A real options model for crowdfunding platforms: optimal project promotion strategies

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February 1, 2020

Abstract

We study in this paper crowdfunding from the platform perspective. We consider a platform where several project campaigns are running and competing on fund collection. The platform manager's objective is to increase the proportion of successful projects and he uses the lever of project promotion on the platform website to influence the funders' and balance the potential future funds between projects. We first consider the platform policy derivation as an optimization problem and show to derive the optimal project promotion policy. We then consider the more realistic setting where the platform manager adapts his policy online when observing the status of fund collection. We model this online strategy as a real option and develop a dynamic programming algorithm that finds the optimal strategy depending on the observed project campaign status.

1 Introduction

Crowdfunding is becoming a popular funding channel among entrepreneurs as it allows them to address directly the crowd via Internet-based Crowdfunding platforms (CFP). A wide pan of the literature on crowdfunding deals with the parameters that make project campaigns successful and aim at guiding project founders in designing their campaigns. For instance, [1] compares two forms of CF, reward-based and equity-based and shows that the choice made by the entrepreneur to select between these two forms depends essentially on the amount of required capital and that equity-based CF is more suitable for large projects.

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[2] shows that the size of the network of the project holder is positively correlated with the success and that the quality signals are also success factors. These signals have been identified as the advertisement videos, the update frequency and even the absence of typos, for reward-based crowdfunding [2, 3], and the clarity of the financial roadmap, the transparency with respect to the risks, the professional experience and the education level of the funders for equity-based crowdfunding [4]. Another set of works focused on the behaviour of funders and its impact on the project success. [5] identify friend and family (F&F) as a source of early funding for projects that account for 15 to 20% of raised funds for equity-based campaigns and 30 to 40% for reward-based campaigns. Other potential funders tend to procrastinate and [6] studies the choice of donors toward funding a project early or waiting until the end of the funding window. [7] modeled the behaviour of the well informed funders and derived their optimal choice among the available projects using a dynamic programming approach.

The above cited body of work, and many others, gives a clear view about the success parameters of CF campaigns and the dynamics of fund raising. However, to the best of our knowledge, the perspective of platform managers is not yet covered. Many questions are open in this context, especially how to select candidate projects for the platform and how to accompany them during their fund raising campaign for maximizing their chance of success. While the first aspect (selection of candidate projects) may be partially addressed by identifying the success factors related to the campaign and project structures, as advocated by [8], the strategy of platform managers wit respect to pre-seleted projects 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, with the objective of maximizing the number of successful projects. The original contributions of the paper are as follows:

- We model the dynamics of fund raising on the platform based on empirical evidence from the literature.
- We consider the promotion strategy of the platform as a real option.
- We derive the optimal strategy using a dynamic programming approach and illustrate using numerical applications the impact of different paramaters on this strategy.

2 Problem statement

2.1 Platform and project model

We consider a crowdfunding platform based on the threshold pledge model (or the all-or-nothing principle(AON)) [9], meaning that if the project is not 100% funded, the funding will be returned to investors without penalty. This platform proposes a set of projects $\mathcal{K} = \{1, 2, \ldots, K\}$ that are of interest to a set of a potential set of funders[1]. The projects start at time t_k and end at T_k. Without loss of generality, we assume that $T_1 \leq T_2 \leq \cdots \leq T_K$. We also consider that $t_k < 0$ for all $k \in \mathcal{K}$.

We define the *next-closing project* index by

$$N(t) = \min\{k \in \mathcal{K} | T_k \geq t\} \tag{1}$$

The pledge made in project k at time t is denoted by $X_k(t)$ with $t, T_k, t_k \in \mathbb{Z}$ (discrete-time system). If a project k collects sufficient funds M_k by the end of its duration, it is said to be successful, i.e., if $X(T_k) \geq M_k$.

Funders typically belong to one of the three groups:

- Friends and family: who invest at the start of the project, and contribute to $X(t_k) > 0$.
- naive investors (referred to as fools): who invest in projects at all time. The average amount of investment made by this group at any time is given by μ_C.
- Rational investors: who invest in project k only at T_k, so as to avoid loss due to interest during the time the investment is locked. The average amount of investment made by this group at any time is given by μ_R.

