UNDERSTANDING CROWDFUNDING PROCESSES: A DYNAMIC EVALUATION AND SIMULATION APPROACH

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ABSTRACT

Crowdfunding (*CF*), an alternative source of financing for startups and creative projects, has gained prominent attention from practitioners and researchers. However, we find few research papers investigating *CF* from the perspective of its dynamic processes. In this paper, we propose a dynamic system framework, which incorporates heterogeneous entrepreneurs and funders, and *CF* platforms. In particular, we formally formulate the interactions among various factors in the *CF* processes. Through simulations we show that first, *CF* platforms are more viable for projects with small-scale capital requirements than those with large-scale requirements. Second, due to information asymmetry, non-profit projects are likely to acquire more funding comparing with for-profit projects. Third, *CF* platforms can reach maximum performance (indicated by the success rate of projects) by applying certain control mechanisms, such as acceptance rate and diffusion density. Our results are consistent with and provide a new and comprehensive angle for understanding the empirical results from current literature. We also discuss important practical insights of our research in details.

Keywords: Crowdfunding; Crowdfunding processes; Dynamic systems; Simulation; Two-sided platforms

1. Introduction

Crowdfunding (CF) platforms, such as Kickstarter and Indiegogo, have become an innovative form of financing for startups and creative projects. They provide new opportunities for entrepreneurs who have difficulty obtaining funding through traditional sources, such as “family, friends, and fools” (FFF) or angel capital, to raise money from potential funders on the Internet [Belleflamme et al. 2014]. For example, an entrepreneur raised over $10,000,000 from about 60,000 funders for a game software development project within one month, through Kickstarter, one of the leading CF platforms[†]. In recent years, crowdfunding has grown rapidly and played an increasingly important role in the capital market [Gerber et al. 2012]. Therefore, it has also received wide attention from entrepreneurs, funders, and regulatory authorities [Marakkath & Attuel-Mendes 2015].

Previous studies, mostly empirical work, have provided important insights into crowdfunding from the perspectives of funders and/or entrepreneurs. For example, some studies investigated motivations to participate in crowdfunding [Belleflamme et al. 2013]. Other studies examined the impact of factors, such as funders’ expertise of crowdfunding [Feng et al. 2015], information revealed by entrepreneurs [Burtch et al. 2013], and institutional

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[†] Ouya: a new kind of video game console, http://www.kickstarter.com/projects/ouya/ouya-a-new-kind-of-video-game-console

environment [Bradford 2012; Cohn 2012] on funders' decisions and project performance. A few analytical studies focused on the interaction between funders and entrepreneurs [Belleflamme et al. 2010; Belleflamme et al. 2014]. However, CF platforms, whose policies affect both funders and entrepreneurs, have received little attention. We also find that studies on the interaction between entrepreneurs and funders have failed to incorporate the dynamics of the crowdfunding process. In our study, we model the crowdfunding process from a systematic perspective and include key factors based on previous literature, such as information asymmetry between funders and entrepreneurs, heterogeneity of crowdfunding participants (funders and entrepreneurs), and CF platform control mechanisms. To the best of our knowledge, this work is among the first to investigate crowdfunding from this aspect. Based on multiple numerical simulations, we find the following interesting results. First, CF platforms are more viable for entrepreneurs with small-scale capital requirements; it is harder to successfully fund projects requiring large capital. Second, due to information asymmetry, non-profit projects, associated with lower variance of value, are more likely to acquire more funding. Therefore, the success rate of non-profit projects is higher than for-profit ones in CF platforms. Third, the settings for acceptance rate, for-profit projects to total projects ratio, and diffusion density can be used to significantly improve the overall success rate. Our simulation results also indicate that diversified investment benefits funders and improves a CF platform's performance. Lastly, treating diffusion density as an endogenous parameter gives us inverted U-shaped and bimodal curves that represent the relationship between a CF platform's performance and its control mechanisms. Thus, we can conclude that utilizing appropriate control mechanisms will lead to maximum performance for the platform.

The contributions of this study are three-fold. First, we propose a mathematical model to describe crowdfunding processes that is more comprehensive and systematic than previous literature. It incorporates important aspects of the crowdfunding process in reality. Our model can also be easily extended to a variety of other complex circumstances. Second, simulation results in this study are consistent with empirical findings in current crowdfunding literature [Mollick 2014]. Further, we provide an alternative perspective to interpret results shown in previous studies [Ghatak & Mueller 2011; Read 2013; Pitschner & Pitschner-Finn 2014]. Third, our study offers important managerial implications. Focusing on the control mechanisms, this study contributes to improving performance and risk control, and maintaining sustainability of CF platforms. In addition, some regulatory opinions can be derived from this study.

