A DECISION-MAKING FRAMEWORK FOR CROWDFUNDING PLATFORM IMPACT MAXIMIZATION

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ABSTRACT

Crowdfunding platforms (CFP) are increasingly interested in enhancing their impact, by funding projects with positive environmental and social impacts. This article is the first that models the CFP strategies in this context. We compare two attitudes: a neutral (passive) facilitating attitude and an active one. In the latter case, the CFP implicitly favors a subset of the projects by promoting them to the crowd. We model the utility of the CFP, linked to its monetary outcome and the impact of the funded projects, and formulate an optimization problem that maximizes it by acting on the promotion strategy. We show how to solve this problem using real options and dynamic programming. For applying this framework, we perform an empirical study based on a large dataset that quantifies the attractiveness gain for projects when they are promoted by the platform. We then propose a novel hybrid empirical/analytical method, where platform data is processed and provides input parameters to the optimization tool. Our results show that substantial gains are expected when applying the optimization framework with respect to a platform adopting a classical passive attitude. Our study provides guidelines for platform managers on how to design and implement strategies that maximize their impact.

Keywords: Crowdfunding; Utility maximization; Environmental and social impact; Decision making; Real options.

1. Introduction

Like other multi-sided platforms, the CFP business model relies on collecting fees on the funds obtained by successful campaigns. However, CFPs are increasingly interested in enhancing their positive impact on society, e.g. by funding projects with positive environmental and social impacts. CFPs have indeed started communicating about their social and environmental impacts and publish articles and newsletters on the assessment of the impact of their funded projects. We consider in this paper CFPs that are willing to maximize their utility, linked to their monetary outcome, but also to the number of funded projects with a positive social and environmental impact. They are however facing challenges being at the same time neutral facilitators, profitable, and with a high impact.

Many questions are open in this context, such as i) how to select candidate projects for the platform and ii) how to accompany the connection between the two sides during the fundraising. While identifying the success factors related to the campaign helps address the first aspect, as advocated by Lukkarinen et al. (2016), the strategy of CFPs for

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managing the money flow is yet to be studied. This paper fills a gap in this domain by considering the role of platform managers in promoting some projects during the lifetime of their campaigns, thus channeling funds towards this subset of projects in a way that maximizes the CFP's utility. It is worth noting that targeted project promotion is a common practice for CFPs. As an example, Kickstarter stamps some of the projects with the "Projects We Love" label. Some platforms have also introduced labels indicating the impact of the project (see for instance the KKBB labels on inclusion, solidarity, waste reduction, etc.). In addition, if the CFP discloses pertinent information about the expected positive impact of some projects and adopts a targeted promotion strategy, this increases its website service quality. This latter has been proven to have a positive impact in e-commerce in general (Collier and Bienstock, 2006), and on the backing intention in crowdfunding in particular (Kuo et al., 2020).

For attaining the CFP objectives, we develop a decision-making framework that helps the manager in the selection of the projects to promote, resulting in a more efficient money channeling between funders and projects. Efficiency here is measured in terms of a utility function, incorporating monetary as well as impact considerations. Our framework does not involve a priori rejection of campaigns by the CFP but relies on ex-post strategic interventions. These ex-post interventions are well-informed by an ex-ante characterization of projects, continuously updated during the campaign lifetime.

1.1. Methodology

We first model the dynamics of fundraising and consider that recommending a project to the crowd increases its attractiveness, resulting in an increased money flow towards it. The optimal recommendation strategy is then derived as follows:

We incorporate the platform objectives (monetary outcome, number of funded projects, impact) in a utility function and model the promotion strategy of the platform as a policy that should be optimized. By selectively highlighting certain projects, the platform effectively endorses them, signaling superior quality or higher alignment with impact goals to potential funders.

In the "offline" setting, where the decision of promoting a project is taken before the campaign launch, we formulate an optimization problem and provide a closed-form solution for it.

In the "online" setting, where the policy is dynamic in the sense that the decision may be taken while the campaign is already running, we develop a real options framework that integrates the dynamics of campaigns on the platform into the decision and derive the optimal strategy using a dynamic programming approach.

We perform an empirical study to consolidate and apply this theoretical model, exploiting a large database of projects on a popular crowdfunding platform. We study the correlation between critical parameters of the project and the success factors (success probability, amount of collected funds). We primarily focus on the "staff pick" parameter, also called "Projects we love", which indicates whether the project has been selected and highlighted by the CFP and estimate the increase of attractiveness of such projects compared with non-promoted projects.

We then propose a novel hybrid empirical/analytical method, where key parameters, including the attractiveness gain, are extracted from the platform historical data, and used as input for the optimization framework.

We illustrate the optimal promotion strategy for different objectives, and different fundraising models. We show that the objective of the platform changes the promotion strategy, and that having an optimization behavior largely increases the utility compared with the neutral case.

1.2. Contribution

Our paper tackles the gap in platform-side optimization that extends beyond traditional campaign success prediction, advancing toward an empirically grounded optimization framework. We empower crowdfunding platforms to dynamically manage project promotion strategies aimed at achieving both financial and impact-oriented goals—an area still underexplored in platform strategy research. Our hybrid empirical–analytical methodology goes beyond purely empirical or theoretical approaches, leveraging platform data to inform strategic recommendation decisions and thereby addressing a key gap in the literature on platform-side optimization.

1.3. Paper structure

The remainder of this paper is organized as follows. Section 2 situates our research in the literature. Section 3 models the dynamics of fund collection on the platform, regarded as a neutral facilitator. Section 4 considers the platform as an active intermediary and formulates the project recommendation problem as an optimization problem. Section 5 conducts an empirical analysis that estimates the parameters that will be used in the numerical evaluation. Section 5 also illustrates the proposed algorithms using numerical simulations and shows the optimal promotion strategy and its advantage with respect to a neutral position. Section 6 concludes the paper and discusses future research directions. Appendix A shows how dynamic programming can be applied and appendix B derives the closed-form optimal solutions for some interesting distributions of the money flow.

2. Related Works

We now present a literature review on topics related to our work, including parameters that influence the success of a campaign, existing methods for predicting this success, as well as project recommendation as a lever for influencing funders' behaviors. For this aim, we also review literature on signaling theory, and recommendation algorithms employed by online platforms.

2.1. Success parameters for crowdfunding campaigns

An important set of works aims at identifying success parameters and "quality signals" of projects. Simple quality signals were identified in Mollick (2014) and Cordova et al. (2015) such as advertisement videos, the absence of typos and the frequency of updates. A more recent work (Pati and Garud, 2021) integrated this frequency of updates within the wider framework of social interaction and showed that the social interaction plays an important role in success. The clarity of the financial roadmap and the risk-transparency were identified as crucial in Ahlers et al. (2015). Buttice et al. (2017) identified internal social capital, i.e. the network the project holder constructed in the platform itself in the past, as an essential success factor.

Recently, a particular attention has been drawn on the impact of the environmental and social orientation of the project on the success of the campaign. Horisch and Tenner (2020) found a positive correlation between the environmental and social orientation of a project and its success, especially in the US. On the contrary, Roma et al. (2021) found a negative correlation between orientation towards environmental sustainability and the success of the crowdfunding campaign. While this result may be counter-intuitive, it is a confirmation of the results of Buttice et al. (2019) who observed that this negative correlation exists in countries where the public policies encourage sustainable development. Based on these studies, the environmental and social orientation impact on crowdfunding campaign outcome can be considered as country-dependent and is less positive when the country has a public investment policy in green and social ventures. However, it is always recommended that projects clearly identify their positive environmental impacts, and Siemroth and Hornuf (2023) conducted a lab-in-the-field experiment that found out that "the majority of investors are willing to give up a higher return as long as the environmental or social impact is large enough". When it comes to sustainability from the platform's perspective, it was only analyzed by Cumming et al. (2024), who showed that listing projects with high sustainability orientation increases the survival chance of the platform.

2.2. Campaign success prediction

The above-cited body of work gives a clear view of the success parameters of CF campaigns, and these success parameters help predict the campaign success. A direct implication is that, knowing these success parameters, it should be possible to predict the campaign success using Artificial Intelligence (AI) techniques. For instance, Song et al. (2020) built a prediction model for crowdfunding success based on public online campaign data, and Etter et al. (2013) developed an Artificial Intelligence (AI) that predicts the campaign success with high accuracy, using only the project data from the first days of the campaigns. Zhong et al. (2022) proposed a machine learning approach that exploits the entrepreneur's previous activity on the platform for enhancing success predictions. Lin et al. (2018) proposed a method that estimates the competitiveness of a project based on its characteristics and updates it during fundraising. Cavalcanti et al. (2024) reviewed ML methods in CF and demonstrated how supervised learning improves predictive accuracy by analyzing campaign features, contributor behavior, and textual content. A more advanced approach, introduced by Cai et al. (2024), uses graph-based models to capture complex relationships among creators and backers. Explainable AI has been exploited by Chaudhary (2024), ensuring transparency in predictions and providing insights into model decisions.

2.3. Algorithmic recommendation systems

Since the 90's, Recommender Systems (RS) appeared as essential tools shaping the world of e-commerce (Schafer et al., 1999). The basic idea is to learn from the user's preferences and recommend products that are likely to interest him. Recommender systems rely on « collaborative filtering » algorithms, inferring user interests from information collected from many users (Herlocker et al., 2004). Early research focused on the design of accurate prediction algorithms (Breese et al. (1998), Billsus and Pazzani (1998), Sarwar et al. (2001)), and then the interest shifted towards the embedding and the evaluation of the user experience with the recommender (Konstan and Riedl, 2012), or on the cross-pollination of content-based and collaborative filtering (Ye et al., 2019). While Machine Learning (ML) was in the heart of recommender systems since their beginnings, the fast development of ML and deep learning techniques resulted in a tremendous amount of RS algorithms (see the surveys by Portugal et al. (2018) and Da'u et al. (2020)). Recently, RSs attracted some interest in crowdfunding research, as CFPs tend to classify projects into categories and recommend them to funders based on predicted preferences. Rakesh et al. (2016) developed a recommendation system that suggests suitable projects to investors and applied it to a Kickstarter database. Yin et al. (2022) proposed a deep collaborative filtering algorithm that constructs a relationship graph between funders and projects.

The aforementioned body of works aims to maximize user utility, and significant effort has been invested in designing user-centric utility, as exemplified by the application of Multi-Attribute Utility theory (Huang, 2011). This approach is based on the underlying promise that maximizing user utility will lead to increased profitability for the e-commerce platform (Konstan and Riedl, 2012). To further enhance the RS utility framework, Zhan et al. (2021) extended it to include both user and content provider utilities. This expansion is intended to sustain more content providers and foster a more diverse content pool, ultimately contributing to long-term user satisfaction. Recently, Xiao et al. (2025) considered project recommendation as an optimization lever for increasing CF platform profitability and proposed a Markov Decision Process (MDP) approach for selecting projects to recommend. Hou et al. (2025) highlighted the importance of staff picks and proposed an optimization framework for platforms to strategically select projects to promote. To the best of our knowledge, our work is the first to explicitly model the CFP utility, which goes beyond profitability, and exploits project recommendation for maximizing it.

2.4. Signaling theory in crowdfunding

To encourage crowdfunders to back their projects, entrepreneurs must send observable signals that provide credible information about otherwise unobservable qualities. Signaling theory, which concerns decision-making and communication under information asymmetry, explains how signalers convey information about unobservable attributes through observable cues (Connelly et al., 2025). This concept is particularly relevant in the context of reward-based crowdfunding, where entrepreneurs signal project quality and viability through various means such as social ties, the thoroughness of investment preparation and presentation, the variety of rewards offered, and proactive communication with the crowd (Kunz et al., 2017). These signals can significantly influence the success of a campaign in reward-based crowdfunding (Mollick, 2014). As of equity crowdfunding, signals like human capital, social capital, and equity retention have been shown to affect campaign outcomes (Ahlers et al., 2015). Huang et al. (2022) showed how signals of entrepreneurs' credibility and project quality produce crowdfunding success. According to Kleinert et al. (2022), equity CFPs exploit these quality signals for selecting new ventures to start fundraising campaigns. Furthermore, signaling in crowdfunding is not limited to entrepreneurs, as independent third parties play an important signaling role, as highlighted by the literature (Calic et (2016), Saluzzo et al. (2021), Huang et al. (2022)). Here, third parties refer to media websites, blogs and newspapers (Calic et al., 2016), but also microfinance institutions (Gama et al., 2023) and certification bodies (Yu and Xiao, 2023).

Besides project founders and third parties, CFPs play an important signaling role as well. Colombo et al. (2015) argued that some CFP platforms facilitate the success of a project by allowing signaling of reciprocity, measured via the number of other projects backed by a creator. Davies et al. (2018) insisted on the role of CFPs in facilitating the activity of signaling to mitigate the negative consequences of asymmetric information. When platforms selectively promote a subset of projects, they implicitly influence investor attention and funding outcomes. This platform-driven promotional behavior aligns closely with signaling theory, suggesting that such endorsements serve as credible signals of project quality or alignment with broader impact goals. Kunz et al. (2017) considered the "staff pick" of Kickstarter to be a high-cost signal, as only outstanding and unique projects are picked. This complements the more traditional understanding of signaling as an entrepreneur-driven process, highlighting the dual role of both entrepreneurs and platforms in influencing campaign success.

2.5. Our positioning within the literature

We now summarize our findings from the literature and position our work with respect to it. First, the platform manager is able, from observing the project characteristics, its sustainability orientation and the first days of its campaign, to estimate the attractiveness of the project and predict its outcome without any external intervention. This estimation is the input of our optimization scheme, where strategic interventions may change the course of the campaigns in a way that maximizes the utility of the platform.

Second, the research in the field of social and environmental impact is still limited to the crowd behavior and does not extend to the CFP as a venture that may be willing at maximizing its impact. Only recently, Cumming et al. (2024) addressed the sustainability from the platforms' perspective and found out that sustainability criteria increase the chance of survival of the platform.