The actual amounts of pledge made by the naive and rational investors are assumed to a Gaussian random variable with averages μ_C and μ_R and variances σ_C^2 and σ_R^2, respectively. It is well known that the design of the project campaign (presentation, videos, pitches, etc.) has an important impact on its attractiveness and, eventually, on its success chances [3]. This is modeled by a parameter $\alpha_k > 0$ for project k, equal to the fraction of the naive and rational investors it attracts when it is active, without any intervention from the platform (projects with larger α's attract more users).

2.2 Promotion strategy and its impact on attractiveness

The CF platform cannot be regarded as passive in the process of fund raising, as it can make strategic choices of highlighting some of them so that their success chances are increased. We'll see afterwards how the project to be promoted is highlighted and what is the objective that the platform pursues.

At any time t, if the platform highlights certain projects, they will attract a larger investment to that project at this time. We use $\gamma(t) \in \{1, G\}^{K-N(t)+1}$ to denote the visibility allocation at time t with $G > 1$, $K - N(t) + 1$ being the number of remaining projects. If a project k is highlighted in the platform at time t, then $\gamma_k(t) = G$ and $\gamma_k(t) = 1$ otherwise.

[1] Note that we focus here on a set of projects that can be regarded as competitors, i.e. that attract funders with common interest, e.g. technology, arts, etc. A platform may propose different types of projects but we focus here on projects belonging to the same domain.

As a result, for any $t \in \{t_k + 1, \ldots, T_k - 1\}$, the expected investment in project k is given by

$$X_k(t) - X_k(t-1) \sim \frac{\alpha_k \gamma_k(t)}{\sum_{j=N(t)}^{K} \alpha_j \gamma_j(t)} \mathcal{N}\left(\mu_C, \sigma_C^2\right) \tag{2}$$

On the other hand, at the closing time, we have

$$X_k(T_k) - X_k(T_k - 1) \sim \frac{\alpha_k \gamma_k(T_k)}{\sum_{j=N(t)}^{K} \alpha_j \gamma_j(T_k)} \mathcal{N}\left(\mu_C, \sigma_C^2\right) + \alpha_k \gamma_k(T_k) \mathcal{N}\left(\mu_R, \sigma_R^2\right) \tag{3}$$

This latter equation takes into account the additional funds received at the campaign closing time from procrastinating funders, and that may be boosted if the project is promoted by the platform at that time.

2.3 Objective

Given $X(0)$, design an optimal promotion strategy, i.e. $\gamma(1), \ldots, \gamma(T_K)$ in order to maximize the number of successful projects. Then the OP can be formalized as

$$\begin{array}{c} \text{Maximize}_\gamma \sum_{k=1}^{K} \Pr(X(T_k) \geq M_k) \\ \text{where } X_k(t) \text{ satisfies } (2), (3) \end{array} \tag{4}$$

This maximization strategy is a natural choice for a platform as it helps increasing its attractiveness for future projects and maximizes its revenues from current ones as platforms usually receive some amount of money from successful project campaign.

2.4 Some definitions

Before analysing the optimal strategy, we start by some definitions and some preliminary, yet useful, results.

Definition 1 *A sequential policy is a policy that promotes a given project for a unique compact interval of time.*

Definition 2 *An offline policy is a policy that is defined at time 0 and that determines* a priori *the switching times between projects. An online policy is based on the observed amount of pledges collected by each project and is updated dynamically when time goes.*

These notions of offline versus online policies is of utmost importance for platform managers. The former are useful for understanding the potential of the available projects at a given time, while the latter is more suitable for dynamically updating the marketing strategy, based on observed campaign outcomes.

Lemma 1 *If there is an optimal offline strategy, there exists at least one sequential offline strategy that is optimal (maximizes the average number of successful projects) while minimizing the switching rate between marketing strategies.*

Proof. For any given strategy, we can find a sequential strategy that induces the same amount of money for each project, and that highlights each project on a compact set of length 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 3 *A One-at-Time (OAT) policy is a policy where the platform increases visibility of a unique project 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 design of the platform 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 that it highlights a unique project per domain (technology, arts, video games, etc.).