The remainder of this paper is organized as follows. Section 2 reviews the literature pertaining to crowdfunding. Section 3 introduces our assumptions and notations, as well as the proposed mathematical framework for modeling crowdfunding processes. We simulate the dynamics of crowdfunding using NetLogo in Section 4 and our research findings. Discussion and conclusions are presented in Section 5.

2. Literature Review

Crowdfunding is a subtype of crowdsourcing [Poetz & Schreier 2012; Thurlow & Yue 2012]. It is a form of online micro-finance, in which an open call is issued/put out, essentially through the Internet, for financial resources in the form of donations or in exchange for some form of reward and/or voting rights in order to support initiatives for specific purposes [Lambert & Schwienbacher 2010]. In this section, we review literature related to crowdfunding from three perspectives: funders, entrepreneurs, and CF platforms.

2.1 Funders

Since participation in crowdfunding is a form of investment, it is not surprising to find many research studies focused on funders. One stream of crowdfunding research on funders investigates their incentives to participate in crowdfunding [Gerber et al. 2012; Bretschneider et al. [2014]. Although economic return is an important incentive, there are also some intrinsic incentives, such as self-accomplishment [Ouwersloot & Odekerken - Schröder 2008], fun [Schau et al. 2009], altruism [White & Peloza 2009], reciprocity [Faraj & Johnson 2010; Gaudeul & Giannetti 2013], and community benefits [Belleflamme et al. 2014]. Along this same line, Lin et al. [2013] and Agrawal et al. [2015] found that family members and friends are important funders in a crowdfunding project's early stages.

Another stream of studies on funders focuses on their funding decisions and/or behavior. Different from professional investors, funders in crowdfunding projects are largely affected by non-standard information [Iyer et al. 2009]. For example, using data from prosper.com, Herzenstein et al. [2011a] found unverifiable information affects the decisions of funders more than the objective and verifiable information. Funders are also affected by previous funders' decisions [Liu et al. 2015; Shen 2010]. For example, projects with more 'backers' or that are closer to being successfully funded can better attract more potential funders, i.e. 'herding effect' [Zhang & Liu 2012; Herzenstein et al. 2011b]. Further, Yum et al. [2012] utilized empirical data from prosper.com and found that herding effects depend on the extent of available information for funders. If enough information on the projects is disclosed, funders tend to make their funding decisions based on project information rather than on previous funders' decisions.

In addition, the Internet can bridge geographical distance, which is considered an advantage of crowdfunding [Rouse 2010; Whitla 2009]. However, researchers also find an evident "home bias" [Hemer 2011] in crowdfunding projects, that is, funders tend to support culturally and/or geographically closer projects [Burtch et al. 2014; Lin & Viswanathan 2015].

2.2 Entrepreneurs

Another branch of related studies focuses on the other side of crowdfunding projects, i.e. entrepreneurs. In addition to acquiring direct economic support, other underlying incentives include relationship building [Kraut & Resnick 2011], validation [Weng & Fesenmaier 2013], replicating others' successes [Cialdini 2001], and using social media to expand awareness of particular issues [Gerber et al. 2012].

In regard to the successful funding projects, a number of studies have focused on entrepreneurs' characteristics and behavior. First, entrepreneurs' social networks play an important role in successfully funded projects due to the influence of social capital [Freedman & Jin 2014; Mollic 2014]. However, social networks and social capital have heterogeneous impacts across different entrepreneurs and different stages of the projects [Greiner & Wang 2009]. Using data collected from the US and China, Xu et al. [2011] found that different cultural backgrounds also contribute to the heterogeneous impacts of entrepreneurs' social networks on crowdfunding success. Further, Lu et al. [2012] divided social capital into online social capital and offline social capital, and found that online social capital is less stable than offline social capital. Hekman & Brussee [2013] found that a sparse social network is more effective for entrepreneurs than a dense social network.

Second, some studies examined the entrepreneurs' previous experience and their decisions during projects. For example, it is easier for entrepreneurs with previous successful projects to get funded [Koning & Model 2013]. In addition, information provided by entrepreneurs, such as detailed plans, financial roadmaps and risk information will be helpful to acquire sufficient funding [Ahlers et al. 2015]. Verhaert & Van den Poel [2012] also showed that the timing of information disclosure during the process of a crowdfunding project is critical to its success. Based on self-determination theory and transportation theory, Liu et al. [2014] examined the information diffusion between entrepreneurs and funders, and suggested that entrepreneurs should customize the information they provide.