This paper fills a gap in the literature, by considering the optimization behavior of the platform, exploiting the lever of project recommendation. This latter is a critical success factor for projects as highlighted by Mollick (2014); Gutsche and Sylla (2018) and demonstrated by our empirical study in section 5. In this context, when the platform detects a high risk of failure of some projects of interest with a subsequent degradation of its utility (either monetary or impact-based), we show how it can take actions for reversing the tendency, thus increasing its utility. The exploited lever by the CFP is the promotion of projects, identified by Kunz et al. (2017) as a high-cost signal. Our findings demonstrate that a strategic, impact-oriented promotion policy leads to substantial utility gains compared to passive strategies. From a theoretical standpoint, this work contributes to the crowdfunding literature by offering a new lens on how platform behavior itself serves as a signaling mechanism, complementing the more traditional entrepreneur-driven signals. Only recently, project recommendation started to be considered as an optimization lever for the CFP (Xiao et al. (2025), Hou et al. (2025)), but we adopt a utility maximization approach, where project recommendation is optimized for maximizing the CFP utility, including not only monetary outcomes but also impact.

As of our methodology, we adopt a hybrid empirical/mathematical approach for modeling the dynamics of fund raising on the CFP and use this model as a basis for a decision-making framework. The mathematical model is based on realistic assumptions on the system parameters backed by empirical observations. This approach has been widely adopted in the literature. For instance, Yang et al. (2016) modeled the interactions between funders and entrepreneurs on the platform and proposed subsequent control mechanisms. Salahaldin et al. (2022) proposed an analytical model for the funding dynamics and derived optimal intervention dates for saving the entrepreneurs' campaign. Shao et al. (2024) modeled the decision process of the funder, considering the current information disclosed by the entrepreneur and derived optimal pricing and information disclosure policies. To the best of our knowledge, our model is the first focusing on the crowdfunding platform perspective. Furthermore, we show how to extract empirical data from the platform and use it directly in the decision model.

Table 1. Notations

Notation	Definition
$\boldsymbol{\mathcal{K} = \{1, 2, \dots, K\}}$	Set of projects on the CFP
$\boldsymbol{N(t)}$	Next project to end
$\boldsymbol{T_k}$, $\boldsymbol{m_k}$	Closing time for project *k*, its target funding and its attractiveness.
$\boldsymbol{X_k(t)}$	The pledge made in project k until time t
x(t),$\boldsymbol{\mu}$	A random variable representing the total amount of pledges made by funders at time t; and its expected value
$\boldsymbol{\alpha_k}$	Attractiveness of project *k*, indicating its relative ability to collect funds. It can be estimated based on the performance of similar projects, and updated online during the first days of the campaigns (section 4.5.4).
$\boldsymbol{\beta_k}$	Parameter related the social and environmental class of a project; can be estimated by an SROI analysis.
G	Attractiveness gain when a project is promoted by the platform. It multiplies the α_k, and can be estimated empirically from historical data (section 5.1)
$\boldsymbol{\mathcal{P}}$	Recommendation policy of the platform, that selects at each moment the project to promote.
$\boldsymbol{\gamma_k(t, \mathcal{P})} \in \{\boldsymbol{1, G}\}$	Recommendation status of project *k* at time step *t* under policy $\mathcal{P}$. 1 means that it is not recommended (attractiveness α_k) and *G* that is recommended (attractiveness $G\alpha_k$)
$\boldsymbol{\tau_{k+1}}$	The switching time from promoting project *k* to promoting project *k+1*, in a sequential policy.
$\boldsymbol{U(\mathcal{P})}$	Utility of the platform under a given policy. The latter impacts the success of individual projects and, consequently, the utility of the platform.

3. Platform model as a neutral facilitator

We consider a CFP based on the threshold pledge model (Cumming et al., 2015), where a project that does not get 100% of requested funds fails. We consider a set of projects $\mathcal{K} = \{1,2, \dots, K\}$. Note that we focus here on a set of projects that can be regarded as competitors, i.e., that attract funders with a common interest, e.g., technology, arts, etc., even if a platform may propose different categories of projects. Project k requests an amount of funds m_k and starts at time t_k and ends at T_k, with $T_1 \leq T_2 \leq \dots \leq T_K$ and $t_k < 0$ for all $k \in \mathcal{K}$. We define the *next-closing project* index by $N(t) = \min\{k \in \mathcal{K} | T_k \geq t\}$.

3.1. Crowd money flow

We consider a discrete time system (e.g. fund evolution on a daily basis). We denote by $X_k(t)$ the pledge made in project k until time t, with $X_k(0) > 0$. Project k is successful if $X_k(T_k) \geq m_k$

We denote by $x(t)$ the total pledges made by the crowd at time t, considered to be a random variable with a known (or estimated) distribution $F_x(m) = P(x \leq m)$, with mean value μ. $x(t)$ is not evenly distributed between active projects as these latter may differ in their attractiveness. We model this attractiveness by a parameter $\alpha_k > 0$ for project k, equal to the fraction of the general investors it attracts when active. Following this model, the investment in project k increases at time $t < T_k$ by the amount:

$$X_k(t) - X_k(t-1) = x_k(t)$$

where $x_k(t) = \frac{\alpha_k}{\sum_{j=N(t)}^{K} \alpha_j} x(t)$ is a random variable that follows the same probability law as $x(t)$), but with modified moments.

The above defined model captures the heterogeneity of project characteristics by the attractiveness parameter α_k. Modeling this heterogeneity by some controllable parameter is common to papers on fundraising dynamics description. For instance, Lin et al. (2018) used a competitiveness variable that is drawn randomly before the campaign start and then updated while observing fundraising evolution. When neglecting heterogeneity of projects (i.e. considering common α), the model reduces to a fair sharing of funds between projects, allowing the modeling of advanced strategies of entrepreneurs in managing their expected funds (see, e.g., Chaddad et al., 2025). Our objective being to model the ability of the CFP to channel funds between projects, we adopt a model with different attractiveness (competitiveness) among projects. We first consider that this attractiveness is known to the platform, based on project characteristics. We will then show how these α_k's can be updated during the fundraising (section 4.5).

3.2. Platform utility

While the platform is considered as neutral in this section, it has nevertheless a utility defined as follows.

3.2.1. *Profit-only*

As a classical financial intermediate, the utility of the CFP is proportional to the money raised by successful projects, as a percentage of this amount is paid back to the platform as a commission:

$$U = E\left[\sum_{k=1}^{K} X_k(T_k)\mathbf{1}_{X_k(T_k)\geq m_k}\right] \tag{1}$$

$\mathbf{1}_C$ denotes the indicator function which takes the value 1 if condition C is verified and 0 otherwise.

3.2.2. *Number of funded projects*

As a variation, the number of projects funded on the platform may be considered as the utility, as a larger number of funded projects may increase the attractiveness of the platform for future projects:

$$U = E\left[\sum_{k=1}^{K} \mathbf{1}_{X_k(T_k)\geq m_k}\right] \tag{2}$$

3.2.3. *Social and environmental impact*

The CFP manager may have a preference towards projects that he/she has identified as having a positive impact from environmental or societal perspectives. This preference is expressed by some bias $\beta \geq 1$ introduced in the utility functions (1) or (2). We introduce two classes of projects: the "regular" projects class with $\beta_k = 1$, and the preferred projects class with $\beta_k = \beta \geq 1$.

This preference could be introduced in both utility functions, as the CFP manager could be interested jointly in its impact and profit, or in its impact and the number of accepted projects. We thus define modified versions of (1) or (2), as follows:

$$U = E\left[\sum_{k=1}^{K} \beta_k X_k(T_k)\mathbf{1}_{X_k(T_k)\geq m_k}\right] \tag{3}$$

when the platform is interested in the amount of collected money, and

$$U = E\left[\sum_{k=1}^{K} \beta_k \mathbf{1}_{X_k(T_k)\geq m_k}\right] \tag{4}$$

when the platform is interested in the number of successful projects.

3.2.4. *Interpretation of the utility function design*

The utility functions of equations (1) and (2) are easily understood as the amount of collected funds and the number of funded projects, respectively. When the impact is taken into consideration, the design of the utility function needs further investigation. Both utility functions of equations (3) and (4) can be interpreted as weighting sums of utilities obtained from individual projects (β_k being the weight for project *k*). Such aggregated utility can be viewed as a Multi-Attribute Utility (MAU) function (Keeney and Raiffa, 1976), the individual project outcome ($\mathbf{1}_{X_k(T_k)\geq m_k}$ or $X_k(T_k)\mathbf{1}_{X_k(T_k)\geq m_k}$) being the single-attribute utility function over attribute (project) *k*.

We now move to the interpretation of the weights β_k; they reflect how the platform values a project with impact compared to a classical one, and their choice is up to the CFP. However, they do not have the same meaning in equations (3) and (4):

-In equation (4), a project with impact is simply β times more important for the CFP than other projects.

-In equation (3), the platform values 1 dollar invested in a project with impact as β>1 dollars invested in non-impact projects. In this context, the methodology of Social Return on Investment (SROI) could be employed for evaluating a per project β_k (Fujiwara, 2015), provided that the CFP has sufficient evaluation information. However, detailed SROI analysis may be difficult to perform, and a common β could be estimated based on the analysis of the social outcomes of previous projects funded on the platform.

In order to illustrate the importance of the utility function design, we present a simple example with 2 projects with the following targets $(m_1, m_2) = (30{,}30)$ (in K$) and impacts $(\beta_1, \beta_2) = (1.5{,}1.2)$ (in $ of impact for each invested $). We consider a theoretical setting where the platform can completely control the money flow towards the projects, by setting the proportion of funds for project 1, say p_1. We suppose that the total amount of funds to distribute between the two projects is equal to F=100 K$ (high) or 40 K$ (low). We plot in Figures 1-a and 1-c the amounts of collected funds by the two projects, for the high and low funding cases, respectively, depending on the platform policy (p_1). In the low funding case, the optimal solution is to channel all funds towards one of the projects, interchangeably for the pure monetary case, and privileging project 1 for the impact maximization case (Figure 1-d). In the high funding case, the same optimal values are observed (the extreme values p_1=1 for both utilities and p_1=0 for a pure monetary utility), but the intermediate region ($p_1 \in [0.3{,}0.7]$) is also interesting.

It is worth noting that the platform cannot completely control the money flow, as it depends on the project attractiveness and the funder's behavior. We will show in the next section how it can influence it using its promotion strategy. The extreme region for utility maximization, e.g. p_1=1 in Figure 1-b, cannot be reached, but the platform can use its influence to maximize its utility within the intermediate region ($p_1 \in [0.3{,}0.7]$), by channeling more money towards the project with impact, thus increasing the red dashed curve, without reducing its monetary utility (the blue curve).

> ***Managerial takeaways:*** The CFP, in its classical role as a neutral facilitator, does not actively intervene in the fundraising process. However, the outcome of this latter determines its utility, naturally linked to its profit, but also to the social and environmental impact of the funded projects. This impact can be estimated using an SROI analysis and integrated using a Multi-Attribute Utility (MAU) function.

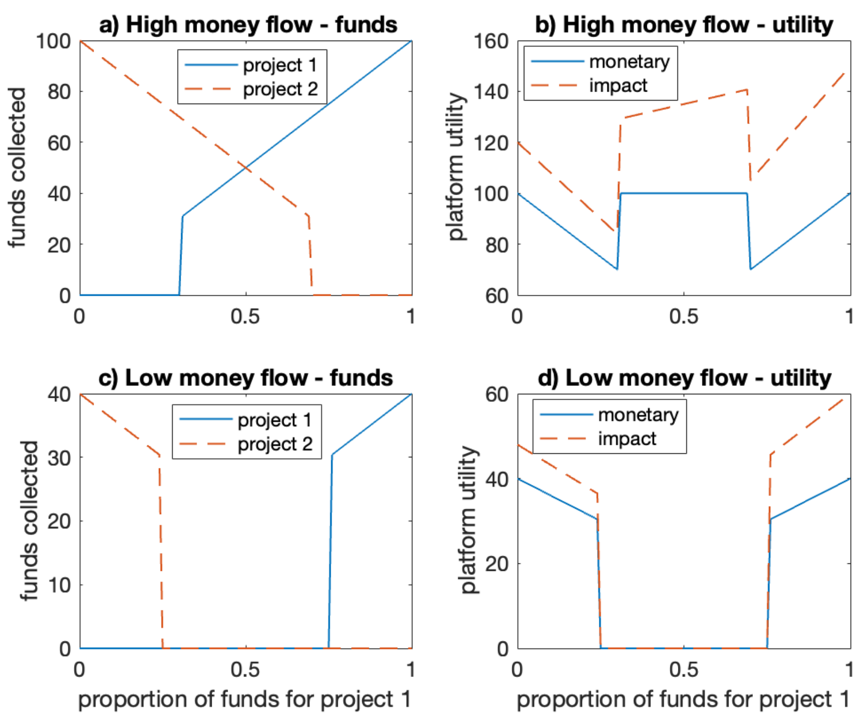

Figure 1. Example of the Impact of the Utility Function.

4. Platform as an active intermediate

The above-defined fund-collection model does not depend on the platform's actions. However, when a platform promotes a project, it is expected that it collects more funds. We formalize hereafter hypotheses about the impact of the platform's actions before integrating them into the fund collection model.

4.1. Working assumptions

We first formulate working assumptions that we will use for developing our mathematical framework. These assumptions are backed by empirical evidence, as will be shown in section 5.

Assumption 1 (qualitative). *There is a positive correlation between the success of a funding campaign and its presence in the platform's recommended set.*

We will show in section 5.1 that empirical evidence validates Assumption 1. Mollick (2014) already observed this positive correlation.

Assumption 2 (quantitative). When *the platform is recommending a project, the amount of collected funds per unit time is multiplied by a constant G > 1 compared to its collected funds per unit time when it is not promoted.*

Assumption 2 will be also investigated empirically in section 5.1, where we derive a typical value of G for the kickstarter platform. It is worth noting that the increase of the amount of collected funds for a staff picked project has been observed in the literature (Hou et al., 2025).