3 Optimal offline policy

We start by a simple case of an OAT policy where the platform operator decides offline (a priori) the promotion strategy. We first derive the optimal policy when there are only two projects in competition, and then move to the general case.

3.1 Optimal OAT policy for 2 projects

Theorem 1 *An optimal sequential offline OAT strategy for the case of two competing projects is given by the switching time $\tau^* \leq T_1$ that verifies:*

$$\begin{aligned}\tau^* = argmax_\tau[erfc(\frac{M_1 - X_1(0) - a_1(\tau)\mu_C - b_1(\tau)\mu_R}{\sqrt{(a_1(\tau)\sigma_C)^2 + (b_1(\tau)\sigma_R)^2}}) \\ +erfc(\frac{M_2 - X_2(0) - a_2(\tau)\mu_C - \alpha_2 G\mu_R}{\sqrt{(a_2(\tau)\sigma_C)^2 + (\alpha_2 G\sigma_R)^2}})]\end{aligned} \quad (5)$$

where

$$a_1(\tau) = \frac{\alpha_1 G\tau}{\alpha_1 G + \alpha_2} + \frac{\alpha_1 \max(T_1 - \tau, 0)}{\alpha_1 + \alpha_2 G} \quad (6)$$

$$b_1(\tau) = \alpha_1(1 + (G-1)\mathbf{1}_{\tau=T_1}) \quad (7)$$

$$a_2(\tau) = \frac{\alpha_2\tau}{\alpha_1 G + \alpha_2} + \frac{\alpha_2 G \max(T_1 - \tau, 0)}{\alpha_1 + \alpha_2 G} + \alpha_2 G(T_2 - T_1) \quad (8)$$

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

Proof. In order to obtain the optimal policy, we first characterize the amount of funds received by project k during an interval of time $[\tau_1 > 0, \tau_2 \leq T_k]$. This is the weighted sum of two Gaussian variables corresponding to the funds collected during the interval $[\tau_1, \tau_2]$ from naive investors plus the funds received at the end of its campaign from rational investors:

$$\left(\sum_{t=\tau_1}^{\tau_2} \frac{\alpha_k \gamma_k(t)}{\sum_{j=N(t)}^{K} \alpha_j \gamma_j(t)}\right) \mathcal{N}\left(\mu_C, \sigma_C^2\right) + \alpha_k \gamma_k(T_k) \mathbf{1}_{\tau_2 = T_k} \mathcal{N}\left(\mu_R, \sigma_R^2\right) \tag{9}$$

Consider now two projects and an OAT policy that starts by promoting project 1 before switching to project 2. For a switching time $\tau < T_1$, the accumulated amount of funds for project 1 at its closing time T_1 is the sum of Gaussian variables as follows :

$$X_1(T_1) = X_1(0) + \left(\frac{\alpha_1 G}{\alpha_1 G + \alpha_2}\tau + \frac{\alpha_1}{\alpha_1 + \alpha_2 G}(T_1 - \tau)\right) \mathcal{N}\left(\mu_C, \sigma_C^2\right) + \alpha_1 \mathcal{N}\left(\mu_R, \sigma_R^2\right) \tag{10}$$

while the accumulated funds of project 2 are :

$$X_2(T_2) = X_2(0) + \left(\frac{\alpha_2(\tau + G(T_1 - \tau)}{\alpha_1 G + \alpha_2} + \alpha_2 G(T_2 - T_1)\right) \mathcal{N}\left(\mu_C, \sigma_C^2\right) + \alpha_2 G \mathcal{N}\left(\mu_R, \sigma_R^2\right) \tag{11}$$

Note that, if the operator promotes project 1 during its whole campaign period, the term multiplying $T_1 - \tau$ disappears and project 1 receives G times more funds at its closing time, leading to the general expressions:

$$X_1(T_1) = X_1(0) + a_1(\tau) \mathcal{N}\left(\mu_C, \sigma_C^2\right) + b_1(\tau) \mathcal{N}\left(\mu_R, \sigma_R^2\right) \tag{12}$$

$$X_2(T_2) = X_2(0) + a_2(\tau) \mathcal{N}\left(\mu_C, \sigma_C^2\right) + \alpha_2 G \mathcal{N}\left(\mu_R, \sigma_R^2\right) \tag{13}$$

