\gamma(v+s)}$. In this case, the pledge level is a constant independent of the value of T , and is equal to $p = v + s$. Differentiating (2) with respect to T , for values of $T > \frac{Mv}{\gamma(v+s)}$, yields $\frac{\partial \mathbb{E}(\Pi_e^L)}{\partial T} = \frac{[R_e - \gamma T]}{(1+\mu)(v+s)\bar{N}}$. Setting this expression to zero yields a target value of $\frac{R_e}{\gamma}$.

The above analysis implies that the optimal target value for the low fractional threshold case to be $T_e^{L*} = \text{Max} \left\{ \frac{Mv}{\gamma(v+s)}, \frac{R_e}{\gamma} \right\}$, as reported in Lemma 2. $\square$

If the reputational cost incurred by the entrepreneur is relatively high (i.e., $R_e \geq \frac{Mv}{v+s}$), the optimal target level is set at R_e/γ . This target level increases in the entrepreneur's reputational cost and decreases in the share of campaign revenues awarded to the entrepreneur. When the reputational cost is not as high (i.e., $R_e < \frac{Mv}{v+s}$), the entrepreneur evaluates the effect of the target on both the expected revenue raised in the campaign and on the long-term profitability. A higher target level may introduce two counteracting effects on the profits of the entrepreneur. On one hand, a higher target reduces the likelihood that the campaign is commercially successful, thus reducing expected profits. On the other hand, it also leads to a higher pledge level and to improved long-term profits because the entrepreneur is less likely to incur reputational costs and more likely to raise sufficient funds to cover the development cost. It turns out that the latter effect dominates, and the entrepreneur chooses the highest target level consistent with the region $T \leq \frac{Mv}{\gamma(v+s)}$, namely $T_e^{L*} = \frac{Mv}{\gamma(v+s)}$ when $R_e < \frac{Mv}{v+s}$. In this case, the target level decreases as backers derive more warm glow from pledging (i.e., s increases) or γ ; the share of campaign revenues awarded to the entrepreneur increases. Note that regardless of the optimal target level chosen, it follows from (2) that the entrepreneur can set the pledge level equal to the maximum willingness to pay of backers, equal to $v + s$.

It is noteworthy that whenever backers derive some altruistic benefit from participating in the campaign, namely if $s > 0$, the target level set by the entrepreneur is lower than the amount of funds necessary to start production. Both $\frac{Mv}{v+s}$ and $\frac{R_e}{\gamma}$ are smaller than $\frac{M}{\gamma}$ in this case. By setting the target at a level lower than $\frac{M}{\gamma}$, the entrepreneur exposes the backers to a greater risk of not receiving the promised product despite a commercially successful campaign. We obtain this result despite our assumption that the entrepreneur can expect positive net profits from the sale of the completed product in the external market. It seems that warm glow causes the entrepreneur to intentionally raise the risk of foregoing future profits in favor of short-term proceeds from the campaign.

Given the optimal pledge and target setting of the entrepreneur, we can now express the expected profits of the platform, $\mathbb{E}(\Pi_p^L)$.

$$\mathbb{E}(\Pi_p^L) = \frac{(1-\gamma)(1+\delta)(v+s)\bar{N}}{2} \left[1 - \left(\frac{T}{(1+\delta)(v+s)\bar{N}} \right)^2 \right] - (1-k)R_p \left(1 - \frac{M}{\gamma(1+\delta)(v+s)\bar{N}} \right) - \frac{R_p(M/\gamma - T)}{(1+\delta)(v+s)\bar{N}} \quad (4)$$

where $T = \frac{Mv}{\gamma(v+s)}$ if $R_e < \frac{Mv}{v+s}$ and $T = \frac{R_e}{\gamma}$ if $R_e \geq \frac{Mv}{v+s}$.

The first term of (4) measures the platform's expected revenue from the campaign, and the last two terms measure the expected reputational cost the platform incurs when sufficient funds are raised in the campaign but the product is not delivered to backers, either because of technical difficulties arising in production (second term) or because of insufficient funds to start production (third term).

It is noteworthy that the platform may be interested in a different target level than that selected by the entrepreneur. Consider, for instance, the environment where the entrepreneur chooses its target as $T_e^{L*} = \frac{R_e}{\gamma}$. In this case, from (2), the pledge equals $v + s$. The optimal target level from the platform's perspective, T_p^{L*} , can be derived by optimizing its payoff function (4) with respect to T . This optimization yields $T_p^{L*} = \frac{R_p}{1-\gamma}$, which may be lower or higher than the level most preferred by the entrepreneur. Specifically, if $R_p > \left(\frac{1-\gamma}{\gamma}\right) R_e$, the platform would have preferred the entrepreneur to set a higher target level, and the opposite is the case if $R_p < \left(\frac{1-\gamma}{\gamma}\right) R_e$. Interestingly, even when the liability borne by the platform for non-delivery of the product by the entrepreneur is lower than that borne by the entrepreneur (i.e., even when $R_p < R_e$), the platform may still sometimes prefer a higher target level than that chosen by the entrepreneur. This happens for relatively large values of the sharing rule γ chosen by the platform. Since for most CF campaigns $\gamma > 0.9$, the platform may indeed prefer a higher target level if its reputational cost is at least as high as $\left(\frac{1-0.9}{0.9}\right) = 1/9$ th of the reputational cost borne by the entrepreneur.

3.1.2. Case 2: Intermediate Fractional Threshold (i.e., $\frac{1}{1+\delta} \leq \alpha < \frac{M}{\gamma T(1+\delta)}$)

In this range of α , a promoted campaign will definitely reach the target amount but may not raise sufficient funds to start production. The effect of changes in the parameters on the pledge level remains as in Case 1. In particular, a higher target level leads to a higher pledge. The expected payoff of the entrepreneur is very similar to that discussed for the entrepreneur's expected profits in Case 1, except that the commercial success of the campaign is now tied to meeting the threshold target required for promotion, αT , instead of meeting the target. The entrepreneur chooses a target that maximizes its expected payoff. In Lemma 3, we report the optimal target levels, T_e^{I*} , that the entrepreneur sets for the intermediate fractional threshold case.

Lemma 3. If $R_e < \frac{Mv}{v+s}$, $T_e^{I*} = \frac{Mv}{\gamma(v+s)\alpha(1+\delta)}$, and if $R_e \geq \frac{Mv}{v+s}$, $T_e^{I*} = \frac{R_e}{\gamma\alpha(1+\delta)}$.

Proof of Lemma 3. The expected payoff of the informed backer in this case, $\mathbb{E}(\Pi_b^I)$ is:

$$\mathbb{E}(\Pi_b^I) = s + \left[v \left(1 - \frac{M}{\gamma(1+\delta)p\bar{N}} \right) - p \left(1 - \frac{\alpha T}{p\bar{N}} \right) \right].$$

Setting $\mathbb{E}(\Pi_b^I) = 0$ yields the highest pledge level that the entrepreneur can set as a function of the target level, as follows:

$$p(T) = \begin{cases} \frac{[(v+s)\bar{N} + \alpha T] + \sqrt{[(v+s)\bar{N} - \alpha T]^2 - 4\bar{N} \left[\frac{vM}{\gamma(1+\delta)} - (v+s)\alpha T \right]}}{2\bar{N}} & \text{if } T < \frac{vM}{\gamma(v+s)}, \\ v+s & \text{if } \frac{vM}{\gamma(v+s)} \leq T. \end{cases}$$

Next, we express the expected payoff of the entrepreneur $\mathbb{E}(\Pi_e^I)$:

$$\mathbb{E}(\Pi_e^I) = \frac{\gamma(1+\delta)p\bar{N}}{2} \left[1 - \left(\frac{\alpha T}{p\bar{N}} \right)^2 \right] + (k\pi - (1-k)R_e - M) \left[1 - \frac{M}{\gamma(1+\delta)p\bar{N}} \right] - R_e \left[\frac{M}{\gamma(1+\delta)p\bar{N}} - \frac{\alpha T}{p\bar{N}} \right],$$

where $T \leq \frac{M}{\gamma}$ and $p = p(T)$ is as stated before.

Differentiating the entrepreneur's expected payoff with respect to the target, we get:

$$\frac{\partial \mathbb{E}(\Pi_e^I)}{\partial T} = \frac{\alpha[R_e - \gamma T \alpha(1+\delta)]}{p\bar{N}} + \frac{\partial p}{\partial T} \left[\frac{\gamma(1+\delta)\bar{N}}{2} \left(1 + \left(\frac{\alpha T}{p\bar{N}} \right)^2 \right) + \frac{[k\pi - (1-k)R_e - M]M + R_e(M - \gamma T \alpha(1+\delta))}{\gamma(1+\delta)p^2\bar{N}} \right],$$

where $\frac{\partial p}{\partial T} = \frac{\alpha p}{\sqrt{[(v+s)\bar{N} - \alpha T]^2 - 4\bar{N} \left[\frac{vM}{\gamma(1+\delta)} - (v+s)\alpha T \right]}}$ follows by taking the differential of p with T .

When $T = \frac{vM}{\gamma(v+s)\alpha(1+\delta)}$, the biggest value consistent with the region $T \leq \frac{vM}{\gamma(v+s)\alpha(1+\delta)}$, $p = v + s$ and $\frac{\partial p}{\partial T} = \frac{\alpha(1+\delta)(v+s)}{[(1+\delta)(v+s)\bar{N} - \frac{vM}{\gamma(v+s)}]}$. Substituting these values yields $\frac{\partial \mathbb{E}(\Pi_e^l)}{\partial T} > 0$ at $T = \frac{vM}{\gamma(v+s)\alpha(1+\delta)}$, the biggest value of the target in the region. Given the concavity of the payoff function, it follows that the highest payoff for the region is obtained when the target value is $\frac{vM}{\gamma(v+s)\alpha(1+\delta)}$.

Next, we consider the region defined by $T > \frac{vM}{\gamma(v+s)\alpha(1+\delta)}$. In this case, the pledge level, p , is a constant and equals $v + s$. Differentiating the expected payoff expression with respect to T , for values of $T > \frac{vM}{\gamma(v+s)\alpha(1+\delta)}$, yields $\frac{\partial \mathbb{E}(\Pi_e^l)}{\partial T} = \frac{\alpha[R_e - \gamma T \alpha(1+\delta)]}{(v+s)\bar{N}}$. This implies that the optimal target level for the region $T > \frac{vM}{\gamma(v+s)\alpha(1+\delta)}$ equals $\frac{R_e}{\gamma\alpha(1+\delta)}$. The above analysis implies that $T_e^{I*} = \text{Max}\left\{\frac{vM}{\gamma(v+s)\alpha(1+\delta)}, \frac{R_e}{\gamma\alpha(1+\delta)}\right\}$, as reported in Lemma 3. $\square$

As in the low fractional threshold case, in both regions of the reputational cost R_e included in Lemma 3, the entrepreneur can extract the entire surplus of backers by setting the pledge at the backers' maximum willingness to pay, $v + s$. Note that the target level in Case 2 is unambiguously lower than in Case 1. When the platform sets a more demanding threshold level α (recall that in Case 2, $\alpha \geq \frac{1}{1+\delta}$), it incentivizes the entrepreneur to lower the target to meet the more demanding threshold level for promotion. Comparing the payoffs of the entrepreneur at the optimal target values, for Cases 1 and 2, we note that the likelihood of non-delivery of the product does not depend on the chosen value of α and is the same for both cases. This also implies that the expected payoff of the platform is independent of the choice of α for Case 2. In Proposition 1, we compare the expected profits of the platform in Cases 1 and 2.

Proposition 1 (Platform's expected profit does not depend on α for Cases 1 and 2). *When the threshold level, α , selected by the platform does not guarantee the production success of the campaign (i.e., $\alpha < \frac{M}{\gamma T(1+\delta)}$), its expected profit does not depend on α .*

Proof of Proposition 1. Substituting the optimal values of the pledge and target selected by the entrepreneur into the expected profits of the platform, for Case 2, yields:

$$\mathbb{E}(\Pi_p^{cl}) = \frac{(1-\gamma)(1+\delta)(v+s)\bar{N}}{2} \left[1 - \left(\frac{\alpha T}{p\bar{N}} \right)^2 \right] - (1-k)R_p \left(1 - \frac{M}{\gamma(1+\delta)(v+s)\bar{N}} \right) - R_p \left[\frac{M}{\gamma(1+\delta)(v+s)\bar{N}} - \frac{\alpha T}{(v+s)\bar{N}} \right]$$

where from Lemma 3, $T = \frac{vM}{\gamma(v+s)\alpha(1+\delta)}$ if $R_e < \frac{vM}{v+s}$ and $T = \frac{R_e}{\gamma\alpha(1+\delta)}$ if $R_e \geq \frac{vM}{v+s}$. Similarly, substituting the optimal values of target and pledge levels from Lemma 2 into the payoff functions of the platform in (4), yields the payoff of the platform in Case 1. We observe that, in the regions of α specified for Cases 1 and 2, the expected payoff of the platform is the same. $\square$

From Proposition 1, it follows that when $\alpha < \frac{M}{\gamma T(1+\delta)}$, the platform's expected profit does not depend on whether the FT rule ensures the commercial success of the campaign. Proposition 1 has another interesting result that we state in Corollary 1.