4.2. Fund collection model including the promotion strategy

As stated in assumption 1, the CF platform cannot be regarded as passive in the process of fundraising, as its choice of recommending some of the projects has a significant influence on the success chances.

Following assumption 2, we consider that, if the platform highlights a certain project at time t, it will attract a larger investment. We use $\gamma(t) \in \{1, G\}^{K-N(t)+1}$ to denote the impact of the recommendation of the platform (promotion decision) at time t, $K - N(t) + 1$ being the number of remaining projects. If a project k is promoted by the platform at time t, then $\gamma_k(t) = G$; it is equal to 1 otherwise.

We denote by $\mathcal{P}$ the policy followed by the platform, that is a collection of promotion decisions at times $t \in [1, T_K]$ resulting in promotion gains $\gamma(t, \mathcal{P})$. For any $t \leq T_k$, the expected investment in project k under policy $\mathcal{P}$ is then:

$$E[x_k(t,\mathcal{P}) = X_k(t,\mathcal{P}) - X_k(t-1,\mathcal{P})] = \frac{\alpha_k \gamma_k(t,\mathcal{P})}{\sum_{j=N(t)}^{K} \alpha_j \gamma_j(t,\mathcal{P})} \mu. \tag{5}$$

4.3. Optimization problem formulation

Given $X_k(0), k \in [1, K]$, the CFP seeks the promotion strategy $\mathcal{P}$ that maximizes its utility $U(\mathcal{P})$:

$$\mathcal{P}^* = \arg\max_{\mathcal{P}} U(\mathcal{P}) \tag{6}$$

The definition of the utility function depends on the objective of the platform discussed above:

$$U(\mathcal{P}) = \begin{cases} E\left[\sum_{k=1}^{K} \beta_k X_k(T_k,\mathcal{P}) \mathbf{1}_{X_k(T_k,\mathcal{P}) \geq m_k}\right], & \text{for a weighted profit} \\ E\left[\sum_{k=1}^{K} \beta_k \mathbf{1}_{X_k(T_k,\mathcal{P}) \geq m_k}\right], & \text{for a weighted number of funded projects} \end{cases} \tag{7}$$

The problem (6) can be solved numerically in the general setting. However, we will show in the following how to derive the optimal policy for some interesting and structured policies.

4.4. Characterizing CFP policies

4.4.1. *Offline versus online policy*

An active platform manager has different decision epochs where the promotion strategy should be decided. In particular, the policy could be continuously updated, depending on the evolution of the fund collection, or updated only at some time epochs.

Definition 1. An *offline policy* is a policy defined at some time instant, and that determines *a priori* the promotion intervals for projects for a long time period *T*.

Definition 2. An *online policy* is updated dynamically as time goes on, exploiting the observed amount of pledges collected by each project.

These policies play different roles. The former are helpful for understanding the potential of the available projects at a given time, while the latter are more suitable for dynamically updating the marketing strategy based on observed campaign outcomes and funds collected in real-time.

4.4.2. *Structured policies*

The set of possible policies is very large, as any collection of decisions at different times constitutes a policy. We then consider a subset of policies with simple structures that provide valuable insights.

Definition 3. A *sequential policy* is a policy that promotes each project for a unique compact interval of time. Such a sequential policy has the advantage of a low switching frequency between promoting actions.

Lemma 1. *If there is an optimal offline strategy, at least one sequential offline strategy is optimal.*

Proof. For any given strategy, we can find a sequential strategy that induces the same amount of money for each project and highlights each project on a compact set of lengths equal to the sum of lengths of the highlighting periods of the original strategy. This is true because the amount of collected funds is Markovian. This policy minimizes the number of switching times.

□

Definition 4. A *One-at-Time (OAT)* policy is a policy where a unique project is promoted at a given time.

While such an OAT policy may be sub-optimal, it is of practical interest as it is suitable for a simple platform design and for maximizing the visibility of the selected project. Note that this does not mean that the platform highlights a unique project on its main page but a unique project per category.

A sequential OAT policy can be denoted by a vector of switching times $\boldsymbol{\tau}=(\tau_2,...,\tau_K)$, where $\tau_{k+1} \leq T_k$ is the time at which the platform switches from recommending project k to recommending project $k+1$. Project k is promoted on the interval $[\tau_{k-1}, \tau_k]$, $\tau_k \in [0, T_k]$, and if $\tau_k = \tau_{k+1}$, project k is never promoted.

4.5. Optimal policy derivation

4.5.1. Framework overview

The objective of the optimization framework is to solve problem (6) that selects the subset of projects whose recommendation maximizes the utility of the platform, as defined in equations (1), (2), (3) or (4). This framework should take as input the list of candidate projects and, for each project, its attractivity and its classification as a project with impact or no. These parameters are estimated as follows:

For the attractivity α_k, it can be estimated ex-ante based on the characteristics of the project and similar projects previously proposed by the CFP. This estimation can be updated ex-post by observing the first days of the campaign, as will be detailed later.

For the impact prediction, it is always performed ex-ante, as the real impact should be revealed once the project is funded and implemented. The classification should then be based on the project description, the self-declaration of founders and possibly by the help of certification bodies (Yu and Xiao, 2023).

Based on these parameters, the pre-optimized policy outputs the set of projects to recommend with a corresponding time schedule. We differentiate between two approaches:

The "offline" approach, where the decision is taken periodically, and the policy is applied during a period of length *T*. In this context, the attractiveness is predicted at time 0 and is not updated during the time interval *[0,T]*. The utility of the CFP for the different policies (equation (7)), estimated at time 0, and then apply the policy that maximizes it during the whole time interval $[0, T_k]$. The optimization problem becomes:

$$\boldsymbol{\tau}^* = \arg\max_{\boldsymbol{\tau}} U(\boldsymbol{\tau}|\boldsymbol{X}(0)) \tag{8}$$

where the utility $U(\boldsymbol{\tau}|\boldsymbol{X}(0))$ is computed at time 0, as in equation (7). We show in Appendix B how to compute this expected utility and derive the maximum for some example money flow distributions. The "online" approach, where the decision is updated continuously, observing the amount of funds collected by the projects. This online approach is detailed next. In this case, the attractiveness can be continuously updated and fed back to the optimization framework, as will be shown in section 4.5.3.

4.5.2. Real options formulation of the online problem

The above-described offline derivation helps the platform manager to understand the impact of the platform strategy on its portfolio of projects. However, offline optimization is not the most suitable policy as the manager may have the opportunity to adjust its policy online in case of an unexpected evolution of the funding campaign of a project.

We model this opportunity as a real option, as it has the following characteristics:

- Irreversibility: Once the manager decides to switch from promoting project k to project $k + 1$, its decision is partially irreversible as the project has to be recommended at least for a significant interval. In the case of a sequential policy, this decision is entirely irreversible (the future opportunities for promoting project k are lost).
- Uncertainty: The uncertainty here is included in the future evolution of collected funds over time. This uncertainty is resolved with time, and the manager's decision can be made contingent upon the resolution of the uncertainty, creating the option.
- Flexibility: This means that depending on new information, the manager can change its decision where the decision is contingent on an event. In our case, the manager has complete or partial flexibility, depending on the structure of the strategy (OAT or completely dynamic, respectively).

To derive the optimal decision for the general case, we adopt a dynamic programming approach. This method breaks a whole sequence of decisions into two components: the immediate decision and a valuation function that encapsulates the consequence of all subsequent decisions (the continuation value). The platform manager can stop promoting project k and switch to project $j > k$, thus lowering the future amount of collected funds for project k and increasing that of project j (following assumption 2). Otherwise, he/she may wait one period and then decide whether to switch or wait another period before making the same decision. This process will depend on the levels of collected funds at each period. We show in Appendix A how dynamic programming can be applied in practice. Appendix B then shows how to solve the problem for some typical money flow distributions, considering the Poisson case as a representative for discrete distributions, as in Shao et al. (2023), and the Gaussian case as a representative for continuous distributions, as in Salahaldin et al. (2022).

4.5.3. Rollout policy

The policy based on dynamic programming, while optimal, may suffer from scalability issues for a large number of concurrent projects K (the total number of states being exponential in K). Therefore, in this section, we propose a computationally tractable method, which is a one-step look-ahead rollout policy (Bertsekas, 2021). The idea of a rollout policy is the following: instead of finding the optimal policy at each time, look for a policy that results in a better utility when compared to a baseline policy. In short, at each time τ, observe the amount of collected funds by all ongoing projects, and pick the project that yields the best expected utility if recommended just for the next time step, with the platform assumed to being neutral for the remaining time. Although this methodology can be generalized to n-step look-ahead rollout, the complexity increases exponentially, and we thus stick to the one-step look-ahead policy.

The rollout policy is an online policy and thus, at the start of the time step τ, we determine the current selection of the project to recommend. For this purpose, we denote by $\mathcal{P}^0_{\tau,k}$ the policy of recommending project k at time step τ and remaining neutral in the future. $\mathcal{P}^0_{\tau,0}$ will denote a neutral policy starting from τ. Thus,

$$\gamma_j(t, \mathcal{P}^0_\tau) = 1, \forall j \in \{N(t), \ldots, K\}, \forall t \geq \tau$$

where $N(t)$ is the next closing project at time t and:

$$\gamma_j\left(t, \mathcal{P}^0_{\tau,k}\right) = \begin{cases} G & \text{if } t = \tau \text{ and } j = k \\ 1 & \text{Otherwise} \end{cases}$$

The expected utility at t, $U\left(\mathcal{P}^0_{t,k} \mid \boldsymbol{X}(t)\right)$, is computed as for the offline case of 4.5.1 but starting from t instead of 0. Next, we select project:

$$k^*(\tau) = \arg\max\left\{U\left(\mathcal{P}^0_{\tau,k} \middle| X(\tau)\right)\right\} \tag{9}$$

Note that this policy is an OAT policy but is not sequential (see definitions 1 and 3), as only one project is highlighted at some time, but we can switch back and forth between projects (or no project recommended) at different times.

4.5.4. *Online estimation of the* attractiveness

In the previous subsection, we proposed a rollout policy to determine which project should be recommended by the platform when all the parameters of the system including the α_k's are known. However, in practice, the attractiveness of new projects that start their campaign may not be known. In this case, we can initialize for each project k started at t^0_k a counter $R_k(t^0_k) = 1$. Whenever project k receives funding $\Delta_k(t)$ at time step $t > t^0_k$, we update:

$$R_k(t + 1) = R_k(t) + \frac{\Delta_k(t)}{\gamma_k(t)} \tag{10}$$

where $\gamma_k(t)$ is the strategy adopted at time t. Then, we can estimate at any time t the attractiveness:

$$\hat{\alpha}_k(t) = \frac{R_k(t)}{\sum_i R_i(t)} \tag{11}$$

Therefore, we start with an uniform estimate of α and then update this estimate according to the funds received during the campaign. For large t, $\hat{\alpha}_k(t)$ converges to the real α_k. In simulations (section 5.5), we observe that even with this simple online estimation, the rollout policy using online attractiveness estimation performs quite well.

4.6. Summary of the methodology

To summarize our proposed hybrid/modeling methodology, the CFP exploits its available data for devising a project promotion strategy that implicitly manages the money flow between campaigns. Figure 2 illustrates this process, described as follows:

1. Pre-campaign screening of projects for evaluating their potential impact (estimation of β_k) and their attractiveness (estimation of α_k),
2. Continuous assessment of the state of the platform for computing general parameters such as the number of active projects (per category) and their goals/maturity dates.
3. Continuous monitoring of the fundraising process and update of the attractiveness, as indicated in section 4.5.4 (using the amount of collected funds and computing the R_k's in equation (10) and then applying equation (11)).
4. Formulation of the utility function based on the pursued objective of the platform, combining the above-described parameters. This utility function is periodically updated.
5. Resolution of the utility optimization problem for deriving the optimal promotion policy, as shown in section 4.5.
6. The frequency for updating the optimal policy depends on the adopted timescale. In the "offline" case, parameter and policy updates are performed at the beginning of a period of size T, and the promotion intervals are scheduled for the next period. In the "online" case, continuous monitoring of the fund-raising process allows adapting the promotion decision, using a dynamic programming approach or a heuristic rollout policy.

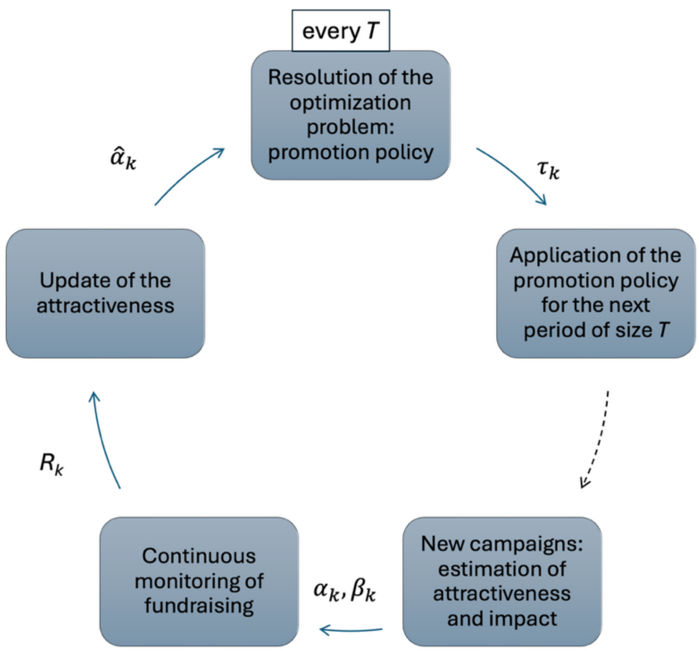

Figure 2. Illustration of the Optimization Process for the Offline Case. The Online Process is Similar, but with a Continuously Updated Policy.