The probability of success of project k being the probability that $X_k(T_k)$ exceeds M_k, we obtain:

$$\Pr(X_1(T_1) \geq M_1) = \frac{1}{2} erfc\left(\frac{M_1 - X_1(0) - a_1(\tau)\mu_C - b_1(\tau)\mu_R}{\sqrt{2(a_1(\tau)\sigma_C)^2 + 2(b_1(\tau)\sigma_R)^2}}\right) \tag{14}$$

and

$$\Pr(X_2(T_2) \geq M_2) = \frac{1}{2} erfc\left(\frac{M_2 - X_2(0) - a_2(\tau)\mu_C - \alpha_2 G \mu_R}{\sqrt{2(a_2(\tau)\sigma_C)^2 + 2(\alpha_2 G \sigma_R)^2}}\right) \tag{15}$$

Maximizing the overall number of successful projects, we obtain the switching time of equation (5).

□

For the first numerical applications, we consider the parameters of projects given in Table 1 (considering only projects 1 and 2). As of the platform parameters, the average and standard deviation of collected funds at any time interval are given by $\mu_C = 3$ and $\sigma_C = 0.5$, plus an additional peak at the closing time with $\mu_R = 5$ and $\sigma_R = 0.5$. If the platform promotes a project, its

Table 1: Project parameters

Project	1	2	3
Initial $X_k(0)$	0	5	0
Target M_k	30	30	40
Attractiveness α_k	1	0.5	0.5
Closing time T_k	15	20	25

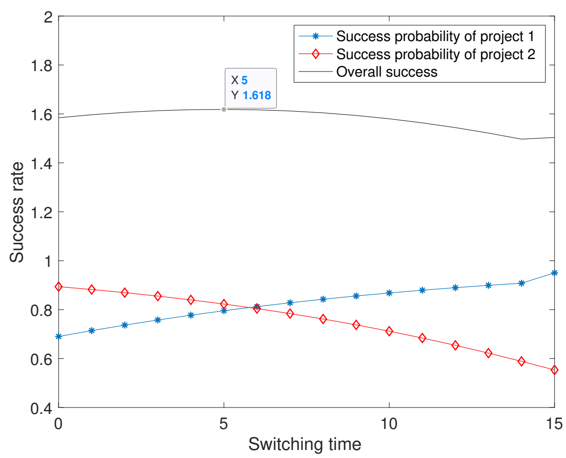

Figure 1: Individual and sum success rates for different timing strategies. Two projects case. The optimal policy is indicated.

attractiveness increases by 30% ($G = 1.3$). We illustrate in Figure 1 the success probabilities when the switching time τ increases from 0 to T_1. Increasing τ increases the chance of success of project 1, but decreases that of project 2; there is an optimal timing $\tau^* = 9$ in this case.

3.2 Optimal OAT policy in the general case

In the general case, where there are $K \geq 2$ projects, a similar approach can be followed for obtaining the optimal strategy. We denote a strategy as a vector of switching times $\tau = (\tau_2, ..., \tau_K)$, where $\tau_{k+1} \leq T_k$ is the time where the platform switches from promoting project k to promoting project $k + 1$. We denote by $p(t, \tau)$ the project that is promoted at time t when policy τ is followed. The amount of funds collected by project k at its closing date is a random variable as follows:

$$X_k(T_k) = X_k(0) + a_k(\tau)\mathcal{N}\left(\mu_C, \sigma_C^2\right) + b_k(\tau)\mathcal{N}\left(\mu_R, \sigma_R^2\right) \tag{16}$$