Corollary 1 (The FT rule is ineffective for Cases 1 and 2). *For a fixed γ , when the FT promotional rule does not guarantee production (i.e., $\alpha < \frac{M}{\gamma T(1+\delta)}$), this rule's effectiveness in guaranteeing product delivery is so limited that it is equivalent to picking projects at random.*

Proof of Corollary 1. When campaigns are selected for promotion either randomly or with the FT rule, uninformed backers observe the realization of the random number of informed backers, n , before contributing. Using this number as a signal, the population of backers expands by multiplicative factor δ . Hence, if the pre-promotion revenue collected in the campaign are pn , the post-promotion revenue is $np(1 + \delta)$. Therefore, the campaign revenues raised by the campaign, when campaigns are promoted randomly, equal the campaign revenues raised with the FT rule. Since γ is the same, the expected commission retained by the platform is the same for both the random selection and FT rules. Moreover, as discussed in the remarks following Lemma 3, the probability of product non-delivery is also the same for both these rules under Cases 1 and 2. This implies that the platform's expected reputational cost from a project is the same for the FT and random selection rules. Therefore, the platform's expected payoff from each project is the same under both the FT and random selection rules for Cases 1 and 2 (i.e., when production success is not guaranteed). Hence, the platform is indifferent between using these two rules. $\square$

Under Cases 1 and 2, the FT rule provides information about campaign quality to uninformed backers only through the realized number of informed backers. The FT promotion rule has additional meaningful informational content beyond random selection only if the threshold selected in the FT rule can offer additional information about the likelihood of delivery or non-delivery of the product. When the FT rule utilizes a relatively low threshold level, backers still face the same risk of production failure in Cases 1 and 2 (despite guaranteed commercial success in Case 2), as they do with a random selection rule. The FT rule provides risk-mitigating information only when it guarantees production success, which we discuss in Case 3.

3.1.3. Case 3: High Fractional Threshold (i.e., $\alpha \geq \frac{M}{\gamma T(1+\delta)}$)

In this case, both the commercial and the production success of the campaign are guaranteed if the campaign is promoted. As a result, we can set the pledge at the maximum level of $v + s$ and express the expected profits of the entrepreneur, $\mathbb{E}(\Pi_e^H)$ as follows:

$$\mathbb{E}(\Pi_e^H) = \frac{\gamma(1+\delta)(v+s)\bar{N}}{2} \left[1 - \left(\frac{\alpha T}{(v+s)\bar{N}} \right)^2 \right] + (k\pi - (1-k)R_e - M) \left[1 - \frac{\alpha T}{(v+s)\bar{N}} \right].$$

We note that the entrepreneur incurs the reputational cost in this case only because of technical failure and not because of a lack of funds to start production. Since this objective value is a decreasing function of the target level, the entrepreneur sets the lowest target consistent with this case, namely $T_e^{H*} = \frac{M}{\alpha\gamma(1+\delta)}$. The expected payoff of the platform, $\mathbb{E}(\Pi_p^H)$, can be expressed as:

$$\mathbb{E}(\Pi_p^H) = \frac{(1-\gamma)(1+\delta)(v+s)\bar{N}}{2} \left[1 - \left(\frac{M}{\gamma(1+\delta)(v+s)\bar{N}} \right)^2 \right] - (1-k)R_p \left(1 - \frac{M}{\gamma(1+\delta)(v+s)\bar{N}} \right). \quad (5)$$

The first term of (5) is the expected revenue the platform collects from the campaign, and the second term is the reputational loss it incurs when technical difficulties prevent the entrepreneur from delivering the product. It is noteworthy that even when ensuring the production success of the campaign, the platform does not completely eliminate the risk of non-delivery of the promised product by the entrepreneur. Unexpected technical difficulties may prevent the entrepreneur from completing production successfully, even when raising sufficient funds to start production. However, by setting the fractional threshold for promotion to be sufficiently high, the platform eliminates the additional risk of non-delivery, backers may face, as the entrepreneur may not have sufficient funds to start production despite a commercially successful campaign. Furthermore, observe that the actual threshold level α for promotion does not affect the platform's expected profit.

Any value of α that ensures production success generates the same expected profits for the platform. When the platform chooses a higher value of α , it incentivizes the entrepreneur to lower the target level T without changing the value of αT , which equals $\frac{M}{\gamma(1+\delta)}$ in all instances that ensure production success.¹⁸ Importantly, the platform faces a tradeoff in its decision of whether to ensure the production success of the campaign. While the platform reduces its liability for product non-delivery, it also reduces its expected revenues from any given campaign. As the requirement for promotion is more demanding, any given campaign is less likely to meet it, and therefore less likely to deliver the platform's revenue share.

In Proposition 2, we use the results from Proposition 1 and the expression of the platform's profit in (5) to report how the platform chooses the promotional threshold level α .

Proposition 2 (The platform ensures production success only for Case 3). *For a fixed value of γ ,*

- (i) $R_e < \frac{vM}{(v+s)}$. (a) If $R_p < \frac{(1-\gamma)M(2v+s)}{2\gamma(v+s)}$, the platform chooses α in a manner that does not guarantee production success (Cases 1 or 2), and (b) if $R_p \geq \frac{(1-\gamma)M(2v+s)}{2\gamma(v+s)}$, the platform chooses α to ensure production success (Case 3).
- (ii) $R_e \geq \frac{vM}{(v+s)}$. (a) If $R_p < \frac{(1-\gamma)(M+R_e)}{2\gamma}$, the platform chooses α in a manner that does not guarantee production success (Cases 1 or 2), and (b) if $R_p \geq \frac{(1-\gamma)(M+R_e)}{2\gamma}$, the platform chooses α to ensure production success (Case 3).

Proof of Proposition 2. Parts (i) and (ii). According to Proposition 1, the expected profits of the platform are the same in Cases 1 and 2. Substituting the equilibrium target and pledge levels in (4) yields:

$$\mathbb{E}(\Pi_p^{CL}) = \begin{cases} \frac{(1-\gamma)(1+\delta)(v+s)\bar{N}}{2} \left[1 - \left(\frac{\frac{vM}{\gamma(v+s)}}{(1+\delta)(v+s)\bar{N}} \right)^2 \right] - (1-k)R_p \left(1 - \frac{\frac{M}{\gamma}}{(1+\delta)(v+s)\bar{N}} \right) - \frac{R_p \left(\frac{sM}{\gamma(v+s)} \right)}{(1+\delta)(v+s)\bar{N}} & \text{when } R_e < \frac{Mv}{(v+s)} \\ \frac{(1-\gamma)(1+\delta)(v+s)\bar{N}}{2} \left[1 - \left(\frac{\frac{R_e}{\gamma}}{(1+\delta)(v+s)\bar{N}} \right)^2 \right] - (1-k)R_p \left(1 - \frac{\frac{M}{\gamma}}{(1+\delta)(v+s)\bar{N}} \right) - \frac{R_p \left(\frac{M}{\gamma} - \frac{R_e}{\gamma} \right)}{(1+\delta)(v+s)\bar{N}} & \text{when } R_e \geq \frac{Mv}{(v+s)} \end{cases}$$

Comparing the payoffs as states above, with the equilibrium profits in (5) for Case 3, yields the cut-off values of R_p reported in Proposition 2. $\square$

According to Proposition 2, the platform does not always have an interest in ensuring the commencement of production unless the harm to its reputation upon non-delivery of the product is sufficiently high. The fact that CF platforms absolve themselves of any responsibility¹⁹ for either non-delivery of rewards or for poor quality of the product delivered implies that backers are exposed to the risk of non-delivery even when the campaign is successful, as it may not lead to the start of production. Note that the platform is more likely to ensure production success if backers derive a higher warm glow (higher s), the development cost (M) is lower, the expected valuation of the product (v) is lower, and the reputational cost incurred by the entrepreneur (R_e) is lower. In all of these instances, the minimum level of the platform's reputational cost that incentivizes the platform to ensure production success, specified in Proposition 2 as $\frac{(1-\gamma)M(2v+s)}{2\gamma(v+s)}$ or $\frac{(1-\gamma)(M+R_e)}{2\gamma}$ is smaller, thus making it more likely that the reputational cost of the platform exceeds these minimum levels. We summarize these results in the next corollary.

Corollary 2 (Campaign attributes affect production success). *The platform's optimal strategy is more likely to ensure production success if (i) the reputational cost incurred by the platform (R_p) is higher, (ii) the backers' altruistic benefit (s) is higher, (iii) the share of campaign*

revenue awarded to the entrepreneur (γ) is higher, (iv) the product valuation (v) is lower, (v) the development cost (M) is lower, or (vi) the entrepreneur's reputational cost (R_e) is lower.

Proof of Corollary 2. Enforcement of production success is more likely when the minimal cut-off levels on R_p reported in Proposition 2 decline. In Part (i) of Proposition 2, the cut-off level declines if s or γ go up or when v or M go down. In Part (ii) of Proposition 2, the cut-off level declines if M or R_e go down or when γ goes up. $\square$

To provide some intuition for the results in Corollary 2, note that when s is higher, v is lower or R_e is lower; the entrepreneur sets a lower target level if the threshold for promotion chosen by the platform does not guarantee production success. The lower target raises the odds that a commercially successful campaign is not a production success. Thus, a reduction in the target level increases the likelihood that the platform suffers reputational losses. The platform is more inclined, therefore, to raise the threshold level α to ensure that sufficient funds for the start of production are available. The comparative statics results with respect to R_p and M are quite intuitive. A higher R_p incentivizes the platform to ensure production success to prevent disgruntled backers from eroding the platform's reputation. A lower M implies that it is easier to generate sufficient campaign revenues to cover the development cost, thus making the FT rule to support production success easier to achieve.

Figure 3 illustrates that when R_p is sufficiently high, production success is guaranteed (region GP) and not otherwise (region PNG). In this figure, Region I corresponds to part (i) (a), Region II to part (i) (b), Region III to part (ii) (a), and Region IV to part (ii) (b) of Proposition 2. The threshold values of R_p and R_e that define the regions GP and PNG depend on the product development cost (M), the value of the product (v), the altruistic benefit derived by the backer (s), and the commission ($1 - \gamma$) charged by the crowd-funding platform.

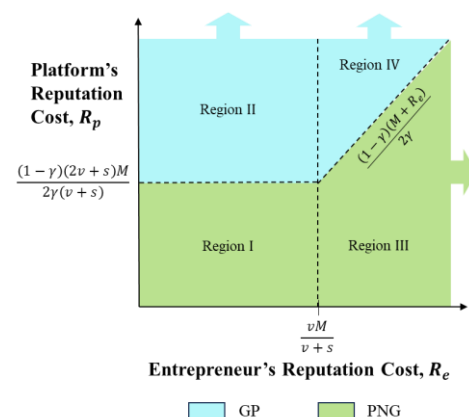


Figure 3. Regions of Guaranteed (GP) and Not Guaranteed (PNG) production as a function of the reputation costs of the entrepreneur and platform.

4. Setting the Revenue Share of Campaigns Endogenously

In Section 3, we assumed that the revenue share was an exogenous parameter. We now build upon the results of the previous section to investigate the case in which campaigns are heterogeneous in their development costs (M), and the platform optimizes the revenue share (γ) given the M values. Although we use the development cost as an observable and auditable parameter for convenience, we can view M as a metric inferred from other observable characteristics of the campaign such as the entrepreneur's record of launching new products, an internal review of the product prototype, or third-party

public audits. The results derived in this section will hold regardless of whether M is observable or inferred. Clearly, these observable metrics, which are correlated with M , can also be used with our approach.

We distinguish between the two environments: (i) *customized* revenue share—when the platform customizes the revenue share for the specific development cost of a campaign, and (ii) *uniform* revenue share—when the platform offers the same, optimally chosen, revenue share across heterogeneous development costs. To distinguish the two environments, we use the scripts c and u for the customized and uniform revenue shares, respectively. We investigate how changes in reputation costs and other model parameters affect the tradeoff between the promotion strategy and the sharing rule in disciplining the behavior of the entrepreneur. From our earlier derivation, the target and pledge selected by the entrepreneur can be summarized as:

$$T_e^{j*} = \begin{cases} \text{Max} \left\{ \frac{Mv}{\gamma(v+s)}, \frac{R_e}{\gamma} \right\} & \text{if } j = L, I \text{ (i.e., the platform doesn't ensure production success),} \\ \frac{M}{\gamma\alpha(1+\delta)} & \text{if } j = H \text{ (i.e., if the platform ensures production success).} \end{cases} \quad (6)$$

$$p = v + s.$$

So far, we have assumed that each project has a product development cost that is lower than the maximum that can be raised through the CF platform. In Section 4.3, we investigate whether an entrepreneur will launch a CF campaign despite knowing that the product development cost is higher than the most that can be raised through CF. Specifically, we delve into the question of whether customizing the revenue share eliminates the participation of all such campaigns that will definitely (with probability one) fail to deliver the product.