2.3 CF platforms

There are a few related studies focusing on CF platforms, i.e. multi-sided platforms linking funders and entrepreneurs [Hu et al. 2015]. Lasrado & Lugmayr [2014] and Pierrakis & Collins [2013] investigated different business models utilized by CF platforms. Through field experiments, Naroditskiy et al. [2014] aimed to establish the relationship between various mechanisms and incentives of participants (funders and entrepreneurs), which is critical for the sustainability of a CF platform. Due to information asymmetry between funders and entrepreneurs, information provided by the platform, such as entrepreneurs' reputations, serve as an important signal for funders [Krumme & Herrero 2009; Packalen 2007]. A survey study by Moritz et al. [2015] showed that endorsements of CF platforms reduce the perceived information asymmetry and lower the importance of pseudo-personal communications from entrepreneurs. In addition, due to the potential risk for funders, some papers studied how to balance entrepreneurs' incentives and protect funders' interests [Hildebrand et al. 2014; Heminway 2014].

Current studies provide important insights for modeling the CF process in this study. First, Lambert & Schwienbacher [2010] and Gerber et al. [2012] analyzed the process of crowdfunding projects, which helps us to structure the general model in this study. Second, we also model behavior of funders and entrepreneurs during the crowdfunding process based on current empirical evidence [Liu et al. 2015; Hemer 2011; Mollic 2014], including the interaction between funders and entrepreneurs based on a model by Belleflamme et al. [2014]. We specifically include information asymmetry between funders and entrepreneurs and information revealed across different stages of the crowdfunding process [Moritz et al. 2015]. Third, the initial status utilized in this study's simulation is based on empirical results from Hu et al. [2015] and Hemer [2011].

Our study contributes to the literature on crowdfunding in two ways. First, previous literature mainly covered funders and entrepreneurs, but only a few studies examined the CF platforms. This study is among the first to investigate CF platforms from a systematic perspective. We model the interactions among funders, entrepreneurs, and the platforms. Second, previous models treated funders and entrepreneurs as homogenous and failed to include idiosyncratic characteristics. In this study, we consider heterogeneous characteristics of funders and entrepreneurs, which is closer to reality.

3. Model

In this paper, we model the interactions among entrepreneurs, funders, and the CF platform, considering the dynamic process of crowdfunding. For consistency, in this research we refer to the participants who request funds as 'entrepreneurs' (referred to as 'creators' in Kickstarter and 'creatives' in RocketHub). We refer to the participants who pledge funds as 'funders' (the same as 'backer' in Kickstarter, 'fuelers' in RocketHub, and 'funders' in Indiegogo).

3.1. Model Notations

We first introduce variables and the definitions used in this research.

Table 1: Notation Table

Variable	Explanation
C	The set of potential funders.
c_i	A specific funder whose identity is represented by the subscript, $c_i \in C$.
N	The number of potential funders, i.e. the cardinality of C.
t	The period of crowdfunding, or iterative steps in the model.
C_t	The set of potential funders who invest in CF platform in period t.
I_i	Volume of funds invested by c_i if c_i participates in crowdfunding.
γ	Level of investment diversification, or number of projects funded by a funder.
E_t	The set of project applications submitted to CF platform in period t.
q_{it}	A specific project submitted to CF platform in period t. $q_{it} \in E_t$.
e_{it}	The entrepreneur of project q_{it}.
m_t	The number of projects submitted to CF platform in period t, or cardinality of E_t.
A_t	The set of projects accepted by CF platform in period t, or a subset of E_t.
μ	The acceptance rate of CF platform, or $\lvert A_t \rvert / \lvert E_t \rvert$.
A_t^f	A subset of A_t, which only contains for-profit projects.
A_t^n	A subset of A_t, which only contains non-profit projects.
φ	For-profit project to total project ratio, or $\lvert A_t^f \rvert / \lvert A_t \rvert$.
S_t	The set of successful projects in period t, or a subset of A_t.
τ_t	Success rate of CF platform in period t, or $\lvert S_t \rvert / \lvert A_t \rvert$.
U_{it}	The set of projects invested in by c_i in period t.
a_{ji}^t	Assessed value of project q_{it} by funder c_j.
$\pi_t(c_j)$	Net utility of c_j in period t.
$\overline{\pi_t}(c_j)$	Normalized $\pi_t(c_j)$ on $[0,1]$
$\pi_{it}(c_j)$	Utility c_j gets from project q_{it}.
K	Average influence of funders in a social network.
$p_t(c_j)$	Probability of funders to participate in crowdfunding affected by c_j in period $t+1$.
α	Density of diffusion in potential funder's network.
$\gamma_t(c_j)$	Boolean Function to describe whether c_j invested in period t.
z_{it}	The value of q_{it}, which is uniformly distributed in $[0,1]$.
δ_{it}	The signal of q_{it}, which is related to z_{it}.
$\sigma_f\ (\sigma_n)$	The variance of signals of for-profit (non-profit) projects.
ρ	The level of public welfare.
θ_{ji}^t	Reservation utility of c_j for q_{it}.
K_{it}	Required capital by e_{it} in period t.