Managerial takeaways: By optimizing its promotion strategy, the CFP can maximize its utility by a channeling of the money flow towards some targeted projects, increasing their success probability. The promotion policy can be modeled as a real option and optimized using a dynamic programming approach or a simple rollout

5. Numerical analysis

We now evaluate the effectiveness of the optimization framework. However, in order to have realistic evaluation, we start by an empirical study that verifies the hypotheses on which the model relies and that extracts important parameters to be used in the optimization examples. The objective of this section is to verify empirically the assumptions of section 4 and estimate the parameter G that will be used in the numerical applications.

5.1. Empirical study

5.1.1. *Dataset description*

The empirical analysis is based on an extracted database of projects from the Kickstarter platform, using a web crawler. We obtained a list of 170428 projects with the following information:

- Category of the project: 12 categories and 126 sub-categories are present. Example of category is “technology” and of sub-category is “Software”.
- Campaign design: this includes the campaign starting and closing dates, and the target funding.
- Funding information: this includes the amount of collected funds, the number of backers and, for closed campaigns, the success information.
- Social network information: This includes the website of the project (if it exists)
- The Kickstarter recommendation: Whether the project is in the **staff pick** or not. This parameter classifies the projects into two categories: those in the staff pick, that are recommended by the platform and highlighted in the first pages of the category, and the others.

In this database, the percentage of successful campaigns (those who attained their target funding) equals 53.91%, and the staff selected 12.8% of the projects. Among these projects, 3387 (2%) were still active at the extraction date. The Key variables of interest in the dataset are:

- Project goal (in $): The amount of money founders seeks to raise using crowdfunding. Kickstarter follows an “all or nothing” or threshold model, so funders’ pledge money is only collected if the goal is reached.
- Funded (in $): money actually raised by founders.
- Backers: The number of funders supporting the project.
- Pledge/Backer (in $): The individual pledges of backers are not known, but this variable is the amount of money raised divided by the number of backers, or the mean pledge per backer.
- Funding level (%): The percentage of a project’s goal that is actually raised by founders. Projects that raise their goal are considered successful, and they receive the total amount pledged to them by bakers. We can observe that, for most of the categories, the average funding level is larger than 100%, as this percentage is biased by some largely over-funded projects.

5.1.2. *Verification of assumption 1*

We first note that, for the 12.8% of the projects that are "staff picked", the success rate is as high as 88.7%, while the remaining projects success rate is only 51.1%. This shows that if you are lucky enough to be selected by the staff, this will greatly increase your success rate.

We now perform a correlation analysis to study the impact of the platform promotion strategy on project success. As some of the variables are Boolean and others real or integer, we applied different methods as follows:

- The Kendall’s correlation coefficient is used between the “success” and “staff pick” indicators and the other parameters.
- The Pearson’s coefficient is used otherwise.

As expected, there is a positive correlation between the number of backers, the pledge per backer, the percentage of collected funds, and the success. Table 2 also validates the findings of the literature about the negative correlation between the project goal and the success, as a highly demanding project has less chance to be funded by reward-based crowdfunding (Belleflamme et al., 2014; Negrao and Brito, 2021). The result that is of interest for the current paper is that there is a positive correlation between a project being in the staff pick (recommended by the CFP) and its success. This result validates assumption 1 and is consistent with the literature identifying staff pick as an important success factor with a significant positive correlation with success rate (Kunz et al. 2017, Buttice et al. 2017, Song et al. 2020).

5.1.3. *Estimation of the promotion gain in assumption 2*

We now move to the quantitative assumption 2. We compute the expected increase in the project attractiveness when it is in the recommended set. We measure the relative amount of collected funds for “staff pick” projects compared to the rest of the projects as follows:

1. Project subset selection: knowing that the estimation is based on comparing the collected funds, the database should be decomposed into subsets of comparable projects concerning the objective of fund collection. We thus construct subsets of projects with similar goals and perform a per subset parameter estimation. Let M be the number of subsets and K_m be the number of projects in subset $m \in [1, M]$.

2. Estimation of the promotion gain: Each subset of projects (characterized by comparable goals) is divided into two classes, depending on whether the project is recommended by Kickstarter or not. We compute the average amount of collected funds per project for the staff pick class, and the average amount of collected funds in the rest of the projects of the subset. Let g_m be the ratio between them for subset *m*.
3. We compute the average gain of being in the staff pick as the average gain obtained in the different subsets, weighted by the number of staff pick projects in each subset:

$$G = \frac{\sum_{m=1}^{M} K_m g_m}{\sum_{m=1}^{M} K_m} \tag{12}$$

In our dataset, we have $M = 5$ subsets, and we obtain an average gain of 45% (G = 1.45).

Note that the current promotion strategy of Kickstarter is static, in the sense that once a project is within the staff pick, it remains in it. Assumption 2 cannot thus be verified completely with our dataset, as it relates to dynamic policies where a project can be promoted on a sub-interval of its campaign time. We nevertheless use the gain *G* that we obtain on the overall collected pledges as a proxy for the gain obtained at any interval of time. A complete empirical analysis of the impact of the staff pick on the fund collection is out of the scope of this paper. Nevertheless, a recent study by Hou et al. (2025) proposed a detailed analysis of the daily funding rate dependence on the staff pick. Using a synthetic control method, it compared targeted projects with control projects that exhibit similar parameters and similar funding trajectories prior to being staff picked. The results exhibit a significant gain on the daily fund collection rate, even in the dynamic case where the list of staff picked projects varies with time, which is consistent with our assumption 2.

Table 2. Correlation Analysis between Project Parameters and Success.

Parameter	**Correlation with success**
Number of backers	0.627
Amount of collected funds	0.598
Funding goal	-0.184
Staff pick	0.265

The first two lines give intuitive results as larger “number of backers” and “amount of collected funds” at the mean a higher success rate. The third row reproduces a known result that states that a larger funding goal reduces the chance of success, and the last row confirms our hypothesis about a positive correlation between the project being in the “staff pick” and the success.

5.2. Offline optimization

We start by applying the offline optimization strategy.

5.2.1. *Optimal policy illustration*

For the first numerical applications, we consider the case where the objective of the CFP manager is to maximize the number of successful projects (utility given by equation (2)). We consider the parameters of projects given in Table 3 but with $\beta=1$ (there is no preference towards a project as we start by neglecting the social and environmental impact). We also start with the case of two projects, namely projects 1 and 2. As of the platform, we

consider that the amount of collected funds at any time is Poisson with parameter μ. If the platform promotes a project, its attractiveness increases by 45% (G = 1.45), as indicated by the empirical analysis of section 5.1.

We start by the objective of maximizing the number of successful projects. We illustrate in Figure 3 the success probabilities when the switching time τ increases from 0 to T_1, for $\mu = 3.5$. Increasing τ increases the chance of success of project 1 but decreases that of project 2; there is an optimal timing $\tau^* = 12$ in this case. The sum utility is concave as the target collected funds $M_k - x_{k0}$, equal to 29 and 25 for projects 1 and 2, respectively, are smaller than the $\min(\alpha_k)\mu$, equal to 30.5 and 31, respectively (see lemma 3 in the appendix).

Table 3. Project Parameters

Project	**1**	**2**	**3**
Initial x_{k0}	1	5	0
Target m_k	30	30	40
Attractiveness α_k	1	0.5	0.5
Closing time T_k	15	20	25
Preference β_k	1	β	1

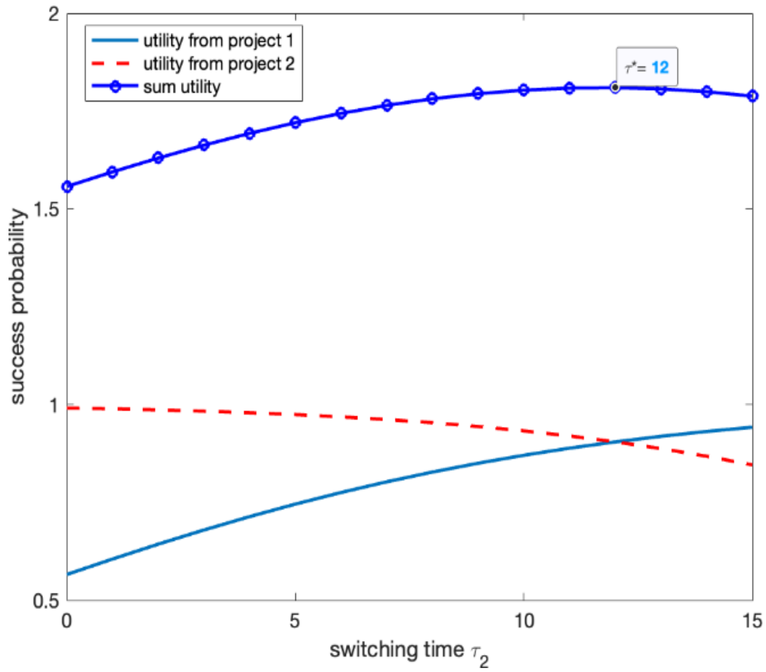

Figure 3. Individual and Sum Success Rates for Different Strategies. Optimal Policy is Indicated.

In order to further illustrate the utility function behavior, we plot in Figure 4 two sets of objective functions (profit or number of successful projects), for two different regimes, as follows:

- Figure 4-a corresponds to the sum success rate, in a regime with high expected outcome (large μ),
- Figure 4-b corresponds to the profit, for the same regime (large μ)
- Figures 4-c and 4-d correspond to utilities in a regime with lower expected outcome (μ = 2, leading to a non-concave utility function as $\max(\alpha_k(\tau_2)\mu) < M_k - x_{k0}$

In the high outcome regime, the optimal timing achieves the balance between projects 1 and 2 and is different depending on the target utility. However, in the low outcome regime, the best policy is to never promote project 1, channeling a largest money flow to project 2 and hoping that it will succeed.

Figure 4 also compares an active platform with a neutral one that does not employ a promotion strategy with the aim to maximize its utility. This corresponds to a random promotion strategy that, by switching randomly from one project to another, does not significantly change the overall flow of money. We observe that, in all scenarios, the active platform can increase its utility.

We now investigate the impact of funders' preferences (translated by the project attractiveness α_k) on the utility.

We consider the same parameters of Figure 4, but with μ = 4, and compare the outcome of the campaign when inter-changing the attractiveness of the projects. We illustrate in Figure 5 the two attractiveness scenarios, and compare the overall success probability for three settings in each scenario, as follows:

- The platform is active (maximizes the overall success rate) and the funders have their own preferences (biased towards the project with a larger attractiveness).
- The platform is neutral (follows the wisdom of the crowd), and the crowd is biased towards a project.
- The platform is neutral, and the funders select randomly the project to fund (α1 = α2 = 1, for a hypothetical setting where the crowd is unbiased).

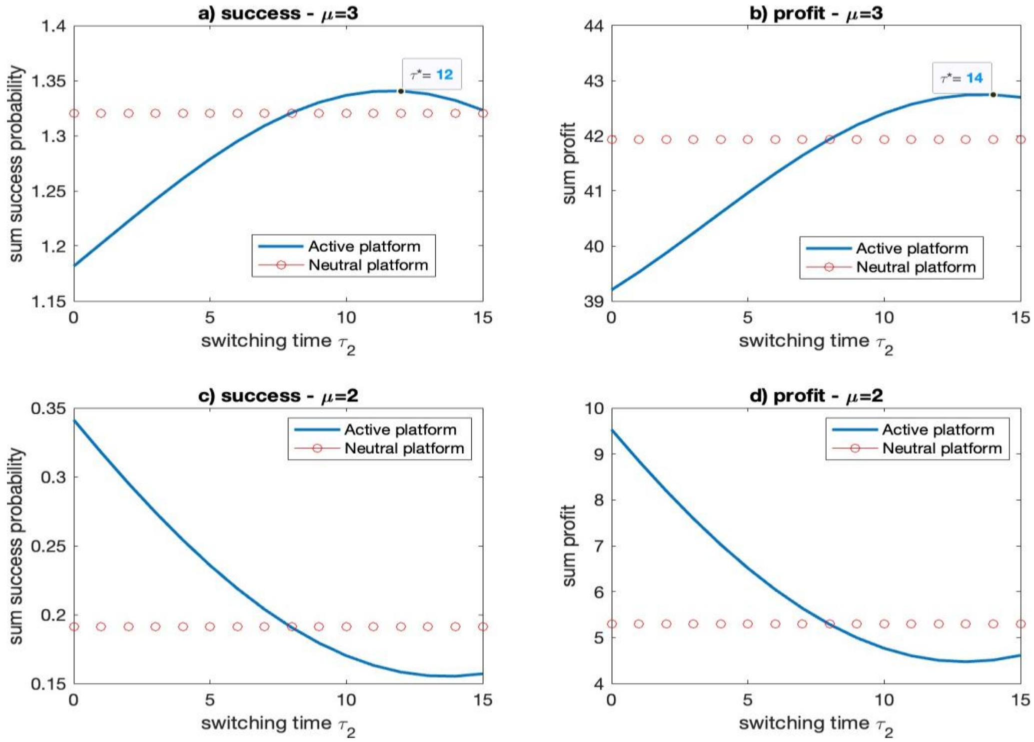

Figure 4. Studying the Different Regimes.

The results show that following the wisdom of the crowd is beneficial in some scenarios (Figure 5-a, where the overall success is increased with respect to the case with random funder selection), but reduces the overall success in other situations (Figure 5-b). An active attitude of the platform can be seen in this latter case as a way for the platform to balance the bias of the crowd, even if this does not completely compensate it.

Before closing this analysis on the utility function, we illustrate in figure 6 the expected monetary outcome and the expected success rate for a particular setting of two projects that have very different attractiveness ((m1, m2) = (30, 30), (α1, α2) = (0.2, 0.8), (T1, T2) = (15, 20), and μ = 5). As the first project has a low chance to succeed, in order to maximize the expected profit (the collected fee), it is better to focus on the second project (τ2∗ = 0). However, the second project will almost always succeed so it's better for the overall success rate if the first is promoted. The two sets of utilities of the platform in equations (1) and (2) may thus lead to contradictory strategies.