4.1. The Platform Can Customize the Sharing Rule for Heterogeneous Campaigns

To obtain the optimal sharing rule for a specific M , we differentiate the expected profits of the platform with respect to γ . The payoff of the platform will depend on whether it chooses a threshold, α , that guarantees production (Case 3) or not (Cases 1 and 2). We note that the expected profit of the platform is a concave function of γ , implying that the first order conditions with respect to γ , included in the Proof of Proposition 3, are both necessary and sufficient.

In Proposition 3, we conduct a sensitivity analysis to investigate how changes in the model parameters affect the optimal revenue share $\gamma(M)$ for a given product development cost M .

Proposition 3 (Comparative Statics—Changes in the platform's reputational cost affect the optimal revenue share $\gamma(M)$ differently). *Assuming that every project has a positive probability of raising the development cost, i.e., $M < \gamma(M)(1+\delta)(v+s)\bar{N}$.*

- (i) *For Low and Intermediate Fractional Threshold cases (i.e., α is sufficiently small), $\frac{\partial \gamma(M)}{\partial R_p} > 0$ if $k > \frac{v}{v+s}$ and $\frac{\partial \gamma(M)}{\partial R_p} \leq 0$ otherwise. Furthermore, $\frac{\partial \gamma(M)}{\partial R_e} \geq 0$.*
- (ii) *For the High Fractional Threshold case (i.e., α is sufficiently large), $\frac{\partial \gamma(M)}{\partial R_p} < 0$ and the sharing rule is independent of R_e ;*
- (iii) *For all three cases (i.e., regardless of the value of α), $\frac{\partial \gamma(M)}{\partial v}, \frac{\partial \gamma(M)}{\partial s}, \frac{\partial \gamma(M)}{\partial \bar{N}}, \frac{\partial \gamma(M)}{\partial \delta} < 0$ and $\frac{\partial \gamma(M)}{\partial M}, \frac{\partial \gamma(M)}{\partial k} > 0$.*

Proof of Proposition 3. When the platform does not choose the threshold level, α , to guarantee production success (i.e., α is sufficiently small), we differentiate (4) with respect to γ (recall that the platform's profits do not depend on α for Cases 1 and 2), and when the

platform chooses α to ensure production success (i.e., α is sufficiently big), we differentiate (5) with respect to γ . The differentiation yields:

$$\frac{\partial \mathbb{E}(\Pi_p^{cj})}{\partial \gamma} = \begin{cases} \left(\frac{vM}{(v+s)^2(1+\delta)\bar{N}} \right)^2 \left[\frac{2-\gamma}{\gamma^3} \right] + \frac{2R_p M}{[\gamma(v+s)(1+\delta)\bar{N}]^2} \left(k - \frac{v}{v+s} \right) - 1 = 0 & \text{if } R_e < \frac{vM}{(v+s)}, \\ \left(\frac{R_e}{(1+\delta)(v+s)\bar{N}} \right)^2 \left[\frac{2-\gamma}{\gamma^3} \right] + \frac{2kR_p M}{[\gamma(v+s)(1+\delta)\bar{N}]^2} - 1 = 0 & \text{if } R_e \geq \frac{vM}{(v+s)}. \end{cases}$$

when production success is not guaranteed. The index j represents L or I in the above expressions. When production success is guaranteed,

$$\frac{\partial \mathbb{E}(\Pi_p^{cH})}{\partial \gamma} = \left(\frac{M}{(v+s)(1+\delta)\bar{N}} \right)^2 \left[\frac{2-\gamma}{\gamma^3} \right] - \frac{2(1-k)R_p M}{[\gamma(v+s)(1+\delta)\bar{N}]^2} - 1 = 0.$$

To obtain the comparative statics results, we use the Implicit Function Theorem by deriving the total differential of the first order condition of the platform payoff when production is guaranteed. To obtain the sign of $\frac{\partial \gamma_c^*}{\partial f}$, where f is any parameter of the model the total differential is: $d \left[\frac{\partial \mathbb{E}(\Pi_p^{ck})}{\partial \gamma} \right]_{\gamma=\gamma_c^*} = \frac{\partial^2 \mathbb{E}(\Pi_p^{ck})}{\partial \gamma^2} d\gamma + \frac{\partial^2 \mathbb{E}(\Pi_p^{ck})}{\partial \gamma \partial f} df = 0$ where $k \in \{L, I, H\}$.

As a result, $\frac{\partial \gamma_c^*}{\partial f} = - \frac{\frac{\partial^2 \mathbb{E}(\Pi_p^{ck})}{\partial \gamma \partial f}}{\frac{\partial^2 \mathbb{E}(\Pi_p^{ck})}{\partial \gamma^2}}$. Since $\mathbb{E}(\Pi_p^{ck})$ is a concave function of γ , it follows that

$\frac{\partial^2 \mathbb{E}(\Pi_p^{ck})}{\partial \gamma^2} < 0$ and the sign of $\frac{\partial \gamma_c^*}{\partial f}$ is determined by the sign of $\frac{\partial^2 \mathbb{E}(\Pi_p^{ck})}{\partial \gamma \partial f}$. Partial differentiation of the expression for $\frac{\partial \mathbb{E}(\Pi_p^{ck})}{\partial \gamma}$ with respect to any parameter, yields, therefore, the results reported in the Proposition. $\square$

Interestingly, a change in the platform's reputational cost has an ambiguous effect on the share of the revenue awarded to the entrepreneur. Part (i) of the Proposition states that when the threshold choice does not guarantee production success, higher reputational costs lead to a higher revenue share awarded to the entrepreneur if $k > \frac{v}{v+s}$. The opposite is the case if $k < \frac{v}{v+s}$. When the choice of threshold does not guarantee production success, there are two reasons for which the platform's reputation might be adversely affected due to non-delivery of the product. The first is technical failure in the production stage, and the second is the entrepreneur's manipulation of the target that ensures commercial success but not production success. By definition, parameter k relates to the former source of reputational losses. To see that the ratio $\frac{v}{v+s}$ relates to the second source of reputational losses, recall that for an exogenous revenue share (γ) awarded to the entrepreneur; when the choice of threshold does not guarantee production success, the entrepreneur sets the target at $\frac{Mv}{\gamma(v+s)}$. Since an amount $\frac{M}{\gamma}$ is required to start production, the ratio $\frac{v}{v+s}$ measures the shortfall in these required funds. This ratio decreases as the investor's warm glow increases. When $k > \frac{v}{v+s}$, there are two reasons why higher reputational costs lead to a larger share being awarded to the entrepreneur. First, a larger k indicates that a more successful and profitable project is worthy of greater support, and second, a relatively small $\frac{v}{v+s}$ implies that the platform should be especially worried that insufficient funds will be available to start production because of target manipulation by the entrepreneur. Raising γ alleviates the latter concern because it raises the odds that the entrepreneur will have enough funds to start production and deliver the product to backers. On the other hand, if $\frac{v}{v+s}$ is relatively large in comparison to k , the platform chooses to reduce γ . A small k indicates that a project is less worthy of support, and a large $\frac{v}{v+s}$ implies that the platform can be less concerned about insufficient funds. In this case, it chooses, therefore, to reduce the share of revenue awarded to the entrepreneur to increase its own share. Practical difficulties with implementing a custom revenue share strategy

can arise if, for example, the entrepreneur underreports the development cost. In such cases, the platform can attempt to infer the development cost based on revealed campaign characteristics and identify mismatches between the offered and optimal revenue shares. As noted previously, we could not find any current reward-based CF platforms that offer customized revenue shares. However, comparable matching platforms such as ride sharing can serve as an aspirational benchmark. In these situations, the driver's share can change based on the ride characteristics such as location, traffic intensity, applicable promotion, etc. Similar customized approaches can be adopted by crowdfunding platforms.

When promotion of the campaign guarantees production success (part (ii) of the Proposition 3), higher reputational costs of the platform lead to a lower share of campaign revenue awarded to the entrepreneur. Since the threshold level α guarantees that sufficient funds for production success are available, the platform is more inclined to lower γ , given that it is less concerned about insufficient funds to start production. The reduction in the entrepreneur's share does not change the odds of the entrepreneur delivering the product. The entrepreneur may still renege on its promises, but only because of technical difficulties unrelated to the revenue-sharing rule chosen by the platform. The comparative statics with respect to R_p illustrate the tradeoff facing the platform when choosing how to utilize the two instruments at its disposal. If the promotion rule does not guarantee production success (part (i)), the platform relies on the sharing rule for guiding the entrepreneur's behavior when the entrepreneur's choice of the target is unlikely to yield sufficient funds to start production (this happens when $\frac{v}{v+s}$ is relatively low in comparison to k). When the promotion rule guarantees production success (part ii), the platform relies more heavily on the promotion rule rather than on the sharing rule for guiding the entrepreneur's behavior.

We also find that the entrepreneur's revenue share increases with R_e when the choice of threshold does not guarantee production success. A large R_e implies that the entrepreneur is more likely to set a higher target and more likely to ensure production success, thus making the project more profitable and thus worthy of greater support.

Finally, part (iii) of Proposition 3 states that the share awarded to the entrepreneur is lower when backers value the product more or when they derive a higher warm glow. In both cases, the campaign can increase revenues, so the platform can lower the entrepreneur's share of the revenue without significantly raising the odds of non-delivery. This argument also applies to $\bar{N}$ and δ . Interestingly, the platform sets a higher revenue share as the development costs, M , increase because a higher M requires more funds to ensure commercial and production success. The revenue share also increases with k because a higher k implies a more profitable and, therefore, more worthy project to support.

4.2. The Platform Sets a Uniform Sharing Rule for Heterogeneous Campaigns

Campaigns active on the platform may differ along many dimensions, including development costs, consumption and altruistic benefits derived by consumers, and the reputation costs incurred by the entrepreneur and platform when the product cannot be delivered to backers. Despite such heterogeneity, platforms usually set a uniform sharing rule for all campaigns. We now investigate how the platform sets its uniform sharing rule for a heterogeneous population of campaigns.

To simplify the analysis, we assume that campaigns differ along one dimension.²⁰ Specifically, all campaigns have the same characteristics except for their development costs. We assume that development costs in the population are distributed uniformly on support $[\underline{M}, \bar{M}]$. We consider the case that for all campaigns, the reputational cost incurred by the entrepreneurs is relatively low, so that $R_e < \frac{v\bar{M}}{(v+s)}$.

To illustrate how a uniform sharing rule affects the composition of campaigns active on the platform, we restrict our attention to the case in which the platform uses a low FT level (Case 1)²¹ because its reputational cost is relatively low. From (4), we note that the platform's expected profits decrease with a campaign's development cost. It is reasonable, therefore, that the platform chooses sharing rule γ to discourage campaigns characterized by relatively high development costs from participating on the platform, so that only campaigns in the interval $[\underline{M}, M_u^*]$, where $\underline{M} < M_u^* \leq \bar{M}$, are active. The threshold campaign, with development cost M_u^* , is indifferent between participating and not participating in the campaign. Specializing the general expression for expected profit (3) to an entrepreneur whose development cost is M_u^* , and setting this profit, $W(M_u^*)$ to zero gives:

$$W(M_u^*) \equiv \frac{\gamma(1+\delta)(v+s)\bar{N}}{2} \left[1 - \left(\frac{vM_u^*}{\gamma(v+s)^2(1+\delta)\bar{N}} \right)^2 \right] + [k\pi - (1-k)R_e - M_u^*] \left[1 - \frac{M_u^*}{\gamma(1+\delta)(v+s)\bar{N}} \right] - R_e \left[\frac{sM_u^*}{\gamma(1+\delta)(v+s)^2\bar{N}} \right] = 0$$

Define $\mu \equiv \gamma(1+\delta)(v+s)\bar{N}$, and $\lambda \equiv k\pi - (1-k)R_e$, where μ measures the highest possible level of funds that can be generated from the campaign when the number of informed backers assumes the highest possible value $\bar{N}$, and λ measures the expected payoff (excluding the funds raised in the campaign) when the entrepreneur is able to start production. If a real solution to the above quadratic equation in M_u^* exists, it can be expressed as follows:²²

$$M_u^* = \left[\frac{v+s}{v^2+4vs+2s^2} \right] \left\{ [(\mu+\lambda)(v+s) + R_es] - \sqrt{[\lambda(v+s) + R_es]^2 - s\mu[(\mu+2\lambda)(2v+s) - 2R_e(v+s)]} \right\}. \quad (7)$$

Note, from (7) that M_u^* increases with μ . Since μ increases with γ , it follows that $\frac{\partial M_u^*}{\partial \gamma} > 0$. Hence, when the platform awards a larger share of revenues to entrepreneurs, campaigns facing higher development costs join the platform. If for any value $\gamma \in (0,1)$ there is no real solution to the equation $W(M_u^*) = 0$, $W(M_u^*) > 0$ for all values of γ , and the entire population of entrepreneurs is active on the platform. We further characterize the solution for M_u^* in Lemma 4.