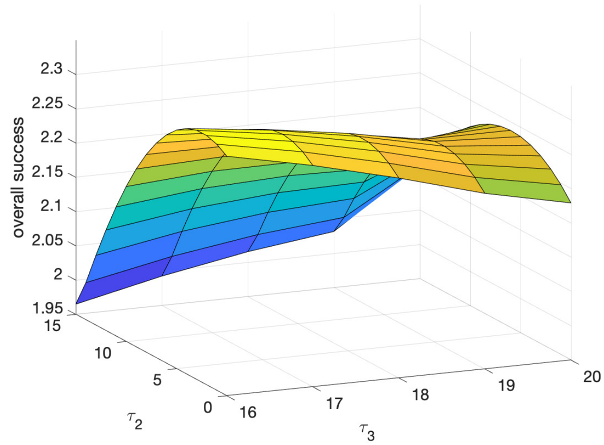

Figure 2: Success rates for three projects for different policies.

where

$$a_k(\tau) = \sum_{t \in [\tau_k, \tau_{k+1}]} \frac{\alpha_k G}{\sum_{j=N(t)}^{K} \alpha_j + (G-1)\alpha_k} + \sum_{t \notin [\tau_k, \tau_{k+1}]} \frac{\alpha_k}{\sum_{j=N(t)}^{K} \alpha_j + (G-1)\alpha_{p(t,\tau)}} \tag{17}$$

and

$$b_k(\tau) = \alpha_k(1 + (G-1)\mathbf{1}_{\tau_k = T_k}) \tag{18}$$

The sum success rate that is to be maximized is thus :

$$\sum_{k=1}^{K} \Pr(X_k(T_k) \geq M_k) = \frac{1}{2} \sum_{k=1}^{K} \frac{1}{2} erfc(\frac{M_k - X_k(0) - a_k(\tau)\mu_C - b_k(\tau)\mu_R}{\sqrt{2(a_k(\tau)\sigma_C)^2 + 2(b_k(\tau)\sigma_R)^2}}) \tag{19}$$

The optimal platform strategy is that the vector $\tau^* = (\tau_2^*, ..., \tau_K^*)$ that maximizes (19).

We illustrate in Figure 2 the impact of changing τ on the sum success probability for 3 projects whose parameters are given in Table 1. There are two parameters to set, τ_2 and τ_3, and there is a clear optimal strategy that consists in choosing $\tau_2 = 5$ and $\tau_3 = 16$ for the considered parameters.

4 Online policy as a real option: Dynamic programming

The optimal policy of the previous section helps the platform manager understanding the impact of the platform strategy on its portfolio of projects. However, an offline optimisation is not the most adequate policy as the manager may have the opportunity, in case of a unexpected evolution of the funding campaign of a project , to adjust online its policy.

4.1 Real options formulation

This opportunity can be modeled 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 promoted at least for a certain interval of time. In the case of a sequential policy, this decision is completely 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 upon time and the manager decision can be made contingent upon the resolution of the uncertainty, creating the option.
- Flexibility: This means that the manager can, function of new information, change its decision where the decision is contingent of an event. In our case, the manager has a complete or partial flexibility, depending on the structure of the strategy (OAT or completely dynamic).

4.2 Dynamic programming approach

In order 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 has the opportunity to stop promoting project 1 and switch to project 2, lowering thus the future amount of collected funds for project 1 and increasing that of project 2. Otherwise, he may wait one period of time and then decide whether to switch or to wait another period before making the same decision. This process will depend on the levels of collected funds at each period of time.

The state space at time t is described by $X(t) = (p, x_1, ..., x_K)$, where p is the index of the project currently promoted at time t, and x_k is the already collected amount of funds. Indeed, we have to keep track of the project that is promoted. 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 make the analysis tractable, we discretize the space of collected funds during one time slot into a finite number of possible values. Let J be the number of intervals for fund collection, c_j being the jth value ($c_1 = 0$ and $c_J = X^{max}$, chosen so that the probability of exceeding the maximum for any project is very small). The step size is equal to $\epsilon = \frac{c_J}{J}$ and at any time t, the additional amount of collected funds by project k may take any value c_j, $j \in [1, J]$.