According to Table 1, the following relationship exists: $S_t \subseteq A_t \subseteq E_t$. γ represents the number of projects a funder invests in with a certain budget. In this study, the projects in the CF platform are assumed to be independent and each funder selects γ projects that he believes are the best in the CF platform. Therefore, γ measures the level of investment diversification.

Due to information asymmetry, funders cannot see/know a project's value; they can only speculate about it. We denote the valuation of project q_{it} by funder c_j as a_{ji}^t. For each funder c_j, his investment in project q_{it} brings him a certain utility, denoted as $\pi_{it}(c_j)$. The net utility of funder c_j in period t, denoted as $\pi_t(c_j)$, measures the amount of utility derived from all projects invested in by c_j in period t.

The proposed model is constructed on six specific assumptions as explained below.

3.2. Model Assumptions

ASSUMPTION 1 (A1): There is one CF platform in the market, where the potential funders form a 'small-world' network.

In practice, different CF platforms have different target groups, and their competition, even among projects from the same category, is weak [Hemer 2011]. Hence, we do not consider competition between CF platforms in our model. We focus on the key aspects, i.e. the dynamic processes of crowdfunding.

In addition, in an online environment, a funder's investment decision can be affected by other potential funders who were closed to him [Zhang & Gu 2015] and the network of potential funders is often seen as an efficient network that links to the broadest range of information, knowledge, and experience, which is accordant with the traits of the 'small-world' network [Benkler 2006]. Further, the topology of the potential funders' network lies between regular networks and completely random networks, which is appropriately characterized as a 'small-world' network [Watts & Strogatz 1998]. Therefore, we use 'small-world' network to describe the potential funders' network in this research.

Following previous literature [Agrawal et al. 2010], we consider N potential funders as N vertices, which are randomly distributed on the coordinate plane initially. Then, we randomly generate K edges for each vertex to connect with other vertices, which leads to a 'small-world' network. In a sparse $(K << N(N-1)/2)$ network, there exists at least one path connecting any two potential funders with a finite number of steps. K measures the average influence of funders.

For any potential funder $c_i \in C_t$, if $\pi_t(c_i) > 0$, c_i will continue to invest in the CF platform in the next period and we rewire each edge between c_i and his first degree connected vertices $c_j \in C / C_t$ with probability $p_t(c_i)$ to make sure these rewired potential funders will appear as first-time participants in crowdfunding in period $t+1$. Otherwise c_i will quit crowdfunding without affecting his neighbors. $p_t(c_i)$ depends on $\pi_t(c_i)$. Considering diminishing marginal utility, we assume the function of $p_t(c_i)$ as follows.

$$p_t(c_i) = [\overline{\pi_t}(c_i)]^{\alpha} \tag{1}$$

where parameter $\alpha \in (0,1)$ represents the density of diffusion in a potential funder's network, and $\overline{\pi_t}(c_i)$ is the normalized net utility of c_i on [0,1] in period t. For any potential funder $c_i \in C$, in period t, we can define a Boolean Function $\gamma_t(c_i)$ whose value is 1 if c_i indeed invests in t and is 0 otherwise. Hence $\gamma_t(c_i)$ depends on net utility of funders in the last period.

$$\gamma_t(c_i) = f[\pi_{t-1}(c_k)] \tag{2}$$

where $c_i \in C_{t-1}$.

ASSUMPTION 2 (A2): The volume of total available investment for each potential funder in a CF platform is constant if he participates in crowdfunding.