Lemma 4. For a given share of campaign revenues γ awarded to the entrepreneurs:

- (i) As the share increases, more entrepreneurs choose to run a CF campaign.
- (ii) If this share is sufficiently high, the solution for M_u^* in (7) may exceed the value of $\bar{M}$. In this case, the entire population of entrepreneurs join the platform.
- (iii) If this share is sufficiently small, the solution for M_u^* in (7) can fall short of the value of $\underline{M}$. In this case, none of the entrepreneurs will be interested in joining the platform.
- (iv) When $s = 0$, $M_u^* = \mu$, and if $\underline{M} < \mu < \bar{M}$, only a portion of the population of entrepreneurs, having relatively low development costs, participates in the campaign.
- (v) When $s > 0$, the platform cannot prevent participation of campaigns that will surely fail to deliver the product.

Proof of Lemma 4.

- (i) Since $\frac{\partial M_u^*}{\partial \gamma} > 0$, when $M_u^* < \bar{M}$, this part follows.
- (ii) The entire population participates in one of two cases:
 - (a) If the term inside the radical of the expression for M_u^* is negative, namely if $s\mu[(\mu+2\lambda)(2v+s) - 2R_e(v+s)] > [\lambda(v+s) + R_es]^2$, there is no real solution to the equation $W(M_u^*) = 0$. This is more likely to happen when the expected revenue in the campaign, μ , is relatively high, when the altruistic benefit, s , derived by backers is high, and when the reputation cost, R_e , incurred by the entrepreneur for non-delivery of the product is low.

- (b) When the real solution derived for M_u^* in (7) is bigger than $\bar{M}$, once again, this is more likely when μ and s are relatively big and R_e is relatively small.
- (iii) When μ and s are relatively small and R_e is relatively big, the solution for M_u^* in (7) may be smaller than $\underline{M}$.
- (iv) Substituting $s = 0$ into the solution for M_u^* in (9), yields the result.
- (v) Proof in document (uniform sharing rule). $\square$

According to Lemma 4, the revenue-sharing rule determines how many entrepreneurs join the platform, where a larger share awarded to the entrepreneur attracts more entrepreneurs. The lemma states that the threshold development cost M_u^* is equal to $\mu \equiv \gamma(1 + \delta)v\bar{N}$, when backers do not derive any altruistic benefit, implying that all campaigns that participate satisfy the inequality $M \leq \gamma(1 + \delta)v\bar{N}$. As pointed out earlier, unless this inequality holds, it is certain that campaign proceeds will not cover the development costs and that the product will not be produced. When backers derive positive altruistic benefits, Lemma 4 states that the platform cannot prevent participation of campaigns that will surely fail to deliver the product. That is, when backers are altruistic, those entrepreneurs that incur development costs that are higher than the maximum possible campaign proceeds, will still participate in the campaign. These are campaigns that will fail to deliver the product with certainty, and yet, these campaigns will participate. In such cases, the proceeds from the CF campaign offsets the impact on an entrepreneur's reputation when the product is not delivered. Specifically, with a uniform sharing rule these bad actors get into CF with the sole purpose of "running away" with the campaign funds. As we show in Section 4.3, customizing the sharing rule to the development cost, besides being more profitable, also eliminates this risk. Note that the heterogeneity in the types of campaigns active on the platform exposes backers to different degrees of risk of losing their pledges. Specifically, backers of campaigns that face higher development costs are more at risk of non-delivery of the product. However, these backers are also submitting lower pledges to compensate for this higher risk of a certain delivery failure. As we find, backers contribute to these high-risk campaigns, despite knowing that the underlying product will never be delivered, because of altruistic motives and a lower pledge.

We now investigate how the platform chooses its optimal uniform sharing rule. We first express the objective function of the platform using the results reported in (4). Since we assume that $R_e < \frac{vM}{(v+s)}$, the platform's payoff as a function of M_u^* , $\mathbb{E}(\Pi_p^{ul}(M_u^*))$ equals:

$$\left\{ \begin{array}{l} \frac{1}{(\bar{M} - \underline{M})} \int_{\underline{M}}^{M_u^*} \left\{ \frac{(1-\gamma)(1+\delta)(v+s)\bar{N}}{2} \left[1 - \left(\frac{vM}{\gamma(v+s)^2(1+\delta)\bar{N}} \right)^2 \right] - R_p \left[1 - k + \frac{\frac{Mk}{\gamma} - \frac{vM}{(v+s)}}{(v+s)(1+\delta)\bar{N}} \right] \right\} dM \text{ if } M_u^* < \bar{M}, \\ \frac{1}{(\bar{M} - \underline{M})} \int_{\underline{M}}^{\bar{M}} \left\{ \frac{(1-\gamma)(1+\delta)(v+s)\bar{N}}{2} \left[1 - \left(\frac{vM}{\gamma(v+s)^2(1+\delta)\bar{N}} \right)^2 \right] - R_p \left[1 - k + \frac{\frac{Mk}{\gamma} - \frac{vM}{(v+s)}}{(v+s)(1+\delta)\bar{N}} \right] \right\} dM \text{ if } M_u^* \geq \bar{M}, \end{array} \right.$$

where M_u^* is given in (7).

The platform chooses the sharing rule to maximize the above payoff function. In Proposition 4, we summarize the properties of the optimal uniform sharing rule, γ_u^* , when production success is not guaranteed (Cases 1 and 2).

Proposition 4 (The optimal uniform sharing rule does not preclude the participation of campaigns that are sure to fail in delivering the product when backers are altruistic).

- (i) Suppose backers derive only consumption benefit and no altruistic benefit, and the platform selects the low fractional threshold for promotion. Then,
 If $\underline{M} < \gamma_u^*(1 + \delta)v\bar{N} < \bar{M}$, the impact of R_p on the optimal share awarded to the entrepreneur is ambiguous depending on the values of k and $\frac{v}{v+s}$.
 If $\bar{M} \leq \gamma_u^*(1 + \delta)v\bar{N}$, the optimal share awarded to the entrepreneur by the platform is larger when R_p is larger.
 Regardless of whether $\gamma_u^*(1 + \delta)v\bar{N}$ is larger or smaller than $\bar{M}$, the optimal share awarded to the entrepreneur is larger when k and $\underline{M}$ are larger and $(1 + \delta)v$ is smaller.
- (ii) Suppose backers derive both consumption and altruistic benefits in the campaign, and the reputation cost of the entrepreneur is relatively low. If the CF platform uses a uniform sharing rule, it cannot prevent participation of projects that are certain to never deliver the product.

Proof of Proposition 4. Differentiating $\mathbb{E}(\Pi_p^{uL}(M_u^*))$ with respect to γ , yields the following first order conditions:

$$\frac{\partial \mathbb{E}(\Pi_p^{uL}(M_u^*))}{\partial \gamma} = \left[\left(\frac{v}{(v+s)^2(1+\delta)\bar{N}} \right)^2 \left[\frac{2-\gamma}{\gamma^3} \right] \frac{(M^{*2} + M^* \underline{M} + \underline{M}^2)}{3} - 1 + \frac{R_p k (M^* + \underline{M})}{[\gamma(v+s)(1+\delta)\bar{N}]^2} \right] (M^* - \underline{M}) + \left[(1 - \gamma) \left\{ 1 - \left(\frac{vM^*}{\gamma(v+s)^2(1+\delta)\bar{N}} \right)^2 \right\} - \frac{2R_p}{[(v+s)(1+\delta)\bar{N}]} \left[1 - k + \frac{M^* \left(\frac{k}{\gamma} - \frac{v}{(v+s)} \right)}{(v+s)(1+\delta)\bar{N}} \right] \right] \frac{\partial M^*}{\partial \gamma} = 0 \text{ if } \underline{M} < M^* < \bar{M} \quad \text{and}$$

$$\frac{\partial \mathbb{E}(\Pi_p^{uL}(M_u^*))}{\partial \gamma} = \left[\left(\frac{v}{(v+s)^2(1+\delta)\bar{N}} \right)^2 \left[\frac{2-\gamma}{\gamma^3} \right] \frac{(\bar{M}^2 + \bar{M} \underline{M} + \underline{M}^2)}{3} - 1 + \frac{R_p k (\underline{M} + \bar{M})}{[\gamma(v+s)(1+\delta)\bar{N}]^2} \right] = 0 \text{ if } \bar{M} \leq M^*.$$

It is apparent that the first order conditions are rather cumbersome but simplify significantly when $s = 0$, namely when backers do not derive any altruistic benefits. From (7), when $s = 0$, $M_u^* = \mu = \gamma v(1 + \delta)\bar{N}$, and therefore, $\partial M_u^* / \partial \gamma = v(1 + \delta)\bar{N}$ when $\underline{M} < \mu < \bar{M}$. Hence, the optimal sharing rule solves the following expression:

$$\frac{(\Pi_p^{uL}(M_u^*))}{\partial \gamma} = \begin{cases} \frac{1}{3} \left[\frac{2-\gamma}{\gamma} \right] \left[1 + \frac{\underline{M}}{\mu} + \left(\frac{\underline{M}}{\mu} \right)^2 \right] - 1 + \frac{R_p k (\underline{M} + \mu)}{\mu^2} - (1 - \gamma)^2 R_p = 0 \text{ if } \mu < \bar{M}, \\ \frac{1}{3} \left[\frac{2-\gamma}{\gamma} \right] \left[\left(\frac{\bar{M}}{\mu} \right)^2 + \frac{\bar{M} \underline{M}}{\mu^2} + \left(\frac{\underline{M}}{\mu} \right)^2 \right] - 1 + \frac{R_p k (\underline{M} + \bar{M})}{\mu^2} = 0 \text{ if } \mu \geq \bar{M}. \end{cases}$$

We note that the platform payoff is a concave function of γ , implying that the first order condition is necessary and sufficient. γ_u^* is obtained by solving the equations above.

Cases (i) (a), (b), and (c) of Proposition 4 follow from the first order condition for γ as stated above. Case (ii) follows because, from (7), $\frac{\partial M_u^*}{\partial s} > 0$, and from Lemma 2, $M_u^* = \mu$ when $s = 0$. Hence, when $s > 0$, $M_u^* > \mu$. As a result, entrepreneurs facing development cost in the interval $M \in (\mu, M_u^*]$ will be active on the platform despite never being able to deliver the promised product. For these entrepreneurs, $M > M_u^* = \gamma_u^*(1 + \delta)(v + s)\bar{N}$, where the right-hand-side of the last inequality measures the maximum revenue that can ever be raised in the campaign. $\square$

Proposition 2 shows that when platforms incur relatively low reputational costs, they set an FT level for promoting campaigns that does not guarantee production success. When backers derive altruistic benefits by merely supporting a campaign, the entrepreneur sets a target level lower than the amount necessary to cover the development cost. As a result, backers face a positive probability that following a commercially successful campaign, the entrepreneur will not be able to start production. Part (ii) of Proposition 4

states the stronger result that with altruistic backers and relatively low reputational cost of the entrepreneur, the platform will not be able to prevent participation of projects that will definitely not deliver the product. Platforms seem to be aware of the consequences of using a common γ , as is currently done. Therefore, the platforms explicitly alert backers to the inherent risks associated with crowdfunding a startup and permit easy refunds (see the discussion following Proposition 2).

4.3. The Role of Customized Revenue Share in Eliminating the Risk of Definite Delivery Failure

When production success cannot be guaranteed (when the platform uses a Low or Intermediate fractional threshold), it is possible that some projects participate in the crowdfunding platform even though they will surely fail to deliver the product. This happens when under the best possible realization of the random variable N (that is, $\bar{N}$), the revenue raised by the entrepreneur is insufficient to cover her product development cost, namely $\gamma p(1 + \delta)\bar{N} < M$. We compare this risk in the two regimes: when the revenue share is customized to development cost and when the same sharing rule is used for all projects.

The backers have a different payoff function than (1) when they know that the campaign will fail to deliver the product with certainty. Specifically, $E(\Pi_b^L) = s - p \left[1 - \frac{T}{(1+\delta)p\bar{N}} \right]$ because the backer does not expect to derive the benefit v from consuming the product. Her benefit is purely altruistic net of the likelihood of losing the pledge. Given the different payoff of backers, the optimal target and pledge set by the entrepreneur change, as characterized in Lemma 5.

Lemma 5. For a given value of γ when $\gamma p(1 + \delta)\bar{N} < M$, the optimal pledge and target set by the entrepreneur are: $p = \frac{M}{\gamma(1+\delta)\bar{N}}$ and $T = \frac{M}{\gamma} - s(1 + \delta)\bar{N}$.