For illustration purposes, we detail the analysis for the case of two projects. 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 X, given by 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:

$$\begin{aligned} U_{T_1}(x_1^i, x_2^j) &= Pr(X_2(T_2) \geq M_2 | X_2(T_1) = x_2^j) + \mathbf{1}_{x_1^i \geq M_1} \\ &= \frac{1}{2} erfc(\frac{M_k - x_2^j - \alpha_2 G(\mu_C(T_2 - T_1) + \mu_R)}{\sqrt{2(\alpha_2 G \sigma_C (T_2 - T_1))^2 + 2(\alpha_2 G \sigma_R)^2}}) + \mathbf{1}_{x_1^i \geq M_1} \end{aligned} \quad (20)$$

We then move backwards step by step and calculate the utility iteratively. For any time $t < T_1$, 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 is given by:

$$W_t(x_1^i, x_2^j) = \sum_{n=i}^{J} \sum_{m=j}^{J} q_1(t, n) q_2(t, m) U_{t+1}(x_1^i + c_n, x_2^j + c_m) \quad (21)$$

where $q_k(t, i, n)$ is the probability that the project k goes up from state i to state $n \geq i$ during the interval $[t, t+1]$, knowing that the strategy of the platform is to promote project 1. These can be approximated by:

$$q_1(t, n) \approx \frac{1}{\sum_{j=1}^{J} q_1(t, j)} \exp - \frac{(c_i - \frac{\alpha_1 G}{\alpha_1 G + \alpha_2} \mu_C - \alpha_1 G \mu_R \mathbf{1}_{t=T_1-1}))^2}{2(\frac{\alpha_1 G}{\alpha_1 G + \alpha_2} \sigma_C)^2 + 2(\alpha_1 G \sigma_R)^2 \mathbf{1}_{t=T_1-1}} \quad (22)$$

$$q_2(t, n) \approx \frac{1}{\sum_{j=1}^{J} q_2(t, j)} \exp - \frac{(c_i \epsilon - \frac{\alpha_2}{\alpha_1 G + \alpha_2} \mu_C)^2}{2(\frac{\alpha_2}{\alpha_1 G + \alpha_2} \sigma_C)^2} \quad (23)$$

Note that the transition probabilities are independent of the time t, except for project 1 at the last time slot where there are the rational investors that contribute to the fund raising.

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

$$\begin{aligned} S_t(x_1^i, x_2^j) = \frac{1}{2} erfc(&\frac{M_2 - x_2^j - \alpha_2 G(\mu_C(T_2 - T_1) + \mu_R) - \frac{\alpha_2 G}{\alpha_2 G + \alpha_1} \mu_C (T_1 - t)}{\sqrt{2(\alpha_2 G \sigma_C (T_2 - T_1))^2 + 2(\alpha_2 G \sigma_R)^2 + 2(\frac{\alpha_2 G}{\alpha_2 G + \alpha_1} \sigma_C (T_1 - t))^2}}) \\ &+ \frac{1}{2} erfc(\frac{M_1 - x_1^j - \frac{\alpha_1}{\alpha_2 G + \alpha_1} \mu_C (T_1 - t) - \alpha_1 \mu_R}{\sqrt{2(\alpha_1 \sigma_R)^2 + 2(\frac{\alpha_1}{\alpha_2 G + \alpha_1} \sigma_C (T_1 - t))^2}}) \end{aligned} \quad (24)$$