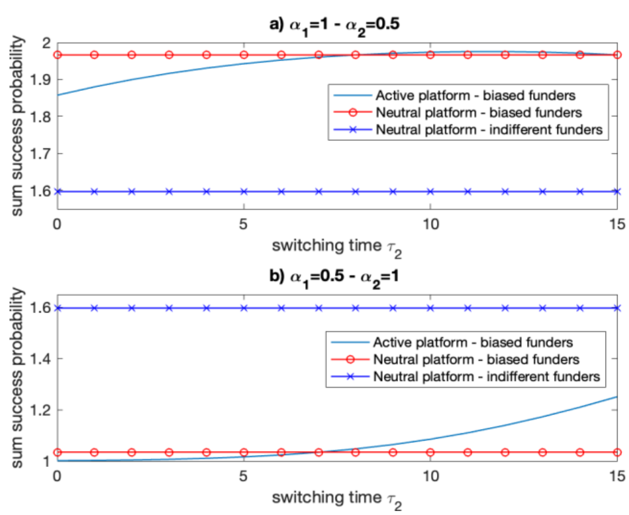

Figure 5. Impact of Funders' Preferences.

5.2.2. *Considering social and environmental impact in the utility*

We have illustrated above the promotion strategy of the platform as a way for enhancing its utility, and for balancing the preferences of the Crowd. We now include the "impact dimension", and consider a platform interested in enhancing its social and environmental impact, by setting a β that is larger to 1 to a subset of projects. Here project 2 is classified among the high impact projects. We also consider for illustration purposes a Gaussian money flow with $\mu = 3$ and $\sigma = 0.5$.

We plot in figure 7 the optimal switching time from promoting project 1 to promoting project 2, for different values of β and for the two types of utilities (profit or success rate). We observe that, for a larger β, the policy switches earlier to the higher project impact, to ensure that it is successful.

We now turn to the joint impact of β and G on the policy. We plot in figure 8 the optimal switching time to project 2 for different impact levels of project 2 ($\beta=1$ (no identified impact), $\beta=1.2$ and $\beta=1.5$), when the promotion gain G increases (the latter being considered till now as constant and equal to 1.45 based on the empirical analysis). Figure 8 shows that, when the expected promotion gain G increases, the switching date is delayed as a smaller promotion period will allow reaching the goal. On the other hand, a larger impact of project 2 incites the platform to promote it earlier in order to ensure its success.

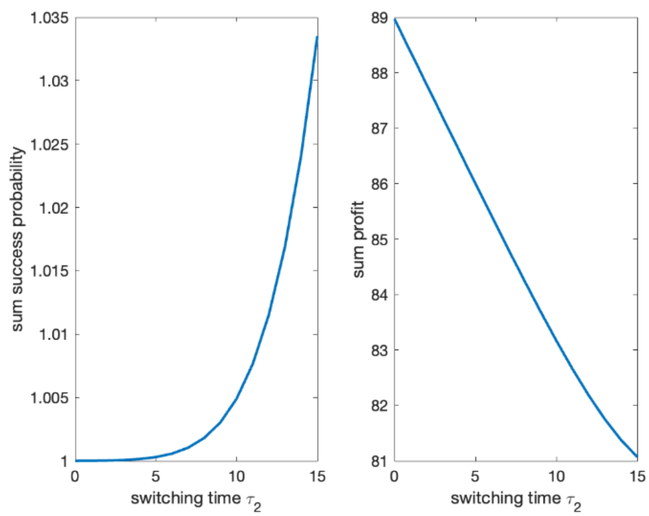

Figure 6. Optimal Switching Time for Two Sets of Utilities: Financial Outcome versus Number of Funded Projects.

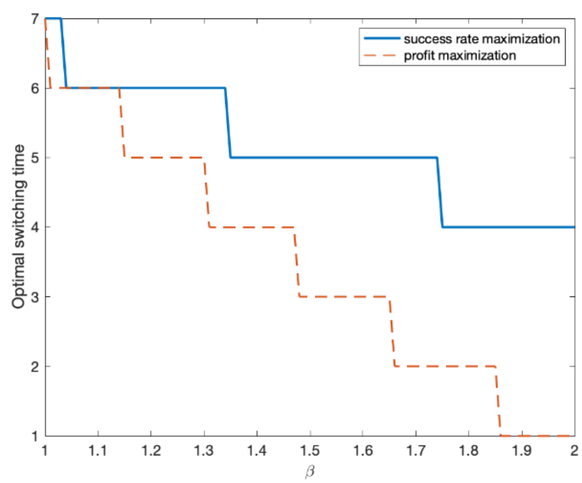

Figure 7. Optimal Switching Time for Different Utility Functions.

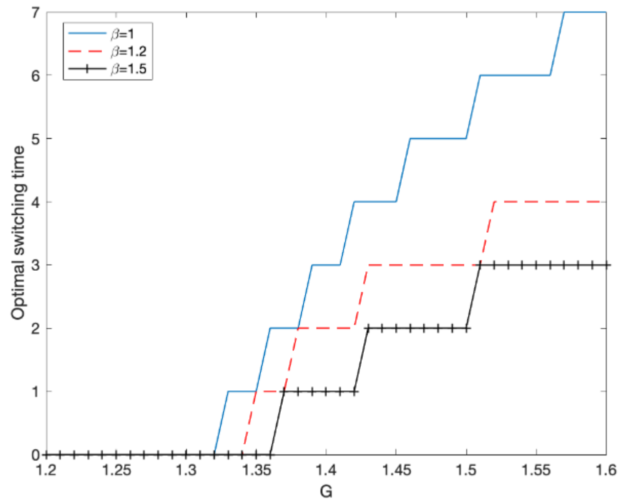

Figure 8. Impact of G and β on the Optimal Policy.

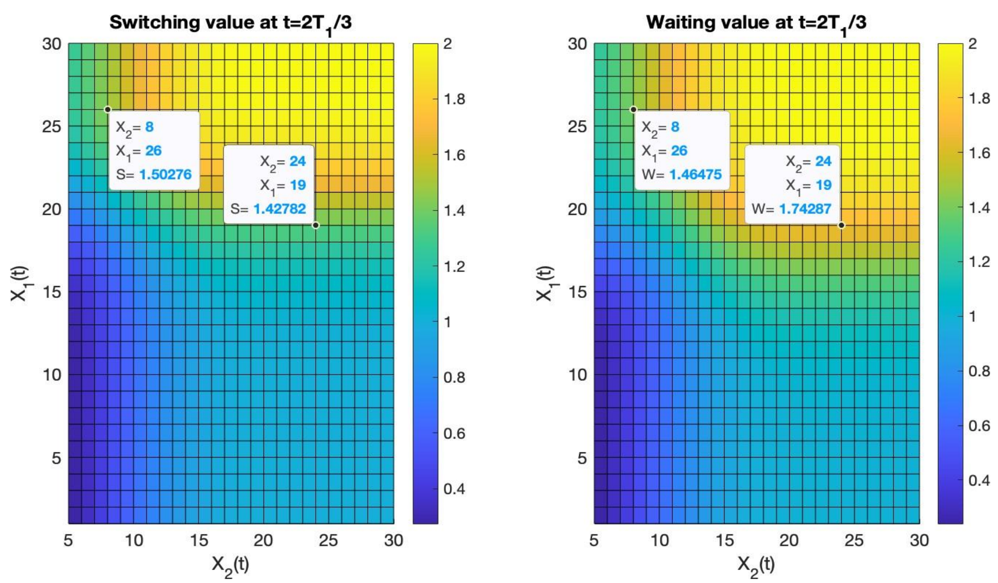

Figure 9. Values of the two Strategies at a Given Time Depending on the State of the Platform.

5.2.3. *Online dynamic programming*

In order to illustrate the online policy, we implement the dynamic programming approach for the two projects case with the parameters of table 3. As the decision of the manager depends on the observed state, we illustrate in Figure 9 the values of the two different policies of the platform manager, estimated at a given time ($t = 2T_1/3$) depending on the amounts of already collected funds by the two projects. If the value of waiting is higher than the switching value, the decision is to maintain the current policy until the following period. We observe that, for the same $X_1(t)$, the value of switching decreases when $X_2(t)$ increases, making "waiting" a better decision. When both projects have collected a large amount of funds, both strategies have the same value, as they are likely to succeed. We also illustrate in Figure 9 the values of switching and waiting for two states of the system and show that for a relatively low amount of funds collected by project 2 ($X_1 = 26$, $X_2 = 8$), "switching" is better, while in the opposite case, e.g. ($X_1 = 19$, $X_2 = 24$), waiting while promoting project 1 is better.

While the manager implements a dynamic online policy, the decisions may be predicted at time 0, based on the estimation of the future state evolution. We plot in Figure 10 the evolution of the state probabilities with time. Figure 10 illustrates the decision of the manager, as the probability of switching to project 2 when time goes on. This probability increases with time. We also illustrate in Figure 11 the impact of the initially collected funds. A lower amount of initial funding for project 2 leads to an earlier switching to increase the overall success rate.

We now compare the outcome of an offline policy, i.e. when the platform decides the promotion strategy at some time and keeps it unchanged for the next period of time, with the online policy where the decision is updated with time. Figure 12 shows the overall success probability for the two methods, showing a better performance for the online policy (obtained using the dynamic programming algorithm). Both methods outperform the case where the platform is neutral. We also plot in Figure 12 the utility obtained when using the rollout developed in section 4.5.3. As the rollout policy does not give a closed-form solution for the expected utility, we simulate the system as follows. We generate trajectories for the fund collections, and apply, at each time step, the decision defined by the rollout policy. The utility is then the average utility over the different paths. We observe that the performance of the rollout policy is very close to that of the online optimal scheme.

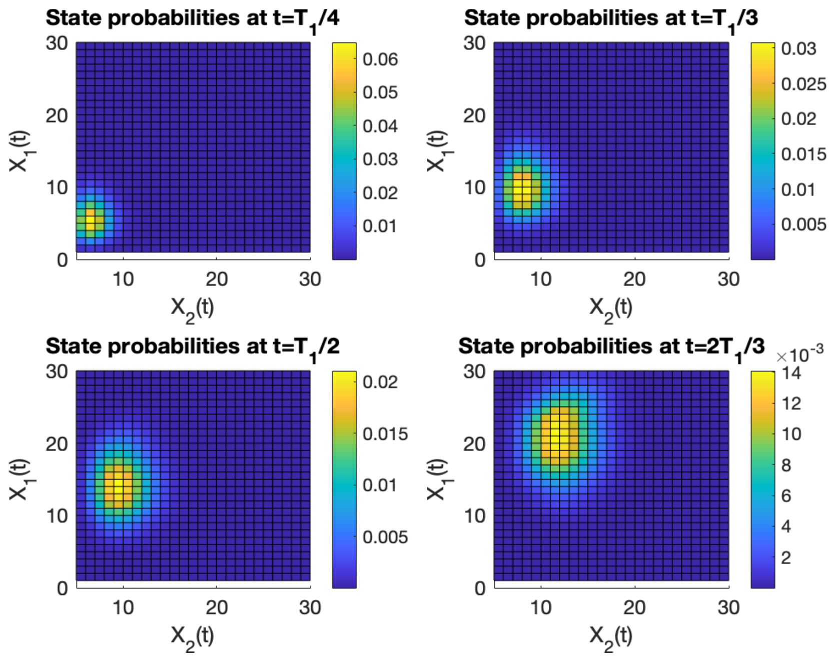

Figure 10. Evolution of State Probabilities with Time

5.2.4. *Policy scalability*

We now move to the case with more than 2 projects. In this case, we increase the overall amount of collected money to $\mu = 4$. We illustrate in Figure 13 the impact of different policies on the sum success probability for three projects whose parameters are in Table 3. There are two parameters to set, τ_2 and τ_3, and there is a clear optimal strategy that consists in choosing $\tau_2 = 8$ and $\tau_3 = 20$ for the considered parameters.

In order to show the scalability of the proposed scheme, we implement the online rollout for a platform with 4 projects with the following parameters: $m = (30, 30, 20, 60)$, $X = (1, 5, 3, 4)$, $T = (15, 20, 22, 25)$ and the attractiveness parameters $\alpha = (1, 0.5, 0.5, 2)$ (that are supposed to be known to the platform manager). The average utility of the platform is shown in Figure 14. We observe that the online scheme outperforms the neutral case. Also note that while the rollout policy itself is easily scalable with a computational complexity that is linear in the number of projects (and the computation being performed at each time step online), the evaluation of the policy is heuristic and is based on large Monte-Carlo simulations of the real-time fund collection. Therefore, we present the case of 4 projects, but many more may be considered if necessary.

Additionally, we also present in table 4 a micro-case illustrating the impact of the preference vector on the strategy of the platform. We use the same parameters that were used in Figure 7. The input parameters in the table are presented using the format $(\mu, (\beta_1, \beta_2, \beta_3, \beta_4))$, which indicate the overall amount of collected money, associated with a vector of impact indicators for the different projects. The values in each line indicate the fraction of time a certain project is promoted (on average, the sum of each line being equal to 100%).

Table 4. Impact of Preference on the Strategy of the Platform.