Proof of Lemma 5. The expected payoff of a backer of such a product is:

$$E(\Pi_b^L) = s - p \left[1 - \frac{T}{(1+\delta)p\bar{N}} \right].$$

The entrepreneur sets the highest price consistent with this payoff, as follows: $p = s + \frac{T}{(1+\delta)\bar{N}}$. The expected payoff of the entrepreneur who will never deliver the product is: $E(\Pi_e^L) = \left\{ \frac{\gamma p(1+\delta)\bar{N}}{2} \left[1 - \left(\frac{T}{(1+\delta)p\bar{N}} \right)^2 \right] - R_e \left[1 - \frac{T}{(1+\delta)p\bar{N}} \right] \right\}$.

Substituting the price from (1) yields after some algebraic derivations:

$$E(\Pi_e^L) = \frac{s(1+\delta)\bar{N}}{[s(1+\delta)\bar{N}+T]} \left[\gamma \left(T + \frac{s(1+\delta)\bar{N}}{2} \right) - R_e \right].$$

The expected payoff in (2) is an increasing function of T , implying that the entrepreneur will set the highest target level consistent with his inability to deliver the product namely consistent with $M > \gamma(1 + \delta)p\bar{N}$. Substituting the value of price from (1) into the last inequality, yields: $T \leq \frac{M}{\gamma} - s(1 + \delta)\bar{N}$.

Setting the highest target level consistent with this inequality, yields that:

$$T = \frac{M}{\gamma} - s(1 + \delta)\bar{N}, \text{ and therefore } p = \frac{M}{\gamma(1+\delta)\bar{N}}. \quad \square$$

By substituting the optimal pledge and target in the payoff function of the platform we find that when using a customized sharing rule, the platform chooses to exclude projects that are doomed to fail with certainty. This result is different from the one we report in Proposition 4, when the platform uses a uniform sharing rule. We summarize this observation in Proposition 5.

Proposition 5. For projects that are certain not to deliver the product, customizing the revenue sharing rule to be contingent on the development cost incentivizes the platform to reduce the entrepreneur's revenue share to ϵ , where ϵ is a small positive number.

Proof of Proposition 5. Customized Sharing Rule: The platform sets the customized revenue share $\gamma(M)$ for the entrepreneur understanding that the target and pledge set by the entrepreneur is given by Lemma 5. The payoff of the platform for a project that is certain to never deliver the product is: $\mathbb{E}(\Pi_p^L) = \frac{(1-\gamma)(1+\delta)p\bar{N}}{2} \left[1 - \left(\frac{T}{(1+\delta)p\bar{N}} \right)^2 \right] - R_p \left[1 - \frac{T}{(1+\delta)p\bar{N}} \right]$.

Substituting for the price and target from Lemma 5, yields:

$$\mathbb{E}(\Pi_p^L) = \frac{\gamma s(1+\delta)\bar{N}}{M} \left[(1-\gamma) \left[\frac{M}{\gamma} - \frac{s(1+\delta)\bar{N}}{2} \right] - R_p \right].$$

Differentiating the platform's objective with respect to γ , yields: $\frac{\partial \mathbb{E}(\Pi_p^L)}{\partial \gamma} = \frac{s(1+\delta)\bar{N}}{M} \left[\left(\gamma - \frac{1}{2} \right) s(1+\delta)\bar{N} - M - R_p \right]$ and $\frac{\partial^2 \mathbb{E}(\Pi_p^L)}{\partial \gamma^2} > 0$.

As the objective of the platform is a convex function of γ , the optimal solution for the sharing rule is an extreme solution. Since $s < p$ and $M > \gamma p(1+\delta)\bar{N}$, it follows that $M > \left(\gamma - \frac{1}{2} \right) s(1+\delta)\bar{N}$. Therefore, $\frac{\partial \mathbb{E}(\Pi_p^L)}{\partial \gamma}$ is negative. Hence, the optimal solution for the customized sharing rule is $\gamma^*(M) = \epsilon$, where ϵ is a small positive number, for all $M > \gamma p(1+\delta)\bar{N}$. This implies that the platform chooses to effectively exclude projects that are certain to fail when the sharing rule can be customized to the development cost of the project.

Uniform Sharing Rule: For any given common share of revenues awarded to projects, γ , the entrepreneur whose product will definitely never be delivered to backers chooses his price and target according to Lemma 5 to maximize the expected payoff. Substituting the optimized price and target yields the expected payoff of the entrepreneur who will not deliver the product with certainty, for a given positive value of γ , as follows:

$$\mathbb{E}(\Pi_e^L) = s(1+\delta)\bar{N} \left[1 - \frac{\gamma s(1+\delta)\bar{N}}{2M} - \frac{R_e}{M} \right].$$

Since $M > \gamma s(1+\delta)\bar{N}$ for projects that are doomed to fail, if R_e is sufficiently small, the expected payoff of a definite failed project is positive as long as there is some warm glow among the backers, namely if $s > 0$. Specifically, if $R_e < M - \frac{\gamma s(1+\delta)\bar{N}}{2}$ the expected payoff of the entrepreneur is positive, and a uniform sharing rule cannot prevent such an entrepreneur from participating in the campaign. $\square$

As discussed in Section 2, altruism and warm glow are strong motives for pledging in CF campaigns and investing in general. Proposition 5 highlights the negative consequence of the warm-glow effect in CF, and customizing the revenue sharing rule can eliminate the risk associated with the crowdfunding participation of projects that are certain not to deliver the product. Warm glow may invite the participation of entrepreneurs who are fully aware of the fact that they will never deliver the product. The participation of such campaigns can put the entire mechanism into question. Previous studies have not considered the platform's role in addressing the problem. This is despite the fact that the platform is an important stakeholder in ensuring that the CF campaigns run with the best intent of developing new products. We find that customizing the revenue share not only improves profits but also eliminates the risk of participation of projects that, due to their development cost, are definite not to deliver the product. Thus, from a practical perspective, the customized revenue sharing rule makes CF campaigns a "safer" place to invest. Potentially, while we have not considered this scenario to be conservative in our analysis, eliminating this risk can also increase the participation of backers, thereby further increasing the platform profits.

5. Managerial and Policy Implications

We demonstrate that CF platform design choices fundamentally influence campaign outcomes. In particular, the promotion rule and the revenue-sharing mechanism constitute two complementary governance instruments through which platforms can simultaneously influence entrepreneur behavior, improve the likelihood of product delivery, and align incentives. The results of our analysis have important implications for the design and governance of reward-based crowdfunding platforms.

5.1. Promotion Thresholds and Revenue Sharing Are Complementary Governance Instruments

A CF platform can jointly determine promotion thresholds and revenue-sharing policies to affect entrepreneur incentives and backer participation and maintain its reputation. When the platform employs a relatively demanding promotion threshold, it relies on the screening effect of its recommendation algorithm to reduce delivery risk. Conversely, when the platform intentionally adopts a less restrictive promotion policy to encourage greater entrepreneurial participation, modifying the entrepreneur's share of campaign proceeds becomes an effective complementary instrument. By increasing the entrepreneur's revenue share, the platform improves the likelihood that commercially successful campaigns can also begin production.

Viewed from this perspective, recommendation algorithms and commission structures perform analogous governance functions. One allocates visibility, while the other allocates financial resources. Both ultimately influence whether entrepreneurs generate sufficient funds to deliver the product.

5.2. Uniform Revenue Sharing Structures May Not Be Appropriate for Heterogeneous Projects

To our knowledge, contemporary reward-based CF platforms employ uniform revenue sharing structures across campaigns regardless of project characteristics. Our analysis suggests that such uniformity may not be optimal when campaigns differ substantially in development costs (which may depend on engineering effort, regulatory approvals, tooling investments, or manufacturing setup costs). Applying identical revenue shares may therefore expose high development cost, commercially successful projects to a greater probability of production failure. Additionally, with customized revenue sharing rules, platforms can prevent the participation of campaigns that are certain to not deliver the product. This risk reduction can, in turn increase the size of the backer population in the future.

Although we model development cost in our framework, we may interpret it more broadly as a proxy for project complexity. When a platform cannot observe development costs perfectly, they can use proxy measures such as prototype maturity, historical entrepreneur performance, independent verification, manufacturing readiness, etc. These observable indicators provide a practical basis for implementing a revenue share that is customized to the project characteristics. As noted earlier, other comparable industries already implement 'job'-specific commission rates.

5.3. Implications for Entrepreneurs

Our analysis also provides guidance for entrepreneurs seeking crowdfunding. Entrepreneurs naturally face incentives to lower their funding targets because lower targets increase the probability of commercial success. However, our analysis demonstrates that this strategy may increase the likelihood of production failure if the entrepreneur's share of campaign proceeds is insufficient to cover development costs. This will lower the chance of CF success in the future (informed backers may not pledge knowing the entrepreneur's past success history). Again, our use of reputation costs models such long-term impact and motivates the entrepreneur to set targets that realistically reflect development costs.

5.4. Broader Implications for Digital Platform Governance

Although our analysis is motivated by reward-based CF, the underlying insights extend more broadly to digital platform governance. Many digital marketplaces—including peer-to-peer lending platforms, creator-economy platforms, freelance labor markets, and online marketplaces—allocate visibility through recommendation algorithms while simultaneously determining the revenue share of platform participants.

Our results suggest that these two policy instruments should be viewed as complementary components rather than independent design choices. More generally, the paper illustrates how digital platforms can strategically combine algorithmic promotion and financial incentives to align participant behavior with platform objectives, reduce fulfillment risk, and strengthen marketplace trust.

6. Conclusions

In this paper, we study a reward-based crowdfunding platform and investigate how campaign characteristics, platform promotion policies, and revenue-sharing rules affect an entrepreneur's optimal target and pledge decisions. Our analysis treats the platform not merely as a passive intermediary connecting entrepreneurs and backers, but as a strategic marketplace designer whose choices shape campaign visibility, commercial and production success, and ultimately product delivery.

Our framework distinguishes between commercial success, which occurs when a campaign reaches its declared funding target, and production success, which occurs only when the entrepreneur receives sufficient funds to initiate production. This critical distinction allows us to identify a source of misalignment that is especially relevant in reward-based CF; a campaign can appear successful to backers and the platform but still fail to generate the resources needed to deliver the promised product.

We find that when backers derive altruistic benefits from participating in a campaign, the entrepreneur may optimally set a target below the funds needed for successful production, thereby increasing the risk borne by backers even when the completed product would generate positive net profits in the external market. Thus, altruism can unintentionally incentivize the entrepreneur to trade off long-term profits and reputation for short-term campaign proceeds.

6.1. Theoretical Insights

Theoretically, our analysis contributes to the literature on crowdfunding and platform governance by showing that platform policies interact with entrepreneur decisions in non-trivial ways. Much of the existing work emphasizes *entrepreneur* signaling, pricing, campaign design, or learning; in contrast, our framework highlights how the *platform's* promotion and revenue sharing policies influence the entrepreneur's equilibrium target setting, pledge levels, and, as a result, fulfillment outcomes. First, we show that the entrepreneur's optimal target may be lower than the level required to cover the development cost. This result arises even though the entrepreneur can expect positive profits from external-market sales after production success. The result underscores that funding success and product delivery are distinct outcomes and that backer altruism can increase the likelihood that commercially successful campaigns fail to deliver.

Second, we demonstrate that the entrepreneur's target-setting strategy may be inconsistent with the platform's interests. Entrepreneurs benefit from lower targets because they increase the probability of campaign success, whereas the platform bears reputational costs when funded campaigns do not lead to product delivery. This conflict creates a governance problem that cannot be resolved by entrepreneur campaign design alone.

Third, we analyze how the platform can use a fractional-threshold promotion rule, under which the platform promotes campaigns only after they raise a sufficient fraction of their targets. Motivated by empirical evidence showing a correlation between a campaign's rank and the fraction of its target amount raised, this rule captures the platform's ability to expand visibility for campaigns that appear promising. However, the fractional threshold rule is effective only when the threshold is high enough to ensure production success; when the threshold is low, it can be no more effective than randomly selecting campaigns for promotion. Thus, the rule may unintentionally encourage campaigns that ultimately fail to fulfill their obligations.

Fourth, we characterize the platform's revenue-sharing trade-off. A higher commission increases the platform's share of campaign proceeds, but it also reduces the funds received by the entrepreneur and may therefore increase the probability of non-delivery. Accounting for this trade-off, the platform should lower its revenue share when the entrepreneur faces a higher development cost, when fewer informed backers are able to assess product quality, and when informed backers have lower willingness to pay. We further find that a uniform revenue share may fail to prevent participation by entrepreneurs who will certainly be unable to deliver, whereas revenue-sharing contracts customized to development costs can both increase the platform's expected payoff and eliminate definite non-delivery risk.

Finally, our results show that promotion thresholds and revenue-sharing rules operate as complementary governance instruments. When the platform has less incentive to ensure production success through a strict promotion threshold, it can partially compensate by allowing the entrepreneur to retain a greater share of campaign revenues.