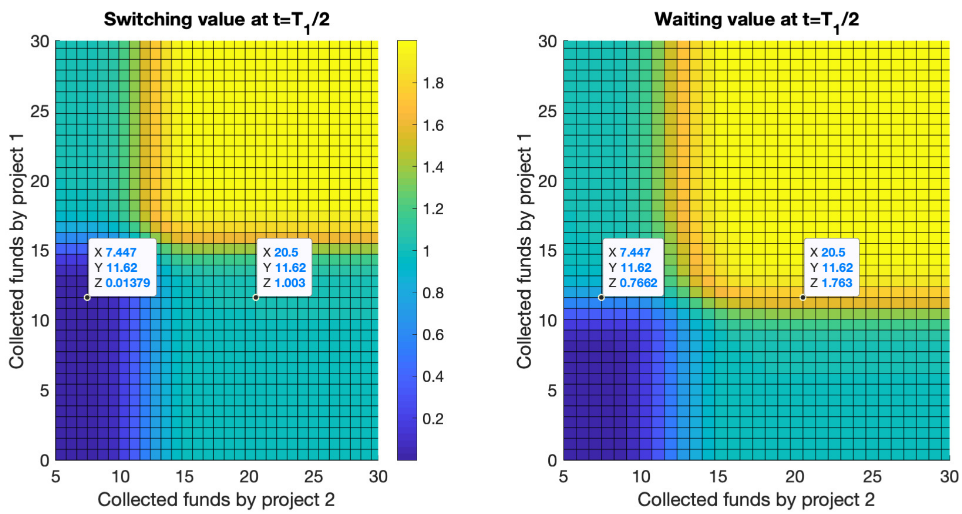

Figure 3: Values of the two strategies at a given time depending on the state of the platform.

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

$$U_t(x_1^i, x_2^j) = \max[W_t(x_1^i, x_2^j), S_t(x_1^i, x_2^j)] \tag{25}$$

4.3 Numerical applications

In order to illustrate the online policy, we implement the dynamic programming approach for the two projects case with the parameters of table 1. As the decision of the manager depends on the observed state, we illustrate in Figure 5 the values of the two different policies of the platform manager at a given time ($t = T_1/2$) 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 at least until the next time 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.

While the manager implements an online dynamic policy, the decisions may be predicted at time 0 based on the estimation of the future state evolution. The Gaussian assumption allows predicting this evolution. We plot in Figure 4 the evolution of the state probabilities with time, supposing that the policy is to maintain promoting project 1. Naturally, the average amount of collected funds increases with time. If we observe simultaneously figures 5 and 4, we can see that the platform is likely to be, at $t = T_1/2$, in a state around $X_1 \in [9, 11]$

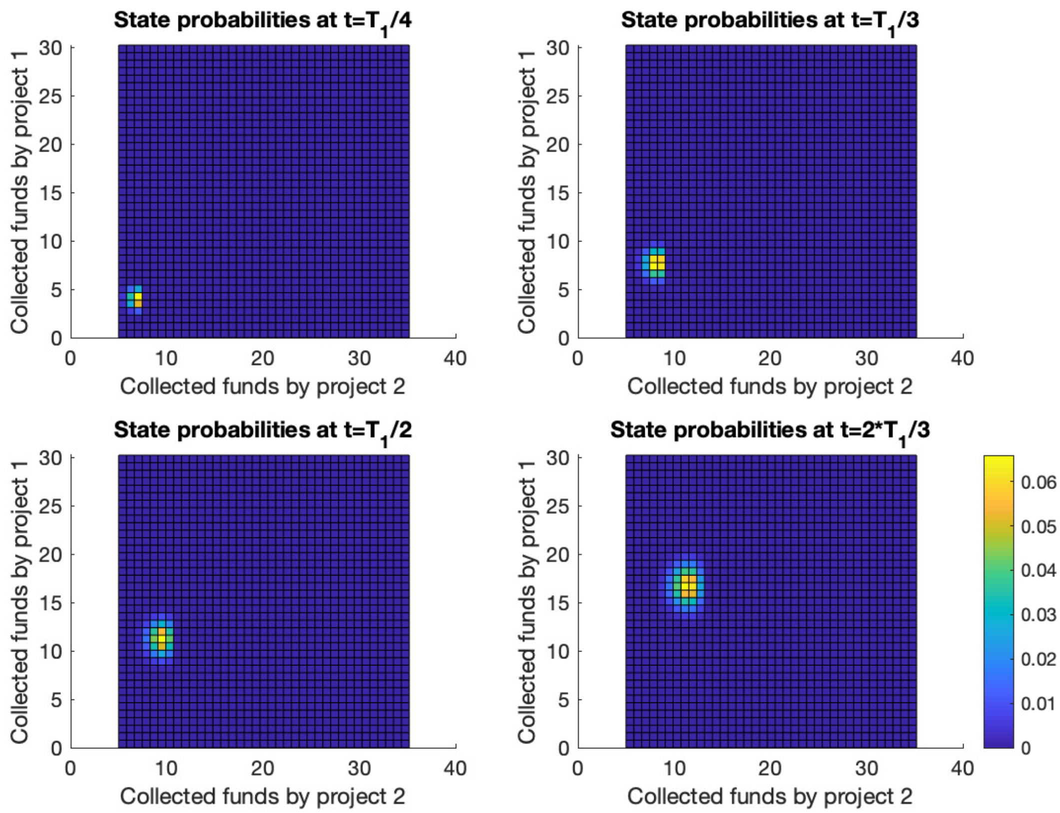

Figure 4: Evolution of state probabilities with time.