μ , $(\beta_1, \beta_2, \beta_3, \beta_4)$	Project 1	Project 2	Project 3	Project 4
4, (1,1,1,1)	0%	0%	78%	22%
4, (1,1,1,**2**)	0%	0%	60%	**40%**
4, (**2**,1,1,1)	**8%**	0%	76%	16%
6, (1,1,1,1)	41%	9%	50%	0%
6, (1,**2**,1,1)	50%	**17%**	33%	0%

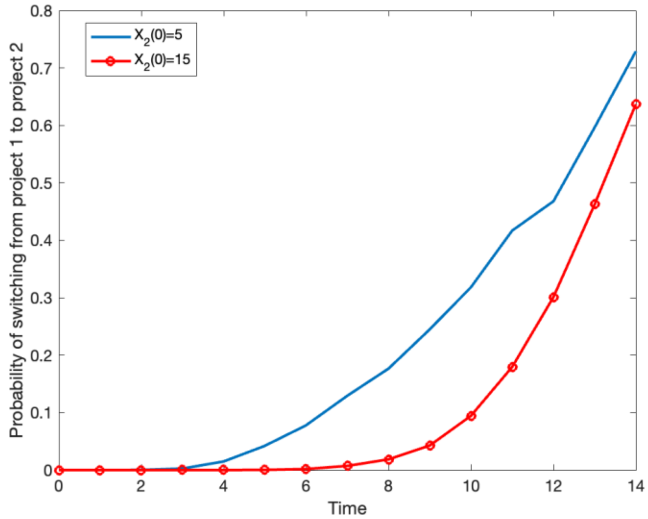

Figure 11. Probability of Switching Strategy Function of Time.

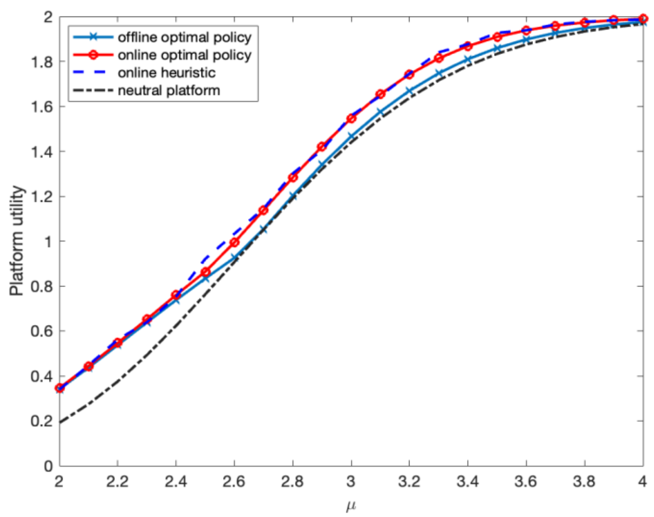

Figure 12. Comparison of the Utility for Online and Offline Policies.

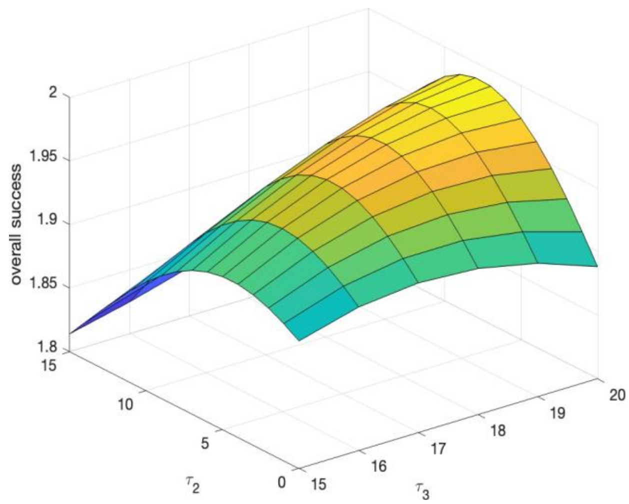

Figure 13. Success Rates for Three Projects for Different Policies.

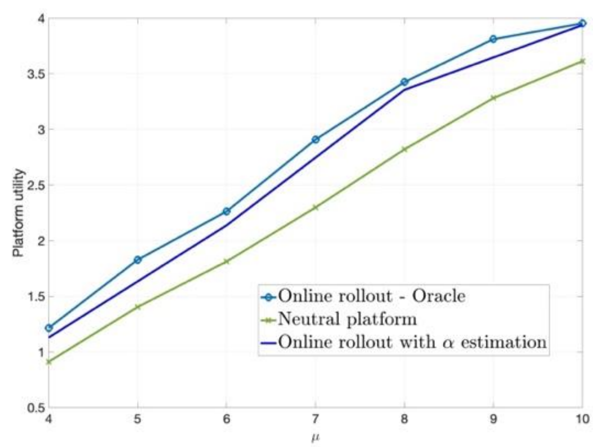

Figure 14. Platform Utility for Four Projects.

When $\mu=4$, the funds are limited and the projects 1 and 2 will almost always fail, so they are almost never selected by the platform. When project 1 has a high impact, it is promoted for some time as its contribution to the utility is large. On the other hand, when $\mu=6$, project 4 always succeeds due to its high natural attractivity and therefore is never promoted. In this case, project 2 is rarely promoted in the nominal case, but if it is preferred by the platform, it can be promoted much more often.

5.3. Online estimation of the attractiveness

We now move to the case where the attractiveness of projects is initially unknown to the platform manager, who estimates it during the campaign lifetime, following the model proposed in subsection 4.5.4. We implement the rollout policy as in 5.4 but replacing the Oracle by the online estimator that starts with a common attractiveness equal to 1 and then updates it while observing the fund collection. Figure 14 illustrates this estimation-based policy, in comparison with the rollout policy with an Oracle (already discussed in 5.4) and to the neutral case. We observe that the estimation performs well, with a slightly degraded utility with respect to the Oracle case.

6. Conclusions and discussion

6.1. Summary of fundings

In this paper, we considered the perspective of a crowdfunding platform manager whose objective is to maximize its utility by managing the money flow between the funders and the entrepreneurs. We developed an optimization framework that balances funds between projects to increase the expected utility, by signaling projects to the crowd through a targeted project promotion strategy. The utility is related to the monetary outcome of the platform, the campaign success rate, or the funded projects' impact and can be constructed using the Multi-Attribute Utility theory (Keeney and Raiffa, 1976). As the "staff pick" is a high-cost signal (Kunz et al. 2017), its usage should be carefully optimized. We then developed an online strategy where the manager observes the project status evolution and adapts its recommendation decision. We modeled this dynamic policy as a real option and developed the corresponding dynamic programming algorithm. Our results show a clear advantage of the optimization behavior compared to a neutral one. This result is in line with the recent crowdfunding literature (Xiao et al., 2025, Hou et al., 2025) that considered project recommendation as an optimization lever for increasing CF platform profitability. However, our framework goes beyond monetary profit maximization to a general utility maximization, including the social and environmental impact. CF literature has confirmed that listing projects with high sustainability orientation increases the survival chance of the platform and attracts investors (Siemroth and Hornuf, 2023, Cumming et al., 2024).

6.2. Implications for crowdfunding practice

The work of this paper is a first step towards building a decision-making framework for crowdfunding platforms. The manager of a CFP can exploit its available data and the framework presented in this paper to accompany projects during their funding campaigns as follows:

1. Based on the historical data, evaluate the impact of promoting a project on its attractiveness (estimate G), as discussed in section 5.1. The methodology of Hou et al. (2025) can be followed for estimating this gain, observing projects on their promotion periods and comparing them to similar non-staff picked projects. Platform managers have all the necessary data for performing this detailed estimation.
2. Extract from the project database on the platform the parameters of the projects. These parameters include the number of active competing projects (per category) and their goals/maturity dates, and the amount of collected funds per project per period (for evaluating the α_k in equation (5)).
3. Depending on the adopted promotion strategy (static or dynamic), and the objective of the CFP manager, apply the offline or the online algorithm described in the paper.

Note that the static and online strategies exploit the project data differently. For the static case (section 4.5.1), similar to the approach adopted in the "staff pick" of Kickstarter, the CFP performs the project selection at the beginning of the campaign; the project parameters are thus estimated based on similar projects (same category, similar goal, and duration). For the online strategy based on real options, the project may be selected for promotion after the start of its campaign, meaning that the parameter estimation is updated after collecting some additional information (the first investors' contributions).

6.3. Transparency and disclosure

Our proposed framework transforms the role of the CFP from a neutral facilitator to an active intermediary seeking a maximal utility. This shift has fairness and transparency implications, as a targeted promotion strategy implicitly channels funds towards a subset of projects to the detriment of others. A transparent communication is thus needed. First, the general decision-making principles must be made public to potential entrepreneurs and to the Crowd. And second, the impact assessment procedure, performed ex-ante, should be shared with entrepreneurs, who provide any information that will help classifying the project (certification, previous projects, etc.). The β_k's have then to be communicated to the entrepreneur before the campaign launch, to ensure transparency. Note that this proposed transparent procedure contrasts with the current practice of platforms, where the "staff pick" label is assigned to projects in an opaque way, without a proper justification.

6.4. Limitations and directions for future research

There is an important latent hypothesis in our model, that is the availability of the information about the future impact of a project on the society or the environment. Indeed, the utility function (3-4) of the platform depends on the aggregated impact of the funded projects, supposing that the CFP is aware of this impact. Acquiring such knowledge on the future impact of projects is an important future work. A direct way would be through certification. A popular approach is to propose, for founders, the possibility to certify their projects by an external certification body. Yu and Xiao (2023) argued that such certification reduces the information asymmetry between project founders and funders, and our research suggests that it also reduces the asymmetry of information between project founders and platforms.

While certification is a possible way for identifying projects with impact, it is usually limited to established corporations and is not adequate for innovative projects proposed by individual entrepreneurs. A classification process, internal to the CFP and that aims at identifying projects with impact, is thus still be needed. While a manual classification is unfeasible, AI-based tools are gaining in importance in crowdfunding context and may be leveraged for the identification of projects with potential impact. As an example, natural language processing (NLP) techniques along with a machine learning algorithm have been exploited in Buttice et al. (2019) for classifying projects into "green" and "non green" classes, based on their description, and Qu et al. (2022) proposed a K-nearest neighbor (K-NN) classifier for matching funders and projects. However, these works rely solely on the analysis of the online campaign information, provided by the project founders. Post-campaign analysis would be a powerful tool for training AI tools by reliably labeled data but is a complex task as it requires tracking successful projects and analyzing their activities long after their campaign. Post-campaign analysis literature focuses on the ability of crowdfunded ventures to deliver promised rewards on-time (Vanacker et al., 2019), or on their survival and development in the subsequent years (Mollick and Kuppuswamy, 2014; Bento et al., 2019). Interesting research would be to exploit post-campaign data for identifying impact ventures and use the collected data for training classification algorithms.

Additionally, our optimization model could be extended to include advanced tools from control theory. For instance, the proposed promotion policy targets the whole CF population that might have interest in the project, and the model could be refined by targeting selected people that occupy central position in the crowd network, as advocated in Kandhway and Kuri (2016). However, while these works focused on the project founder's perspective, our framework should profit from applying these principles to the CFP promotion strategy. Other works also proposed control methods for entrepreneurs to increase their chance of success, like Shao et al. (2023) who derived the optimal reward pricing and funding target, and Salahaldin et al. (2022) who derived the optimal intervention for an entrepreneur for saving its campaign. An interesting extension of our model is to consider the reaction of entrepreneurs to the platform strategy and the subsequent interactions.

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REFERENCES

Ahlers, G. K., Cumming, D., Günther, C., & Schweizer, D. (2015). Signaling in equity crowdfunding. *Entrepreneurship Theory and Practice, 39*(4), 955–980.

Belleflamme, P., Lambert, T., & Schwienbacher, A. (2014). Crowdfunding: Tapping the right crowd. Journal of Business Venturing, 29(5), 585–609.

Bento, N., Gianfrate, G., & Thoni, M. H. (2019). Crowdfunding for sustainability ventures. Journal of Cleaner Production, 237, Article 117749.

Bertsekas, D. (2021). Rollout, policy iteration, and distributed reinforcement learning. Athena Scientific.

Billsus, D., & Pazzani, M. J. (1998, July). Learning collaborative information filters. In Proceedings of the 15th International Conference on Machine Learning (pp. 46–54).

Breese, J. S., Heckerman, D., & Kadie, C. (1998, July). Empirical analysis of predictive algorithms for collaborative filtering. In Proceedings of the Fourteenth Conference on Uncertainty in Artificial Intelligence (pp. 43–52).

Butticè, V., Colombo, M. G., Fumagalli, E., & Orsenigo, C. (2019). Green oriented crowdfunding campaigns: Their characteristics and diffusion in different institutional settings. Technological Forecasting and Social Change, 141, 85–97.

Butticè, V., Colombo, M. G., & Wright, M. (2017). Serial crowdfunding, social capital, and project success. Entrepreneurship Theory and Practice, 41(2), 183–207.

Cai, Z., Ding, H., Xu, M., & Cui, X. (2024). Multimodal dynamic graph convolutional network for crowdfunding success prediction. Applied Soft Computing, 154, Article 111313.

Calic, G., & Mosakowski, E. (2016). Kicking off social entrepreneurship: How a sustainability orientation influences crowdfunding success. Journal of Management Studies, 53(5), 738–767.

Cavalcanti, G. D., Mendes-da-Silva, W., dos Santos Felipe, I. J., & Santos, L. A. (2024). Recent advances in applications of machine learning in reward crowdfunding success forecasting. Neural Computing and Applications, 36(26), 16485–16501.

Chaddad, S., Hayel, Y., & Varma, V. (2025). A stochastic model for optimizing crowdfunding campaign success. Operations Research Letters, Article 107303.

Chaudhary, S. (2024, June). Enhancing success prediction in crowdfunding platforms using LIME-explainable AI method. In 2024 IEEE Students Conference on Engineering and Systems (SCES) (pp. 1–6). IEEE.

Collier, J. E., & Bienstock, C. C. (2006). Measuring service quality in e-retailing. Journal of Service Research, 8(3), 260–275.

Colombo, M. G., Franzoni, C., & Rossi-Lamastra, C. (2015). Internal social capital and the attraction of early contributions in crowdfunding. Entrepreneurship Theory and Practice, 39(1), 75–100.

Connelly, B. L., Certo, S. T., Reutzel, C. R., DesJardine, M. R., & Zhou, Y. S. (2025). Signaling theory: State of the theory and its future. Journal of Management, 51(1), 24–61.