In other words, the volume of total available investment in the CF platform by any potential funder is fixed. In our model, the volume of total available investment in the CF platform by a potential funder only depends on his initial wealth, which is assumed to be exogenous. If the wealth of individuals is linearly correlated with the volume of total available investment, it can be directly initialized following the general wealth distribution. Therefore, we assign an initial value I_i to the potential funder c_i as his volume of total available investment. We also assume I_i has an exponential distribution, i.e. $Exp(\varepsilon)$, based on previous research [Katriel 2014]. If we denote the rate parameter of I_i as ε, we have probability density function for I_i.

$$f(x,\varepsilon)=\begin{cases}\varepsilon e^{-\varepsilon x}, & x\geq 0\\ 0, & x<0\end{cases} \tag{3}$$

In addition, we assume that the number of projects that a potential funder supported is a fixed value γ, i.e. $|U_{it}|=\gamma$. Then the volume of investment for a specific project is I_i/γ for any funder $c_i \in C_t$. We acknowledge two basic intuitions to simplify our model setting of funders' investment behavior. According to previous studies [Aaker & Akutsu, 2009; Glazer & Konrad, 1996; Gerber & Hui, 2014; Rick et al. 2007], funders often focus more on helping others, being part of a community, and collecting rewards than on personal/financial benefit/gain. The amount invested by a specific funder, which is highly correlated with his wealth, tends to be evenly distributed in projects. However, our focus is on the macro dynamic process of crowdfunding and control mechanisms of CF platforms in this paper. This setting for individuals simplifies the technical processing, but also retains the heterogeneity influence of funders and entrepreneurs on the crowdfunding process in reality. Note that γ can be used to measure the level of investment diversification. A higher γ means a more diversified investment portfolio.

ASSUMPTION 3 (A3): The number of crowdfunding projects submitted to the CF platform increases as the success rate increases.

The intuition of A3 is that the higher the success rate, the more attractive the CF platform is to entrepreneurs. The influx of new projects exhibits a significant difference in practice, varying from an average of 29 per month (e.g., RocketHub) up to 571 per month (e.g., Kickstarter) according to web research by Hemer [2011]. Therefore, we simply generate initial m_0 projects first, and the number of projects over time will evolve following equation (4).

$$m_t = m_{t-1}\left(1+\frac{|S_{t-1}|}{|A_{t-1}|}\right) \tag{4}$$

The iteration of the number of submitted projects on a CF platform ignores the possibility of negative growth for three main reasons. First, learning from the samples used by Hemer [2011], since crowdfunding in general is in an initial growth stage, active users have increased in recent years for almost all CF platforms. Second, this simplifies the mathematical treatment of the interaction between entrepreneurs and funders. Last, as shown later, the main conclusions of this paper still hold even if the negative growth of the number of submitted projects is considered.

ASSUMPTION 4 (A4): The value of each project is private information of the entrepreneurs when the project is accepted by the CF platform. However, in the following period it will become public information.

A4 explains the provision of information structure between entrepreneurs and both CF platform and potential funders. Practically, the information structure in crowdfunding is perplexing and it may be one of the most important factors influencing potential funders' participation [Agrawal et al. 2010].

Suppose the value of any $q_{it} \in E_t$ identified by z_{it}, with z_{it} uniformly distributed on [0,1]. z_{it} is the private information of entrepreneur e_{it} and cannot be captured accurately by the CF platform or potential funders. However, potential funders can observe a signal δ_{it} related to z_{it}. This signal represents information from project materials of the e_{it}, such as the capital plan, technical reports, and project profile. To describe the relationship between δ_{it} and z_{it}, in general, we assume that δ_{it} follows a normal distribution with mean z_{it}, i.e. $\delta_{it} \sim N(z_{it},\sigma^2)$. σ represents the degree of information asymmetry. We denote $F_{\delta_{it}}$ as the cumulative distribution function. We assume that $F_{\delta_{it}}$ has first-order stochastic dominance over $F_{\delta_{jt}}$, if $z_{it} > z_{jt}$.

$$F_{\delta_{it}} \underset{FSD}{\succ} F_{\delta_{jt}} \tag{5}$$

ASSUMPTION 5 (A5): There are two types of projects in CF platforms: for-profit and non-profit.

In this paper, we divided projects into two types, i.e. for-profit projects and non-profit projects. Previous research has examined the essential differences of the two types of projects in terms of their motivation, mobilizing, and performance empirically and theoretically [Carvajal et al. 2012].