6.2. Practical Insights

The model also generates several practical insights for crowdfunding platforms and entrepreneurs. First, distinguishing between metrics that predict fundraising success from those that predict successful fulfillment is important. A campaign that has raised a high fraction of its target may obtain greater visibility, but it may still impose reputational risk if the target itself is too low to support production. Supplementing funding performance with indicators of production feasibility, such as prototype readiness, historical fulfillment outcomes, or third-party verification can improve performance.

Second, platforms should recognize the trade-off between short-term commission and long-term marketplace trust. Aggressively promoting campaigns or charging high commissions can increase platform revenue in the short run, but these choices may leave entrepreneurs with insufficient retained funds and expose the platform to reputational damage from product non-delivery. When the reputational consequences of non-delivery are large, stricter promotion thresholds or lower platform revenue shares may be optimal even if they reduce immediate proceeds.

Third, the analysis suggests that a uniform revenue share may be inferior when campaigns differ substantially in development costs or fulfillment likelihood. Although development cost is modeled explicitly in our framework, it can be interpreted more broadly as a proxy for production complexity, supply-chain risk, or fulfillment uncertainty. Tailoring the revenue share to observable measures of project risk can therefore improve both platform profitability and marketplace trustworthiness by lowering non-delivery risk.

Finally, our findings provide guidance for entrepreneurs. Lowering the funding target can increase the probability of reaching the target and receiving campaign proceeds, particularly when backers are altruistic. However, a low target also increases the risk that the entrepreneur will be unable to deliver, thereby jeopardizing future profits and damaging credibility with both backers and the platform. Entrepreneurs, therefore, face a stra-

tegic trade-off between maximizing campaign completion and preserving the resources needed for successful fulfillment.

6.3. Directions for Future Research

Several promising avenues emerge from this work if some assumptions of the model are relaxed. First, we assume that entrepreneurs do not have access to funding sources other than crowdfunding. Allowing entrepreneurs to supplement campaign proceeds with loans, venture capital, or other external financing may lead them to set even lower campaign targets because outside funds can cover shortfalls not raised through the campaign. At the same time, external financing may reduce the risk borne by backers if such funds are available for production, especially when financing is contingent on campaign performance. Studying how external financing interacts with target setting, promotion, and delivery risk would therefore be a useful extension.

Second, our model assumes homogeneous informed backer valuations and does not explicitly model consumer valuations in the external market. If backers and external market consumers have different valuations, or if backers themselves are heterogeneous, the entrepreneur may use the crowdfunding campaign as a vehicle for price discrimination. Incorporating heterogeneous valuations would enrich the analysis of pledge levels, target choice, and post-campaign market outcomes.

Third, future work could model learning more explicitly. In our framework, informed backers know their valuations with certainty, and the expansion of the backer population after promotion is represented by a known factor. A Bayesian learning approach in which heterogeneous, uninformed backers update their beliefs about product quality or backer participation based on early campaign activity would endogenize the expansion in backer demand. Basing the participation of uninformed backers on such a micro foundation can result in newer insights. Similarly, one can include the option of entrepreneurs abandoning projects when CF attracts too few backers.

Fourth, our analysis can be extended to settings with asymmetric information. Entrepreneurs may know more than backers or platforms about product quality, production costs, or delivery feasibility. In such environments, target and pledge choices may serve as signals of project quality, while customized revenue-sharing contracts may require screening or mechanism-design approaches when development costs are privately known.

Finally, richer empirical work could examine the causal relationship between recommendation rules, campaign visibility, funding outcomes, and fulfillment performance. Field experiments or detailed campaign-level datasets could help test whether stricter promotion thresholds, customized commissions, or broader production-feasibility metrics improve both profitability and delivery reliability.

Overall, our study shows that promotion policies and revenue-sharing mechanisms should be viewed as an integrated governance system rather than as independent platform decisions. By jointly designing these instruments, crowdfunding platforms can improve profitability, reduce delivery risk, and strengthen marketplace trust while preserving the entrepreneurial incentives that make crowdfunding attractive.

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Appendix A. Model Extensions

Appendix A.1. General Distribution Function of the Informed Backer Population

In this section, we explore whether the results derived for the uniform distribution can be extended to other distribution functions. For simplicity, we assume that the probability of technical success is one, namely $k = 1, \beta = 0$, and the reputational cost of the platform is sufficiently small, so that the threshold level of promotion does not guarantee the commercial success of the campaign. Let $f(n)$ and $F(n)$ denote the density and cumulative distribution functions, respectively, of the number of informed backers. The expected payoff of the informed backers is:

$$\mathbb{E}(\Pi_b^L) = \left\{ v \left[1 - F\left(\frac{M}{\gamma(1+\delta)p}\right) \right] - p \left[1 - F\left(\frac{T}{(1+\delta)p}\right) \right] + s \right\}.$$

The entrepreneur sets the highest pledge possible to ensure that the informed backer obtains a non-negative payoff. This pledge can never exceed the maximum willingness to pay of backers $v + s$. Setting $\mathbb{E}(\Pi_b^L) = 0$ for $p \leq v + s$, yields two observations. First, the maximum pledge of $v + s$ is attained at a target level $T^u < \frac{M}{\gamma}$ when $s > 0$.

Specifically, $T^u = (1 + \mu)(v + s)F^{-1}\left[\frac{v}{v+s}F\left(\frac{M}{\gamma(1+\delta)(v+s)}\right)\right] < \frac{M}{\gamma}$ if $s > 0$. Hence, as in the case of a uniform distribution, the pledge reaches its maximum value at a target level strictly lower than the funds necessary to cover the development costs. Second, we can obtain the expression for $\frac{\partial p}{\partial T}$ by total differentiation of the equation $\mathbb{E}(\Pi_b^L) = 0$, for $p \leq v + s$. Define $x \equiv \frac{T}{(1+\delta)p}$ and $y \equiv \frac{M}{\gamma(1+\delta)p}$, then $\frac{\partial p}{\partial T} = \frac{f(x)x_T^p}{[1-F(x)]+f(x)x-vf(y)\frac{y}{p}}$. However, when $\mathbb{E}(\Pi_b^L) = 0$, $F(x) = \frac{vF(y)-(v+s-p)}{p}$, implying that $f(x) = \frac{v}{p} \frac{M}{\gamma T} f(y)$. Substituting into the derivative, we obtain that $\frac{\partial p}{\partial T} = \frac{f(x)x}{[1-F(x)](1+\delta)} > 0$. Hence, as in the case of the uniform distribution, a higher target level allows the entrepreneur to set a higher pledge. Moreover, for $T \geq T^u$, the pledge is a constant equal to the maximum willingness to pay ($v + s$).

The expected payoff of the entrepreneur can be expressed as follows:

$$\mathbb{E}(\Pi_e^L) = (1 + \mu)p\gamma \int_x^{\bar{N}} nf(n)dn + (\pi - M)[1 - F(y)] - R_e[F(y) - F(x)].$$

When $T \geq T^u$, the pledge level is a constant equal to $v + s$. Hence, in this case, the optimal level of the target satisfies the first order condition $f\left(\frac{T}{(1+\delta)(v+s)}\right)\left[\frac{R_e - \gamma T}{(1+\delta)(v+s)}\right] = 0$, yielding the solution $T_{opt}^e = \frac{R_e}{\gamma}$ if $\frac{R_e}{\gamma} \geq T^u$. When $\frac{R_e}{\gamma} < T^u$, the optimal solution for the target level falls in the region where $p < v + s$. We differentiate the expected profits of the entrepreneur with respect to the target level:

$$\frac{\partial \mathbb{E}(\Pi_e^L)}{\partial T} = \gamma x f(x) \left[\mathbb{E}(N|N \geq x) - 1 + \frac{x f(x)}{1-F(x)} \right] + \frac{(\pi - M)[x f(x)]^2}{(1+\delta)(1-F(x))v} + \frac{R_e f(x)}{p(1+\delta)} \left[1 + \frac{x^2 f(x)}{1-F(x)} \left(\frac{p}{v} - 1 \right) \right] > 0.$$

Since the profit of the entrepreneur increases with T throughout the region, it follows that $T_{opt}^e = T^u$ when $\frac{R_e}{\gamma} < T^u$. To summarize $T_{opt}^e = \begin{cases} T^u & \text{when } \frac{R_e}{\gamma} < T^u \\ \frac{R_e}{\gamma} & \text{if } \frac{R_e}{\gamma} \geq T^u \end{cases}$. The solution is very similar to that derived under the uniform distribution.

Appendix A.2. Allowing Informed Backers to Withdraw Pledges When Few Other Informed Backers Participate

In this extension, we consider the possibility that when the number of informed backers is revealed post promotion, some informed backers who have already pledged may change their mind and withdraw their pledges. We formulate this possibility by assuming

that the total number of backers after the promotion is $[n(1 + \delta) - \beta\delta]$. Hence, if $n < \beta$, the total size of the backer population actually declines because some informed withdraw their pledges. In this case, the campaign definitely fails commercially, given our assumption that $(v + s)\bar{N} < T$. Hence, promotion leads to an expansion of the backer population only if $n > \beta$. In this case, the threshold level on α that determines the three cases we considered in the main case are as follows:

Case A1. $\alpha < \left(1 + \frac{\delta\beta p}{T}\right)/(1 + \delta)$ (Commercial success is not guaranteed).

Case A2. $\left(1 + \frac{\delta\beta p}{T}\right)/(1 + \delta) \leq \alpha < \left(\frac{M}{\gamma T} + \frac{\delta\beta p}{T}\right)/(1 + \delta)$ (Commercial success guaranteed but production success is not guaranteed).

Case A3. $\alpha \geq \left(\frac{M}{\gamma T} + \frac{\delta\beta p}{T}\right)/(1 + \delta)$ (Production success is guaranteed by commercial success).

Most of the qualitative results we obtained in the main text, when $\beta = 0$, remain similar, with the exception being that the expected profits of the platform may be different in Cases A1 and A2 compared to Cases 1 and 2 in the main text, respectively. The next proposition reports the comparison of the expected profits of the platform in these two cases.

Proposition A1. For a fixed sharing rule γ of campaign revenue:

- (i) When $R_e < \left[\frac{Mv}{(v+s)} - \delta\beta s\gamma\right]$ or when $R_e \geq \left[\frac{vM}{(v+s)} + v\gamma\delta\beta\right]$, the platform's expected profits are the same irrespective of whether the threshold value α selected by the platform ensures the commercial success of the campaign (Cases A1 or A2).
- (ii) When $\left[\frac{Mv}{(v+s)} - \delta\beta s\gamma\right] < R_e < \left[\frac{vM}{(v+s)} + v\gamma\delta\beta\right]$, the expected profits of the platform are higher when the threshold level for promotion selected by the platform cannot ensure the commercial success of the campaign (Case A1) if $R_p > \frac{1-\gamma}{2} \left[\frac{Mv}{\gamma(v+s)} - \delta\beta s + \frac{R_e}{\gamma}\right]$. Otherwise the platform prefers to choose the threshold to ensure the commercial success of the campaign.

Hence, only for intermediate values of the reputational cost incurred by the entrepreneur, reported in part (ii) of the Proposition, the platform may have a strict preference between Cases A1 and A2. Due to this different result, the decision of the platform of whether to enforce production success (i.e., Case A3) changes as well, as we report in Proposition A2.

Proposition A2. For a fixed value of γ , there exist threshold levels R_{p1}^* and R_{p2}^* indicating indifference between ensuring and not ensuring production success so that:

- (i) When $R_e < \left[\frac{Mv}{(v+s)} - \delta\beta s\gamma\right]$:
 - (a) If $R_p < R_{p1}^*$, the platform chooses α in a manner that does not guarantee production success (Cases A1 or A2).
 - (b) $R_p \geq R_{p1}^*$, the platform chooses α to ensure production success (Case A3).
- (ii) When $\left[\frac{Mv}{(v+s)} - \delta\beta s\gamma\right] \leq R_e < \left[\frac{vM}{(v+s)} + v\gamma\delta\beta\right]$:
 - (a) If $R_p < \frac{1-\gamma}{2} \left[\frac{Mv}{\gamma(v+s)} - \delta\beta s + \frac{R_e}{\gamma}\right]$, the platform chooses α in a manner that guarantees commercial success but does not guarantee production success (Case A2).
 - (b) If $\frac{1-\gamma}{2} \left[\frac{Mv}{\gamma(v+s)} - \delta\beta s + \frac{R_e}{\gamma}\right] \leq R_p < R_{p2}^*$, the platform chooses α in a manner that does not guarantee either commercial or production success (Case A1).
 - (c) If $R_p \geq R_{p2}^*$, the platform chooses α to ensure the production success of the campaign (Case A3).

- (iii) When $R_e \geq \left[\frac{vM}{(v+s)} + v\gamma\delta\beta \right]$:
- (a) If $R_p < R_{p2}^*$, the platform chooses α in a manner that does not guarantee production success (Cases A1 or A2).
 - (b) If $R_p \geq R_{p2}^*$, the platform chooses α to ensure the production success of the campaign (Case A3).
- (iv) $R_{p1}^* < R_{p2}^*$. The threshold levels decrease with the values of the parameters s, γ, δ, β and increase with the values of the parameters v, M , and R_e .