Cordova, A., Dolci, J., & Gianfrate, G. (2015). The determinants of crowdfunding success: Evidence from technology projects. Procedia – Social and Behavioral Sciences, 181, 115–124.

Cumming, D., Leboeuf, G., & Schwienbacher, A. (2015). Crowdfunding models: Keep-it-all vs. all-or-nothing. Financial Management, 49, 331–360.

Cumming, D., Meoli, M., Rossi, A., & Vismara, S. (2024). ESG and crowdfunding platforms. Journal of Business Venturing, 39(1), 106362

Da'u, A., & Salim, N. (2020). Recommendation system based on deep learning methods: A systematic review and new directions. Artificial Intelligence Review, 53(4), 2709–2748.

Davies, W. E., & Giovannetti, E. (2018). Signalling experience & reciprocity to temper asymmetric information in crowdfunding: Evidence from 10,000 projects. Technological Forecasting and Social Change, 133, 118–131.

Etter, V., Grossglauser, M., & Thiran, P. (2013). Launch hard or go home! Predicting the success of Kickstarter campaigns. In Proceedings of the First ACM Conference on Online Social Networks (pp. 177–182).

Fujiwara, D. (2015). The seven principle problems of SROI (p. 105). Simetrica Ltd.

Gama, A. P. M., Correia, R. E., Augusto, M., & Duarte, F. (2023). Third-party signals in crowdfunded microfinance: Which microfinance institutions boost crowdfunding among refugee entrepreneurs? Small Business Economics, 61(2), 559–586.

Gutsche, J., & Sylla, S. (2018). Success factors of crowdfunding projects on the Kickstarter platform. In German-Turkish Perspectives on IT and Innovation Management (pp. 361–374). Springer.

Herlocker, J. L., Konstan, J. A., Terveen, L. G., & Riedl, J. T. (2004). Evaluating collaborative filtering recommender systems. ACM Transactions on Information Systems, 22(1), 5–53.

Hörisch, J., & Tenner, I. (2020). How environmental and social orientations influence the funding success of investment-based crowdfunding. Technological Forecasting and Social Change, 161, 120311.

Hou, T., He, L., Keppo, J., & Guo, X. (2025). The role and optimization of staff picks in crowdfunding. SSRN, Article 5234468.

Huang, S.-L. (2011). Designing utility-based recommender systems for e-commerce: Evaluation of preference-elicitation methods. Electronic Commerce Research and Applications, 10(4), 398–407.

Huang, S., Pickernell, D., Battisti, M., & Nguyen, T. (2022). Signalling entrepreneurs' credibility and project quality for crowdfunding success : cases from the Kickstarter and Indiegogo environments. Small Business Economics, 58(4), 1801-1821.

Kandhway, K., & Kuri, J. (2016). Optimal resource allocation for maximizing information dissemination in social networks. IEEE/ACM Transactions on Networking, 24(5), 3204–3217.

Keeney, R. L., & Raiffa, H. (1993). Decisions with multiple objectives: Preferences and value trade-offs. Cambridge University Press.

Kleinert, S., Bafera, J., Urbig, D., & Volkmann, C. K. (2022). Access denied: How equity crowdfunding platforms use quality signals to select new ventures. Entrepreneurship Theory and Practice, 46(6), 1626–1657.

Konstan, J. A., & Riedl, J. (2012). Recommender systems: From algorithms to user experience. User Modeling and User-Adapted Interaction, 22, 101–123.

Kunz, M. M., Bretschneider, U., Erler, M., & Leimeister, J. M. (2017). An empirical investigation of signaling in reward-based crowdfunding. Electronic Commerce Research, 17, 425–461.

Kuo, Y.-F., Lin, C.-S., & Wu, C.-H. (2020). Why do people back crowdfunding projects? A perspective on social cognitive theory. Journal of Electronic Commerce Research, 21(3).

Lin, Y., Yin, P., & Lee, W.-C. (2018, April). Modeling dynamic competition on crowdfunding markets. In Proceedings of the 2018 World Wide Web Conference (pp. 1815–1824).

Lukkarinen, A., Teich, J. E., Wallenius, H., & Wallenius, J. (2016). Success drivers of online equity crowdfunding campaigns. Decision Support Systems, 87, 26–38.

Mollick, E. (2014). The dynamics of crowdfunding: An exploratory study. Journal of Business Venturing, 29(1), 1–16.

Mollick, E. R., & Kuppuswamy, V. (2014). After the campaign: Outcomes of crowdfunding. UNC Kenan-Flagler Working Paper, (2376997).

Negrão, C. S. V., & Brito, J. A. F. (2021). An empirical study on the determinants of success of crowdfunding projects: Kickstarter. In Multidisciplinary Approaches to Crowdfunding Platforms (pp. 1–20). IGI Global.

Pati, R., & Garud, N. (2021). Social interaction and crowdfunding project success. IEEE Transactions on Engineering Management, 70(9), 3128-3142

Portugal, I., Alencar, P., & Cowan, D. (2018). The use of machine learning algorithms in recommender systems: A systematic review. Expert Systems with Applications, 97, 205–227.

Qu, S., Xu, L., Mangla, S. K., Chan, F. T., Zhu, J., & Arisian, S. (2022). Matchmaking in reward-based crowdfunding platforms: A hybrid machine learning approach. International Journal of Production Research, 60(24), 7551–7571.

Rakesh, V., Lee, W.-C., & Reddy, C. K. (2016, February). Probabilistic group recommendation model for crowdfunding domains. In Proceedings of the Ninth ACM International Conference on Web Search and Data Mining (pp. 257–266).

Roma, P., Vasi, M., Testa, S., & Perrone, G. (2021). Environmental sustainability orientation, reward-based crowdfunding, and venture capital: The Mediating Role of Crowdfunding Performance for New Technology Ventures. IEEE Transactions on Engineering Management, 70(9), 3198-3212.

Salahaldin, L., Varma, V. S., & Elayoubi, S. E. (2022). When and how to intervene for saving an entrepreneur's crowdfunding campaign. Finance Research Letters, 50, 103189.

Sarwar, B., Karypis, G., Konstan, J., & Riedl, J. (2001, April). Item-based collaborative filtering recommendation algorithms. In Proceedings of the 10th International Conference on World Wide Web (pp. 285–295).

Schafer, J. B., Konstan, J., & Riedl, J. (1999, November). Recommender systems in e-commerce. In Proceedings of the 1st ACM Conference on Electronic Commerce (pp. 158–166).

Shao, Q., Cheung, M. H., & Huang, J. (2023). Crowdfunding with cognitive limitations. IEEE/ACM Transactions on Networking, 31(6), 2714–2729.

Shao, Q., Cheung, M. H., & Huang, J. (2024). Strategic pricing and information disclosure in crowdfunding. IEEE/ACM Transactions on Networking, 32(4), 2988-3001

Siemroth, C., & Hornuf, L. (2023). Why do retail investors pick green investments? A lab-in-the-field experiment with crowdfunders. Journal of Economic Behavior & Organization, 209, 74–90.

Song, C., Luo, J., Holtta-Otto, K., Seering, W., & Otto, K. (2020). Crowdfunding for design innovation: Prediction model with critical factors. IEEE Transactions on Engineering Management, 69(4), 1565-1576.

Vanacker, T., Vismara, S., & Walthoff-Borm, X. (2019). What happens after a crowdfunding campaign. In Handbook of Research on Crowdfunding (pp. 227–246).

Xiao, Y., & Li, Z. (2025). Enhancing platform profitability in crowdfunding through project recommendation: A deep reinforcement learning approach. Information Sciences, Article 122409.

Yang, Y., Wang, H.-J., & Wang, G. (2016). Understanding crowdfunding processes: A dynamic evaluation and simulation approach. Journal of Electronic Commerce Research, 17(1), 47–67.

Ye, B. K., Tu, Y. J. T., & Liang, T.-P. (2019). A hybrid system for personalized content recommendation. Journal of Electronic Commerce Research, 20(2), 91–104.

Yin, P., Wang, J., Zhao, J., Wang, H., & Gan, H. (2022). Deep collaborative filtering for crowdfunding project recommendation. Mathematical Problems in Engineering, 2022, Article 4655030.

Yu, J., & Xiao, S. (2023). Project certification and screening in the reward-based crowdfunding market. Journal of Business Research, 165, 114004.

Zhan, R., Christakopoulou, K., Le, Y., Ooi, J., Mladenov, M., Beutel, A., Boutilier, C., Chi, E., & Chen, M. (2021, April). Towards content provider aware recommender systems. In Proceedings of the Web Conference 2021 (pp. 3872–3883).

Zhong, C., Xu, W., & Du, W. (2022). Success prediction of crowdfunding campaigns with project network: A machine learning approach. Journal of Electronic Commerce Research, 23(2), 99–114.

APPENDIXES

Appendix A. Dynamic programming approach

We denote by $p(t, \tau)$ the project promoted at time t under policy $\boldsymbol{\tau}$. The state space at time t is $S(t) = (p, c_1, \ldots, c_K)$, where p is the index of the project currently promoted at time t, and c_k is the already collected amount by project k. The dynamic programming tree is then split into branches determined by the currently promoted project. We can jump between branch p and branch $p + 1$ at any time.

In order to be able to describe the evolution of the resulting discrete process, we compute the transition probabilities between intervals at any time t. Note that the event that triggers moving from an interval to another is not completely exogenous, as the amount of collected funds depends on the promotion decision of the platform, even if the total amount of collected funds is exogenous (modeled as a variable with distribution $F_x(.)$).

Denote by $q_k(t, c_k, c_k', p)$ the probability that the project k goes up from state c_k to state $c_k' \geq c_k$ during the interval $[t, t+1]$, knowing that the strategy of the platform is to promote project p. This is computed depending on the distribution $F_x(.)$. In the case of a continuous distribution of the amount of collected funds (e.g. Gaussian), a discretization is needed to make the analysis tractable. Let J be the number of intervals for the possible amount of fund collection. The j-th interval is denoted by $[c_j, c_{j+1}]$, with $c_1 = 0$ and $c_{J+1} = X^{\max}$. $X^{\max}$ is chosen so that the probability of exceeding it for any project is very small (e.g. 0.01%). The step size for the discretization is equal to $\epsilon = \frac{X^{\max}}{J}$. At any time t, the additional amount of collected funds by project k may fall in any interval $j \in [1, J]$.

For illustration purposes, we detail the analysis for the case of two projects and a utility given by the weighted sum probability of success. We start by time T_1 when no decision is expected from the platform manager. We compute the utility at time T_1 knowing that the system is in state (c_1, c_2).

When the objective is to maximize the "weighted" sum of success probabilities (equation (4)), this utility is the expected success rate of project 2 (whose evolution is still uncertain), plus 1 or 0, depending on the final state of fund collection of project 1, weighted by the β's:

$$U_{T_1}(c_1, c_2) = \begin{cases} \beta_2 E\left(X_2(T_2)\mathbf{1}_{X_2(T_2)\geq m_2} \mid X_2(T_1) = c_2\right) + \beta_1 c_1 \mathbf{1}_{c_1 \geq m_1}, & \text{for profit} \\ \beta_2 \Pr(X_2(T_2) \geq m_2 \mid X_2(T_1) = c_2) + \beta_1 \mathbf{1}_{c_i \geq m_1}, & \text{for success rate} \end{cases} \quad (13)$$

We then move backward step by step and calculate the utility iteratively. For any time t < T1, as there are only two projects, the only branch where the manager still has a decision to make corresponds to p = 1; we may then drop p from the state space. If the decision is to keep the same strategy one more step and decide later (waiting strategy), the expected sum utility in this case is the average utility in the next time interval, knowing the transition rates:

$$W_t(c_1, c_2) = \sum_{c_1' \geq c_1} \sum_{c_2' \geq c_2} q_1(t, c_1, c_1') q_2(t, c_2, c_2') U_{t+1}(c_1', c_2') \quad (14)$$

On the other hand, if the manager decides to "switch" its strategy from project 1 to project 2, he/she loses the future decision opportunities, and the expected sum utility is:

$$S_t(c_1, c_2) = \beta_2 E\left(X_2(T_2)\mathbf{1}_{X_2(T_2)\geq m_2} \mid X_2(t) = c_2, p = 2\right)$$

$$+\beta_1 E\left(X_1(T_1)\mathbf{1}_{X_1(T_1)\geq m_1} \mid X_1(t) = c_1, p = 2\right)$$

for a weighted profit, and

$$S_t(c_1, c_2) = \beta_2 \Pr(X_2(T_2) \geq m_2 \mid X_2(T_1) = c_2, p = 2)$$

$$+\beta_1 \Pr(X_1(T_1) \geq m_1 \mid X_1(t) = c_1, p = 2),$$

for a weighted number of funded projects.

The utility of the platform at time t is thus the maximum of the utilities in cases of "waiting" and "switching":

$$U_t(c_1, c_2) = \max[W_t(c_1, c_2), S_t(c_1, c_2)] \quad (15)$$

Appendix B. Application for some money flow distributions

We now show how to solve the problem for some typical money flow distributions.

1. Poisson distribution

We start by the practical case where, at each time epoch, an integer number of funders contributes to the CFP, and each contribution has a constant value. The target goal mk corresponds in this case to a number of contributions. We model the number of contributions during interval t by a Poisson distribution of parameter μ.

The amount of collected funds at time t by project k is thus:

$$x_k(t,\mathcal{P}) \sim \text{Poisson}\left(\frac{\alpha_k\gamma_k(t,\mathcal{P})}{\sum_{j=N(t)}^{K}\ \alpha_j\gamma_j(t,\mathcal{P})}\mu\right)$$

and the amount of accumulated pledges, without accounting for the initial amount x_{k0} is also Poisson with parameter $a_k(\mathcal{P})\mu$ with

$$a_k(\mathcal{P}) = \sum_{t=0}^{T_k}\frac{\alpha_k\gamma_k(t,\mathcal{P})}{\sum_{j=N(t)}^{K}\ \alpha_j\gamma_j(t,\mathcal{P})} \tag{16}$$

1.1 Utility derivation

In order to derive the utility functions (1, 2, 3, 4), we show hereafter how to derive the outcome of an individual campaign, denoted *k*, for different utility flavors.