and $X_2 \in [8, 10]$. In these states, the waiting value is higher than the switching value, leading to a low switching probability. Figure 4 shows that this switching probability increases with time. We also illustrate in Figure 4 the impact of the initial collected funds on the strategy. A lower amount of initial funding for project 2 leads to an earlier switching in order to increase the overall success rate.

5 Conclusion

In this paper, we consider the perspective of a crowdfunding platform manager whose objective is to maximize the success ratio of his platform. We develop an optimization framework for the project promotion strategy that aims at balancing funds between projects and increasing the expected campaign success rate. We then developed an online strategy where the manager observes the project

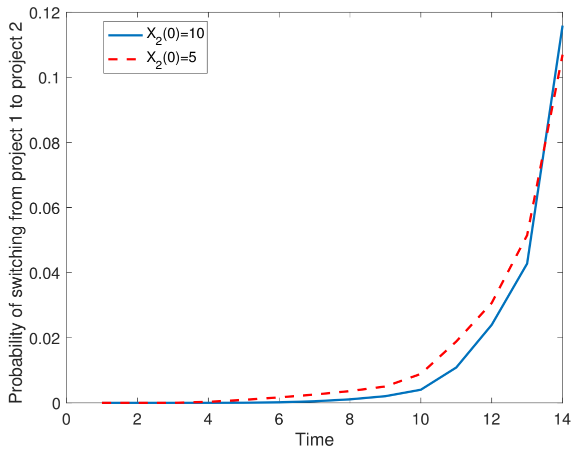

Figure 5: Probability of switching strategy function of time.

status evolution and adapts its strategy. We model this dynamic policy as a real option and developed the corresponding dynamic programming algorithm. The work of this paper is a first step towards a decision-making framework for crowdfunding platforms to pick projects and accompany them during their funding campaigns.

References

[1] P. Belleflamme, T. Lambert, and A. Schwienbacher, "Crowdfunding: Tapping the right crowd," *Journal of business venturing*, vol. 29, no. 5, pp. 585–609, 2014.

[2] E. Mollick, "The dynamics of crowdfunding: An exploratory study," *Journal of business venturing*, vol. 29, no. 1, pp. 1–16, 2014.

[3] A. Cordova, J. Dolci, and G. Gianfrate, "The determinants of crowdfunding success: evidence from technology projects," *Procedia-Social and Behavioral Sciences*, vol. 181, pp. 115–124, 2015.

[4] G. K. Ahlers, D. Cumming, C. Günther, and D. Schweizer, "Signaling in equity crowdfunding," *Entrepreneurship Theory and Practice*, vol. 39, no. 4, pp. 955–980, 2015.

[5] A. K. Agrawal, C. Catalini, and A. Goldfarb, "The geography of crowdfunding," National bureau of economic research, Tech. Rep., 2011.

[6] J. Solomon, W. Ma, and R. Wash, "Don't wait!: How timing affects coordination of crowdfunding donations," in *Proceedings of the 18th acm confer-*

ence on computer supported cooperative work & social computing. ACM, 2015, pp. 547–556.

[7] L. Salahaldin, M. Angerer, S. Kraus, and D. Trabelsi, "A duration-based model of crowdfunding project choice," *Finance Research Letters*, vol. 29, pp. 404–410, 2019.

[8] A. Lukkarinen, J. E. Teich, H. Wallenius, and J. Wallenius, "Success drivers of online equity crowdfunding campaigns," *Decision Support Systems*, vol. 87, pp. 26–38, 2016.

[9] D. Cumming, G. Leboeuf, and A. Schwienbacher, "Crowdfunding models: Keep-it-all vs. all-or-nothing," 2015.