R_{p1}^* and R_{p2}^* are defined as follows:

When $R_e < \left[\frac{Mv}{(v+s)} - \delta\beta s\gamma \right]$,

$$R_{p1}^* \equiv \frac{(1-\gamma)[(1+\delta)(v+s)\bar{N}]^2}{2\left(\frac{sM}{\gamma(v+s)} + \delta\beta s\right)} \left[\frac{\left(\frac{sM}{\gamma(v+s)} + \delta\beta(v+2s)\right)\left(\frac{(2v+s)M}{\gamma(v+s)} + \delta\beta v\right)}{[(1+\delta)(v+s)\bar{N}]^2} - \frac{\delta\beta}{(1+\delta)\bar{N}} \left(2 - \frac{\delta\beta}{(1+\delta)\bar{N}}\right) \right]$$

when $R_e \geq \left[\frac{vM}{(v+s)} + v\gamma\delta\beta \right]$,

$$R_{p2}^* \equiv \frac{(1-\gamma)[(1+\delta)(v+s)\bar{N}]^2}{2\left(\frac{M-R_e}{\gamma}\right)} \left[\frac{\left(\frac{M-R_e}{\gamma} + \delta\beta(v+s)\right)\left(\frac{M+R_e}{\gamma} + \delta\beta(v+s)\right)}{[(1+\delta)(v+s)\bar{N}]^2} - \frac{\delta\beta}{(1+\delta)\bar{N}} \left(2 - \frac{\delta\beta}{(1+\delta)\bar{N}}\right) \right]$$

The results implied by Proposition A2 are similar to those reported in Proposition A1 of the main text. Specifically, the platform is more likely to enforce production success when R_e is relatively small and/or when R_p is relatively large (note that $R_{p1}^* < R_{p2}^*$), when s and γ are big, and when M and v are small. The only difference with the case where $\beta = 0$ is that for intermediate levels of reputational cost incurred by the entrepreneur (in part (ii) of Proposition A2), the platform has a strict preference for ensuring commercial success over not ensuring such success when $R_p < \frac{1-\gamma}{2} \left[\frac{Mv}{\gamma(v+s)} - \delta\beta s + \frac{R_e}{\gamma} \right]$ and the opposite when $\frac{1-\gamma}{2} \left[\frac{Mv}{\gamma(v+s)} - \delta\beta s + \frac{R_e}{\gamma} \right] \leq R_p < R_{p2}^*$.

Appendix B. Empirical Motivation for the Fractional Threshold Promotion Mechanism

This Appendix investigates whether the Fractional Threshold promotion mechanism can be empirically motivated.²³ It is well established in the literature that people rely on results on the first few pages of a search engine to determine which pages to visit (Ghose et al., 2014; Agarwal et al., 2011; Ghose & Yang, 2009; Ursu, 2018). We extend this search rationale to a CF platform. Campaigns that have a lower rank appear in the first pages, and therefore, draw a larger backer population. To empirically investigate whether a higher ‘Percentage of Target’ results in promotion, we compile a dataset comprised of campaigns that are promoted, based on specific sorting categories, in the first 10 pages of Kickstarter.²⁴ Each page consists of 12 campaigns. Since there are 120 (10 × 12) campaigns for each sorting category and 4 sorting categories, there are 480 campaigns in each sample. We extracted the data by running a Python 3.8 script that scraped specific fields of the Kickstarter html page featuring, and thereby promoting, the campaigns. We took six samples every day from 27 June to 15 August 2020 (a total of 50 days), at randomly chosen time points to avoid a consistent pattern of browsing and time zone effects. There are many potential search categories that one can use to browse through the different campaigns in Kickstarter. A prospective backer can do a focused search for a campaign, browse for products under the various ‘product categories’, or obtain ‘suggestions’ from the platform. These ‘suggestions’ are further sorted depending on a backer’s preference for products, which are ‘just launched’, ‘popular’, ‘recommended’, or ‘staff picks’.²⁵ Our intention in choosing all the sorting categories is to show that, regardless of how the back-

ers choose to navigate the crowdfunding platform, campaigns that raise a higher ‘Percentage of Target’ have a lower (better) rank. Since there were 480 campaigns in each sample and we took 6 samples per day for 50 days, the raw data size we started with had $480 \times 50 \times 6$ (139,680) observations. The number of unique campaigns in the raw dataset was 1605. The dataset can be accessed from Laik (2024).

Several observations were removed before estimation. Specifically, we excluded observations with non-positive backer arrival rates, infinite arrival rates arising from zero elapsed time between observations, negative increments in pledged revenue, missing campaign identifiers, or incomplete lagged variables. Additionally, due to the lagged variable in our model, the first appearance of campaign in any set of its consecutive appearances is deleted. The final estimation sample contains 52,620 observations across 1540 campaigns.

Table A1. Summary of observations and number of unique campaigns in the raw and final estimation sample.

	Number of Observations and Unique Campaigns	
	Observations	Unique Campaigns
Raw Dataset	139,680	1605
Final estimation sample	52,620	1540

We tracked the following metrics for each campaign:

Name: Campaign name which also serves a unique identifier.²⁶

Demographic details: Country of Origin and Location of the campaign.

Amount Pledged: \$ amount pledged, including for campaigns that originate outside the US.²⁷

Backer Count: Number of backers who have already pledged.

Launch Date: Date when the campaign was launched.

End Date: Date when the campaign is scheduled to end.

Target: Amount to be raised through the campaign.

Sorting Category: Specific category (recommended, popularity, staff pick, or just launched) in which the campaign is ranked.

Rank: Order in which the campaigns are presented to an unregistered onlooker, for the specific sorting category.

Percentage Funded: Amount raised as a percentage of the target level.

Product Category: Specific category in which the campaign is listed.

Time Stamp: Time epoch when the sample is taken.

We converted all Unix timestamps into calendar dates and constructed campaign duration, days remaining, running day, time elapsed between observations, backer arrivals, incremental pledged revenue, average pledge size, lagged percentage funded, lagged rank, and change in percentage funded.

In our estimation sample of 52,620 observations, around 79% of the campaigns had met their targets, and 20% had raised 10 times (1000%) the target amount. Among the 108 product categories, the highest number of campaigns were listed under Tabletop Games followed by Product Design. Products under the “Product Design” category are technologically intensive and require substantial development cost. Hardware on average had the highest backer count. Most listed campaigns originated in the United States (58%) followed by the United Kingdom (15%). Of the campaigns, 77% had a target level less than \$20,000. We now describe the models that guide our research questions.

As our objective is to validate how the rank of a campaign is affected by the Percentage of Target, we designate the rank of a campaign as the dependent variable, where $Rank_{it}$ is the rank of campaign i at time t . The independent variables are as follows. $CampDur_i$ measures the duration of the campaign, $DaysToEnd_{it}$ measures a potential

‘end effect’ for the campaign as cited in Burtch et al. (2013) and Chakraborty and Swinney (2021). We also control for the target that each campaign keeps $Target_i$. We include both a continuous variable for the lagged percentage of target raised, $PercFun_{i(t-1)}$, and a binary variable Threshold Percent Funded TPF_{it} , which equals one if campaign i has reached a specific threshold percentage of target at time t . We use three different percentage threshold values, 100%, 300%, and 500%, to test our hypotheses.²⁸ Variable X_i controls for the product category to which the campaign belongs, and the specific sorting method a backer uses (i.e., ‘just launched’, ‘popularity’, ‘recommended’, and ‘staff picks’). This first model (Model 1) reports a pooled specification with campaign and category controls and is the baseline over which alternate model specifications are developed to check for robustness. To find the significance of each estimator, we use the clustered standard error, measured at the ‘campaign’ level, as it is repeated in our panel dataset. Unlike Godes and Silva (2012), we could not control for the backer’s identity, as it is confidential. The model is given below:

$$Rank_{it} = \beta_0 + \beta_1 CampDur_i + \beta_2 DaysToEnd_i + \beta_3 PercFun_{i(t-1)} + \beta_4 Target_i + \beta_5 TPF_{it} + \gamma X_i + \epsilon_{it} \text{ (Model 1)}$$

We estimated two other models with alternate specifications. Model 2 augments the Model 1 specification with lagged rank, change in percentage funded, and backer arrival rate to account for rank persistence and recent campaign momentum. Model 3 repeats the dynamic specification (from Model 2) for Tabletop Games, the largest category in the sample, as a category-specific robustness check.

Table A2. Effect of the threshold Percentage of Target (TPF) on campaign rank.

	Model 1 (Existing)	Model 2 (Lagged Rank and Arrival Rate)	Model 3 (Model 2 Applied to Product Category ‘Tabletop’)
Intercept	69.00 ***	33.45 ***	29.17 ***
Campaign Duration	−0.11	−0.22 *	−0.15
Days to End	−0.12 *	0.2 ***	0.31 **
Percent Funded (Lagged)	−0.001 *	0.00	0.00
Increase in Percent Funded		0.00	0.00 *
Arrival Rate (backers/hour)		−0.07 *	−0.10 **
Lagged Rank		0.6 ***	0.62 ***
Target	0.000 *	0.000	0.000
Threshold Percent Funded (TPF = 300%)	−4.35 **	−2.92 *	−4.83 *
Sort by “Popularity”	7.53 **	4.28 **	4.24 *
Sort by “Recommended”	−10.11 ***	−2.45	−5.75
Sort by “Staff Picks”	21.51 ***	15.53	13.55 ***
Campaign Fixed Effect	No	No	No
Category Fixed Effect	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes
Adjusted R ²	0.2	0.51	0.51

*** Significant at 0.01, ** Significant at 0.05, * Significant at 0.1.

The results in Table A1 clearly show that an increase in the Percentage of Target raised results in an improvement (reduction) of rank. The baseline specification (Model 1) indicates that campaigns exhibiting stronger funding performance receive more favorable ranking positions after controlling for campaign duration, remaining campaign duration, campaign goal, search-sorting method, and campaign category. The threshold indicator remains statistically significant at conventional levels, providing evidence consistent with the FT promotion mechanism. The rank of a campaign improves (reduces) when the cam-

campaign is funded three times over ($TPF = 300\%$), with all the other variables held constant. Interestingly, we observe that the campaign ranking worsens (increases) when the campaign is just funded ($TPF = 100\%$). It may be that because the platform is assured of its commissions, once a campaign is fully funded, the platform prefers giving priority to other campaigns that raise a higher amount, thus guaranteeing a higher commission for itself. With a higher threshold than 300%, the impact on rank becomes progressively stronger. Furthermore, the continuous lagged percentage funded variable is significant although the size effect is negligible. We also find that there is an improvement in the rank of a campaign as the campaign draws to a close (*Days To End*). Campaigns with a longer duration have a lower rank. We also find that campaigns are ranked better (lower) on average, when a backer alters their sorting category from campaigns that are 'just launched' to 'recommended' campaigns. These results are robust both in direction and statistical significance if either of the two variables (but not both), the continuous lagged percentage funded variable and the threshold percent funded, are included as independent variables.

Models 2 and 3 complement the results of Model 1 by focusing on cross-sectional differences across campaigns while continuing to report campaign-clustered standard errors. The threshold indicator remains statistically significant in these specifications, indicating that campaigns that have progressed more than three times their funding goals occupy systematically better (lower) ranking positions relative to otherwise comparable campaigns. The arrival rates of backers also increase as rankings improve.

When we introduce campaign fixed effects (not reported), the model becomes considerably more restrictive. The estimated threshold effect becomes statistically insignificant. This result is not unexpected. Campaign fixed effects identify the relationship using only within-campaign variation over time. As crowdfunding campaigns mature, they naturally accumulate funding while simultaneously experiencing declining visibility as newer campaigns enter the marketplace. Consequently, this specification primarily captures campaign life-cycle dynamics rather than the cross-sectional differences in campaign visibility that motivate the theoretical framework.

We further explored several interaction specifications, allowing the effects of backer arrival rates, funding momentum, and lagged funding progress to vary across funding thresholds. Once campaign fixed effects and campaign-clustered standard errors were introduced, none of the interaction terms remained statistically significant. This suggests that while campaigns occupying different funding stages exhibit systematically different visibility, the marginal effect of additional backers or incremental funding does not appear to vary significantly across funding thresholds after campaign-specific heterogeneity is taken into account. Consequently, these interaction models are not reported here.

Taken together, the empirical results provide evidence that campaign funding progress is associated with platform visibility. The relationship is strongest in pooled specifications comparing campaigns with different funding outcomes, while becoming considerably weaker once campaign-specific heterogeneity is fully absorbed through campaign fixed effects.

This distinction is economically intuitive. The theoretical model developed in the paper concerns the platform's allocation of visibility across competing campaigns. By contrast, the campaign fixed-effects specification examines whether an individual campaign continues improving its ranking after becoming more highly funded. Because crowdfunding campaigns naturally progress through their life cycle by simultaneously accumulating funding and gradually declining in visibility as newer campaigns enter the marketplace, these two empirical questions need not yield identical conclusions.