Lemma 2. The utility obtained by the platform from project k in the Poisson case under policy $\mathcal{P}$ is:

$$u_k(\mathcal{P}) = \begin{cases}\beta_k a_k(\mathcal{P})\mu\left[1-\dfrac{\Gamma(m_k-x_{k0}-1,a_k(\mathcal{P})\mu)}{(m_k-x_{k0}-2)!}\right], & \text{for a weighted profit}\\ \beta_k\left[1-\dfrac{\Gamma(m_k-x_{k0},a_k(\mathcal{P})\mu)}{(m_k-x_{k0}-1)!}\right], & \text{for a weighted number of funded projects}\end{cases} \tag{17}$$

where $\Gamma(m,x)$ is the upper incomplete gamma function defined by:

$$\Gamma(m,x) = \int_x^{\infty} t^{m-1}e^{-t}dt \tag{18}$$

Proof. Using the cumulative distribution function of the Poisson law, the expected success of project k is:

$$P(X_k(T_k,\mathcal{P}) \geq m_k) = P(\text{Poisson}(a_k(\mathcal{P})\mu) \geq m_k - x_{k0}) = 1-\frac{\Gamma(m_k-x_{k0},a_k(\mathcal{P})\mu)}{(m_k-x_{k0}-1)!}$$

which gives the utility in the case where the platform is interested in maximizing the number of successful projects. For the case of sum profit, we have:

$$E\left[X_k(T_k,\mathcal{P})\mathbf{1}_{X_k(T_k,\mathcal{P})\geq m_k}\right] = \sum_{m=m_k-x_{k0}}^{\infty} me^{-a_k(\mathcal{P})\mu}\frac{(a_k(\mathcal{P})\mu)^m}{m!} = a_k(\mathcal{P})\mu\left[1-\frac{\Gamma(m_k-x_{k0}-1,a_k(\mathcal{P})\mu)}{(m_k-x_{k0}-2)!}\right]$$

which concludes the proof.

The global utility of the platform is thus calculated as:

□

$$U(\mathcal{P}) = \sum_{k=1}^{K} u_k(\mathcal{P}) \tag{19}$$

1.2. OAT policy characterization for the Poisson case

We now provide some hints about the shape of the optimal OAT policy.

1.2.1. Monotonicity of the utility

Lemma 3. Under the approximation of a continuous policy $\tau \in [0, T_1] \times \ldots \times [0, T_K]$, the utility u_{k-1} is increasing with τ_k and u_k is decreasing with τ_k.*Proof.* For a sequential OAT policy, the additional amount of funds collected by project k after time 0 is $\text{Poisson}(a_k(\tau))$, with

$$a_k(\boldsymbol{\tau}) = \sum_{i \neq k} \frac{\alpha_k(\tau_{i+1} - \tau_i)}{\sum_{j=N_i(\tau)}^{K} \alpha_j + (G-1)\alpha_i} + \frac{\alpha_k G(\tau_{k+1} - \tau_k)}{\sum_{j=N(t)}^{K} \alpha_j + (G-1)\alpha_k} \tag{20}$$

a_k is adapted from equation (16) and $N(\tau_i)$ is the number of projects still active at τ_i.

For clarity, we continue the proof for the case of two projects; it can be easily generalized to K projects. In this case, we have one parameter to optimize that is τ_2, and:

$$a_1(\tau_2) = \frac{\alpha_1 G \tau_2}{\alpha_1 G + \alpha_2} + \frac{\alpha_1(T_1 - \tau_2)}{\alpha_1 + \alpha_2 G}$$

and

$$a_2(\tau_2) = \frac{\alpha_2 \tau_2}{\alpha_1 G + \alpha_2} + \frac{\alpha_2 G(T_1 - \tau_2)}{\alpha_1 + \alpha_2 G} + T_2 - T_1$$

We start with the expected success case where we have:

$$\frac{du_1}{d\tau_2} = \frac{\alpha_1\alpha_2(G^2-1)\mu}{(\alpha_1 G + \alpha_2)(\alpha_1 + \alpha_2 G)} \frac{\beta_1}{(m_1 - x_{10})!} (a_1(\tau_2)\mu)^{(m_1 - x_{10} - 1)} e^{-a_1(\tau_2)\mu} > 0$$

and

$$\frac{du_2}{d\tau_2} = -\frac{\alpha_1\alpha_2(G^2-1)\mu}{(\alpha_1 G + \alpha_2)(\alpha_1 + \alpha_2 G)} \frac{\beta_2}{(m_2 - x_{20})!} (a_2(\tau_2)\mu)^{(m_2 - x_{20} - 1)} e^{-a_2(\tau_2)\mu} < 0$$

As of the expected money, we can show that:

$$\begin{aligned} \frac{du_1}{d\tau_2} =& \frac{\alpha_1\alpha_2(G^2-1)\mu}{(\alpha_1 G + \alpha_2)(\alpha_1 + \alpha_2 G)} \times \\ & \left[1 - \frac{\Gamma(m_1 - x_{10} - 1, a_1(\tau_2)\mu)}{(m_1 - x_{10} - 2)!} + \frac{\beta_1}{(m_1 - x_{10})!} (a_1(\tau_2)\mu)^{(m_1 - x_{10})} e^{-a_1(\tau_2)\mu}\right] > 0 \end{aligned}$$

$$\begin{aligned} \frac{du_2}{d\tau_2} =& -\frac{\alpha_1\alpha_2(G^2-1)\mu}{(\alpha_1 G + \alpha_2)(\alpha_1 + \alpha_2 G)} \times \\ & \left[1 - \frac{\Gamma(m_2 - x_{20} - 1, a_2(\tau_2)\mu)}{(m_2 - x_{20} - 2)!} + \frac{\beta_2}{(m_2 - x_{20})!} (a_2(\tau_2)\mu)^{(m_2 - x_{20})} e^{-a_2(\tau_2)\mu}\right] < 0 \end{aligned}$$

as $\frac{\Gamma(m,x)}{(x-1)!} < 1$, for all $m > 0$ and $x > 0$, which concludes the proof. □

1.2.2. Convexity of the utility

The utility of the platform is thus the sum of an increasing function and a decreasing one. Even if this function is not necessarily concave, finding τ_k where $\frac{\partial u_{k-1}}{\partial \tau_k} + \frac{\partial u_k}{\partial \tau_k} = 0$ is helpful for giving insight about the optimal policy.

We now show that, for the case of two projects, there is a low outcome region, i.e. a region where the goal set by the projects is too high compared to the average money flow, where there is no obvious balance to seek for the policy. On the contrary, when the goals are reasonably set, the utility is concave and there is a unique maximal value on [*0*, T_1].

Lemma 4. *If the required goals m_k are large compared to the expected collected funds $a_k\mu$, the utility function is not concave. If m_k is small compared to $a_k\mu$, the utility function is concave.*

Proof. The second derivative of the utility is calculated by:

$$\frac{d^2U}{d\tau_2^2} = \left(\frac{\alpha_1\alpha_2(G^2-1)\mu}{(\alpha_1 G+\alpha_2)(\alpha_1+\alpha_2 G)}\right)^2 \left[\frac{\beta_1(a_1(\tau_2)\mu)^{(m_1-x_{10}-2)}e^{-a_1(\tau_2)\mu}(m_1-x_{10}-1-a_1(\tau_2)\mu)}{(m_1-x_{10})!} + \frac{\beta_2(a_2(\tau_2)\mu)^{(m_2-x_{20}-2)}e^{-a_2(\tau_2)\mu}(m_2-x_{20}-1-a_2(\tau_2)\mu)}{(m_2-x_{20})!}\right]$$

□

We can observe that, if $m_k > x_{k0} + a_k(\tau_2)\mu = E[X_k(T_k)]$ for both projects, the second derivative is positive, and the utility is not concave. However, for projects with larger expected outcomes (i.e. when the target is not larger than the maximal expected amount of collected funds), the second derivative may be concave, and the utility admits a maximum within the interval $[0, T_1]$.

1.3. Dynamic programming

For he dynamic programming, we define the system state at time *t*, as $s_t = (X_1, \dots, X_K, p)$, where $(X_1, \dots, X_K)$ are the amounts of funds collected by the different projects and $p \in [N(t-1, K]$ is the promoted project at $t-1$.

We need to start at time T_{K-1}, where there is no further action to undertake as only project K can be funded after this time. We illustrate the case where the utility is equal to the sum probability of success, the other cases are derived in a similar way. The utility at time T_{K-1} is:

$$U_{T_{K-1}}(X_1, \dots, X_K) = \sum_{k=1}^{K-1} \beta_k \mathbf{1}_{X_k \geq m_k} + \beta_K \left[1 - \frac{\Gamma(m_K - X_K, (T_K - T_{K-1})\mu)}{(m_K - X_K - 1)!}\right] \tag{21}$$

Moving backwards one time step, at $t = T_{K-1} - 1$, there are two possible scenarios: either the platform is already promoting project $K (\text{i.e.}, p = K)$, and there is no possible action, or the platform is promoting project $K-1$, i.e. *p=K-1*, and can either maintain its action, or switch to promoting project K. In the former scenario, the utility is:

$$U_t(X_1, \dots, X_K, K) = \sum_{k=1}^{K-2} \beta_k \mathbf{1}_{X_k \geq m_k} + \beta_K [1 - \frac{\Gamma\left(m_K - X_K, (T_K - T_{K-1})\mu + \frac{\alpha_K G}{\alpha_K G + \alpha_{K-1}}\right)}{(m_K - X_K - 1)!}\Bigg] + \beta_{K-1}\left[1 - \frac{\Gamma\left(m_{K-1} - X_{K-1}, \frac{\alpha_{K-1}}{\alpha_K G + \alpha_{K-1}}\right)}{(m_{K-1} - X_{K-1} - 1)!}\right]$$

In the scenario where $p = K - 1$, the "waiting value" is given by:

$$W_{T_{K-1}-1}(X_1, \dots, X_K, p) = \sum_{k=1}^{K-2} \beta_k \mathbf{1}_{X_k \geq m_k} + \beta_K \left[1 - \frac{\Gamma\left(m_K - X_K, (T_K - T_{K-1})\mu + \frac{\alpha_K}{\alpha_K + \alpha_{K-1} G}\right)}{(m_K - X_K - 1)!}\right] + \beta_{K-1}\left[1 - \frac{\Gamma\left(m_{K-1} - X_{K-1}, \frac{\alpha_{K-1} G}{\alpha_K + \alpha_{K-1} G}\right)}{(m_{K-1} - X_{K-1} - 1)!}\right]$$

while the "switching value" is equal to the utility in scenario 1, computed above:

$$S_{T_{K-1}-1}(X_1, \dots, X_K, p) = U_{T_{K-1}-1}(X_1, \dots, X_K, K) \tag{22}$$

and the utility for this state is:

$$U_{T_{K-1}-1}(X_1, \dots, X_K, p) = \max\left[S_{T_{K-1}-1}(X_1, \dots, X_K, p), W_{T_{K-1}-1}(X_1, \dots, X_K, p)\right] \tag{23}$$

This procedure is repeated by moving backwards and studying the available options, until time 0.

2. Gaussian distribution

When the number of contributors is large and the amount of each contribution is not constant, a good approximation is to consider $x(t)$ as a Gaussian variable of mean μ and variance σ. At time T_k, the accumulated funds by campaign k is also Gaussian with mean:

$$\mu_k(\mathcal{P}) = x_{k0} + a_k(\mathcal{P})\mu \tag{24}$$

and variance

$$S_k^2(\mathcal{P}) = \sum_{t=0}^{T_k} \left(\frac{\alpha_k \gamma_k(t, \mathcal{P})}{\sum_{j=N(t)}^{K} \alpha_j \gamma_j(t, \mathcal{P})}\right)^2 \sigma^2 \tag{25}$$

Lemma 5. The utility obtained by the platform from project k in the Gaussian case under policy $\mathcal{P}$ is:

$$u_k(\mathcal{P}) = \begin{cases} \beta_k \dfrac{S_k(\mathcal{P})}{\sqrt{2\pi}} \exp\left(-\dfrac{(m_k - \mu_k(\mathcal{P}))^2}{2S_k(\mathcal{P})^2}\right) + \dfrac{\mu_k(\mathcal{P})}{2} \operatorname{erfc}\left(\dfrac{m_k - \mu_k(\mathcal{P})}{\sqrt{2}S_k(\mathcal{P})}\right), & \text{for profit} \\ \dfrac{\beta_k}{2} \operatorname{erfc}\left(\dfrac{m_k - \mu_k(\mathcal{P})}{\sqrt{2}S_k(\mathcal{P})}\right), & \text{for success rate} \end{cases} \tag{26}$$

where erfc is the complementary error function defined by:

$$\operatorname{erfc}(x) = \frac{2}{\sqrt{\pi}} \int_x^{\infty} \exp(-t^2) dt$$

Proof. The expected success of project k is the probability that it collects more than the target. Knowing that X_k is Gaussian, this probability is computed by:

$$E\left[\mathbf{1}_{X_k(T_k) \geq m_k}\right] = P(X_k(T_k) \geq m_k) = \int_{m_k}^{\infty} \frac{1}{S_k\sqrt{2\pi}} \exp\left(-\frac{(x-\mu_k)^2}{2S_k^2}\right) dx = \frac{1}{2} \operatorname{erfc}\left(\frac{m_k - \mu_k}{\sqrt{2}S_k}\right)$$

The expected amount of money collected by a successful project is:

$$E\left[X_k(T_k)\mathbf{1}_{X_k(T_k)}\right] = \int_{m_k}^{\infty} \frac{x}{S_k\sqrt{2\pi}} \exp\left(-\frac{(x-\mu_k)^2}{2S_k^2} dx\right).$$

After some operations, we obtain the result of equation (26).

□