Accordingly, we interpret the empirical analysis as providing evidence consistent with the premise that funding progress is associated with campaign visibility rather than

identifying Kickstarter's exact recommendation algorithm. The fractional threshold promotion mechanism should therefore be viewed as a stylized representation of platform governance that captures the principal economic tradeoffs associated with recommendation policies and customized revenue-sharing decisions, rather than as a literal reconstruction of Kickstarter's proprietary promotion rule.

Appendix C. Numerical Illustration

Appendix C.1. Example to Illustrate Notions of Commercial and Production Success

Consider a simple reward-based crowdfunding campaign for a new consumer gadget. There are two groups of backers. A group of informed backers observes the campaign early and can evaluate the product. A larger group of uninformed backers becomes aware of the campaign only if the platform promotes it.

Table A3. Parameters and decision values (illustrative, not optimal).

Parameters and Decisions	Interpretation	Value
v	Backer valuation if the product is delivered	\$100
s	Warm-glow benefit from supporting the entrepreneur	\$10
M	Product development cost	\$8000
γ	Entrepreneur's revenue share	80%
δ	Expansion factor from platform promotion	2
n	Number of informed backers	100
p	Pledge	\$50
T	Target	\$5000

The pledge is optimally chosen by the entrepreneur, and the commission by the platform. The number of informed backers, n , is a random realization from the sample space of backers. If the campaign is promoted, uninformed backers enter. Since the expansion factor, $\delta = 2$, each informed backer attracts two uninformed backers. Thus, the total number of backers after promotion equal $(1 + \delta)n = 3n$ or 300. Total campaign revenue is therefore $(1 + \delta)np$ or \$15,000. Since the entrepreneur retains 80% of the amount raised, the entrepreneur's amount is $\gamma(1 + \delta)np$, \$12,000. This amount can be compared to the development cost $M = \$8000$. Since the entrepreneur's retained amount is more than the development cost of \$8000 the campaign generates enough retained funds for production.

This simple example highlights the key objects in the model:

Commercial success depends on whether total pledged revenue, $(1 + \delta)np = \$15,000$, reaches the target, $T = \$5000$. Therefore, this campaign is a commercial success.

Production success depends on whether the entrepreneur's retained share of revenue, $\gamma(1 + \delta)np = \$12,000$, covers development cost $M = 8000$. Hence, this campaign is a production success.

The notation introduced here is used throughout the analysis to study how promotion policies and revenue sharing affect campaign outcomes.

Appendix C.2. The Platform's Use of the FT Rule to Guarantee Production Success

Now suppose the entrepreneur and platform decide on the fractional threshold (α) for promotion, and the entrepreneur decides the pledge (p) and target (T) optimally. All other CF parameters are the same as in Table A3. If the entrepreneur wants to extract the maximum willingness to pay ($v + s = \$110$), it can set a target that is large enough to cover the product development cost after settling the platform's commissions. That is, the entrepreneur could set a target of \$10,000. If the target is reached, \$2000 goes to the platform, and the remaining \$8000 that the entrepreneur keeps is enough to cover the \$8000

product development cost. The question we investigate is whether the entrepreneur can keep a lower target (which makes it easier to attain commercial success) and still extract the backer's entire willingness to pay.

At its core, a backer wants to be assured that if the campaign attains commercial success (at which point the pledge will be transferred to the entrepreneur), production success is also guaranteed.

To illustrate a scenario where the platform would keep its fractional threshold such that all promoted campaigns produce and deliver the product, we check what the ambient parameter values should be. First, the fractional threshold should be such that it is at least $\frac{M}{\gamma T(1+\delta)}$ (Case 3 in Section 3). For simplicity, we assume $\alpha = \frac{M}{\gamma T(1+\delta)} = 80\%$. We can find the range of reputation cost of the entrepreneur when it will keep a target that is lower than the product development cost M , thereby exposing the backers to a risk of production failure even when the campaign is a commercial success. How high should the reputation cost of the platform be to ensure that there is enough at stake for the platform? Figure 3 gives certain important thresholds that will help us find these bounds. For example, as long as the entrepreneur's reputation cost (R_e) does not exceed $\frac{vM}{v+s} \approx \$7273$ and the reputation cost of the platform (R_p) is at least $\frac{(1-\gamma)(2v+s)M}{2\gamma(v+s)} \approx \1909 , the platform's strategies will correspond to Region II of Figure 3 (also refer Proposition 2, i (b)). In other words, the optimal target $T = \frac{M}{\gamma\alpha(1+\delta)} = \4167 , and the entrepreneur can extract the entire willingness to pay of \$100 plus the warm glow of \$10. That is, $p = \$110/\text{unit}$. As long as the informed backers raise 80% of the target (\$3333), the campaign gets promoted in the recommended pages of the crowdfunding platform. Getting promoted brings in twice as many ($\delta = 2$) uninformed backers so that a total of \$10,000 is raised. Of this, the platform keeps \$2000, and the entrepreneur keeps the remaining \$8000 to just have enough to start production.

A fractional threshold that is less than $\frac{M}{\gamma T(1+\delta)} = 80\%$ will be ineffectual in guaranteeing production to the backers (Cases 1 and 2). Furthermore, in the stated region of reputation cost of the platform ($R_p \geq \frac{(1-\gamma)(2v+s)M}{2\gamma(v+s)} \approx \1909) and entrepreneur ($R_e \leq \frac{vM}{v+s} \approx \7273), there is no guarantee that production will be dominated by the platform guaranteeing production.

What if the reputation cost of the platform is lower than \$1909? In this case, the platform's promotion threshold will not be a meaningful lever to screen campaigns (refer Corollary 1). From Lemma 3, the entrepreneur's optimal target if its reputation cost is lower than \$7273 will be $T_e^{I*} = \frac{Mv}{\gamma(v+s)\alpha(1+\delta)} = \3788 , lower than a situation when the platform's reputation cost is higher than \$1909. In this situation, even if a lower threshold (for example 75%) gets the campaign promoted, then as long as the informed backers raise \$2841, the campaign gets promoted. Since promotion results in twice as much revenue from the uninformed backers, a total of \$8523 is raised. However, since the entrepreneur gets only 80% of the proceeds after paying the platform's revenue share, the entrepreneur is left with \$6819 which does not cover the development cost. In this situation, the platform, given its relatively lower cost of reputation, still gets its commission (\$1704) from a commercially successful campaign but does not feel compelled to protect the backers against non-delivery. The entrepreneur extracts the maximum willingness to pay of the backers, \$110. This second case corresponds to Proposition 2, i (a) of the paper.

We note that the platform has a better payoff by keeping a threshold that ensures production (\$1704 < \$2000), and the entrepreneur gets a better payoff by keeping a target of \$4167 and pledge of \$110 (\$6819 – reputation cost < \$8000 + post-market sales). Thus, given the parameters, the crowdfunding platform is better off (dominant alternative) ensuring production success.

Notes

1. For terms prevalent in the crowdfunding community, we refer the reader to <https://help.kickstarter.com/hc/en-us/articles/115005028514-What-are-the-basics-> (accessed on 14 July 2026).
2. Such a rule is popularly known as All-or-Nothing, and is the focus of this paper. In other formats, a campaign keeps the amount even if the raised amount falls short of the target.
3. Adomavicius et al. (2018) conduct a controlled experiment to show that willingness to pay increases for a highly recommended product, even if it is of poor quality.
4. Hildebrand et al. (2016) demonstrate this possibility in the context of a peer-to-peer lending platform (Prosper.com), where the early investment of ‘group leaders’ incentivizes unsophisticated investors to extend loans to borrowers.
5. The recommended section is accessed under the “Discover” category when exploring campaigns.
6. [https://updates.kickstarter.com/kickstarter-fees-a-comprehensive-guide-for-creators/#:~:text=If%20a%20project%20is%20successfully,\(roughly%203%2D5%25\)](https://updates.kickstarter.com/kickstarter-fees-a-comprehensive-guide-for-creators/#:~:text=If%20a%20project%20is%20successfully,(roughly%203%2D5%25)) (accessed on 14 July 2026).
7. The word ‘altruistic’ is used synonymously with warm glow. See the Section 2 for papers that take a similar approach.
8. Because crowdfunding platforms use the “Load More” or “Show More” buttons at the bottom of each page of recommended campaigns to continue displaying additional campaigns from the recommended list, we use improvement in the ranking of a campaign as a measure of the recommendation in our empirical investigation.
9. In Appendix B, we demonstrate that the ability of a campaign to cover a significant share of its declared target soon after its launch guides Kickstarter in its promotion strategy.
10. In Appendix A.1, we show that our results remain qualitatively similar for a general distribution function.
11. We could qualify informed backers as those that have information above a certain information threshold about the underlying product. The information can be articulated as quality, value or serviceability. If the available information exceeds a threshold, the first set of ‘informed’ backers back the campaign. Our results remain the same even with this qualification of informed backers. The ‘uninformed’ backers will be those that do not have enough information and therefore do not back the campaigns, but rely on whether the campaigns get promoted.
12. In Appendix A.2, we extend our investigation to allow for the possibility that some informed backers may withdraw their pledge upon observing a low number of other informed backers participating in the campaign.
13. The backer gets the product only if the campaign is a production success. Thus, when a backer gets the product, all other informed and uninformed backers, as well as the external market, get the product. In other words, others are helped due to the backer’s pledge. By including any pure altruistic benefits in the willingness to pay due to the consumption, g , our analysis can incorporate the Andreoni (1989) model of impure altruism.
14. To support our assumption that informed backers are not exposed to the risk that they lose their pledges even when the campaign is not promoted, one of two scenarios are necessary. Either $\alpha < 1$, or if $\alpha \geq 1$ then $T > \bar{N}p$. Given the result that we report in Lemma 2, the last inequality imposes an additional condition on the parameters of the model when $\alpha \geq 1$, namely that $\text{Max}\{\frac{Mv}{\gamma(v+s)}, \frac{R_E}{\gamma}\} > \bar{N}(v+s)$. The latter condition does not violate the requirement that the campaign is viable, namely that $(1+\delta)\bar{N}(v+s) > \frac{M}{\gamma}$, if δ is sufficiently big. Hence, when δ is sufficiently big, we are assured that there are parameter values that support the assumption we make regarding the reduced risk to backers.
15. Our model can be easily extended to allow for the possibility that informed backers are exposed to the additional risk of losing their pledge even when the campaign is not promoted. Our qualitative results remain the same with such an extension.
16. Recall that $v = kg$, thus the informed backers incorporate the likelihood of the technical success of the entrepreneur in forming their expected benefit.
17. We implicitly assume that capital markets are perfect, implying that backers don’t face a budget constraint. Specifically, they can procure funds to invest in any project that they perceive to be profitable. The fact that many backers, especially those who are better informed, may be venture capital funds (Roma et al., 2018; Babich et al., 2021) justifies this assumption.
18. For instance, when $\alpha = (1+\delta)$, $T = \frac{M}{\gamma(1+\delta)^2}$. This implies that $n > \alpha T$ implies $n > \frac{M}{\gamma(1+\delta)}$, and any project that qualifies for promotion will definitely lead to the start of production.
19. Refer “Can Kickstarter refund the money if a project is unable to fulfill?” in the link <https://www.kickstarter.com/blog/accountability-on-kickstarter>, accessed on 14 July 2026. Indiegogo, a competing crowdfunding platform, lists similar disclaimers at <https://www.indiegogo.com/en/terms/backers>, accessed on 14 July 2026.
20. It is possible to extend the analysis to consider heterogeneity along multiple dimensions without changing the qualitative results of our investigation.

21. The authors can provide upon request the derivations for the case that the platform chooses the threshold for promotion to ensure commercial and production success of some campaigns.
22. The solution exists if the term inside the radical in (13) is positive. Namely, if $[\lambda(v + s) + R_e s]^2 - s\mu[(\mu + 2\lambda)(2v + s) - 2R_e(v + s)] > 0$.
23. Because crowdfunding platforms use the “Load More” or “Show More” buttons at the bottom of each page of recommended campaigns to continue displaying additional campaigns from the recommended list, we use improvement in the ranking of a campaign as a measure of the recommendation in this investigation.
24. Kickstarter does not list campaigns in distinct pages but appear as one scrolls down the page. The page numbers, however, appear in the HTML script.
25. The Kickstarter platform uses the following names for sorting the campaigns, ‘Trending’ for ‘Popular’ campaigns, ‘Everything’ for ‘Recommended’ campaigns and ‘Project We Love’ for ‘Staff Picks’.
26. The name of the entrepreneur and a short description of the dataset are also available.
27. Rather than converting foreign currencies ourselves, we rely on the \$ amount that Kickstarter provides.
28. We report the impact of a change in the threshold percentage of target funded at 300% only, while comment on the results obtained for the other thresholds.

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