Further, based on Read [2013], we argue that compared with for-profit projects, the uncertainty of benefits for funders, including community benefits, from non-profit projects is lower. Specifically, non-profit projects differ from for-profit projects because of smaller variance of signals related to the real value. Suppose $\sigma_n = (1-\rho)\sigma_f$, $\rho \in [0,1]$, where σ_f and σ_n represent the variance of signals of for-profit and non-profit projects respectively, and ρ is the parameter that represents the level of public welfare of the projects. Our model differentiates the two types of projects and can be regarded as an extension of a study by Mollick [2014].

Note that equation (5) implies that the CF platform can reveal which project is relatively better based on the signal δ_{it}, if $z_{it} > z_{jt}$. That is, screening projects in terms of stochastic dominance becomes possible for the CF platform. Hence, the CF platform can make its decision in each period t. First, the platform decides how many projects to accept according to the acceptance rate μ. Second, the CF platform determines the number of for-profit projects $\mu\varphi m_t$ and the number of non-profit projects $\mu(1-\varphi)m_t$. Third, the CF platform accepts $\mu\varphi$ for-profit projects and $\mu(1-\varphi)$ non-profit projects with biggest δ_{it}. Most CF platforms require entrepreneurs to label the type of project when they solicit money through the platforms. However, in reality, the boundary between for-profit and non-profit projects is not always explicit. Many projects marked as non-profit in CF platforms operate with a certain degree of profitability, while those projects marked as for-profit often have some non-profit purposes. In addition, as the value of non-profit projects may not always be easy to judge, it is sometimes difficult for funders and CF platforms to differentiate the type of project. Therefore, in this paper we have assumed the type of projects as a continuous variable ρ, so that the identifiable features of types can be captured by our model. In the special case, $\rho = 0$, there is only one type of projects in the CF platform.

ASSUMPTION 6 (A6): The behavior of both entrepreneurs and funders depends on the historical information.

The "crowd" consists of funders c_j, from whom an entrepreneur e_{it} solicits funding for his projects. Funder $c_j \in C_t$ has reservation utility θ_{ji}^t, with θ_{ji}^t uniformly distributed on [0,1] for project q_{it}. A funder's reservation utility is private information in period t, but will become public information from period $t+1$.

3.3. Model Calibration

Since the information sharing among potential funders is crucial for fast response to the changing online market, we partly draw on Liu et al. [2015] to describe the decision-making sequence as follows (see Fig. 1). In the first stage, the entrepreneur e_{it} sets the required capital K_{it} based on observations in period $t-1$. In the second stage, the funders decide which projects invest in to maximize their expected utility. The decision mechanism of funders also serves as a condition for entrepreneurs to make their decision.

1st Stage. Entrepreneurs make their decisions based on historical observations. If q_{it} solicited money through the CF platform in period $t-1$ instead of period t, i.e. there is a funder c_j, so that $q_{it} \in U_{jt-1}$. Denote D_i^t as a set of funders who invest in projects in period $t-1$. According to A2, subject to (*s.t.*) the constraint of projects invested in during the last period, the entrepreneur's decision is to maximize the cardinality of set D_i^t,

Thus the general form of behaviors of entrepreneurs and funders can be given as

$$\begin{aligned} &\max_{K_{it}} \left| D_i^t \right| \\ &s.t.\ U_{jt-1} \\ &\qquad s.t.\ \max_{q_{kt-1}} E[\pi_t(c_j)] \\ &\qquad U_{st} \end{aligned} \tag{6}$$

2nd Stage. Because potential funder c_j cannot discern the real value of project q_{it}, he assesses the value of the project based on signal δ_{it} and required capital K_{it}. Since funders' evaluation of the project's value is jointly decided by the signal and required capital, and both of them have diminishing marginal contribution for the cognition of funders, the format of the Cobb-Douglas function [Douglas 1976] is appropriate to describe the value perceived by a funder, i.e.

$$a_{ji}^{t} = \overline{K_{it}}^{\beta} \delta_{it}^{1-\beta} \tag{7}$$

where β represents weight of importance, and $\overline{K_{it}} \in [0,1]$ is the normalized value of K_{it}. δ_{it} is the signal of project q_{it} as explained above.

Denote B_{ji}^{t} as a set of l projects in period $t-1$ whose values assessed by c_j are closet to a_{ji}^{t}. c_j's expected utility from q_{it} is $E[\pi_{it}(c_j)]$.

$$E[\pi_{it}(c_j)] = \frac{1}{l} \sum\nolimits_{q_{jt-1} \in B_{ji}^{t}} (z_{kt-1} - \theta_{jk}^{t-1}) \tag{8}$$

Therefore funder c_j invests in projects contained by set U_{jt}, which can bring the highest expected utility.

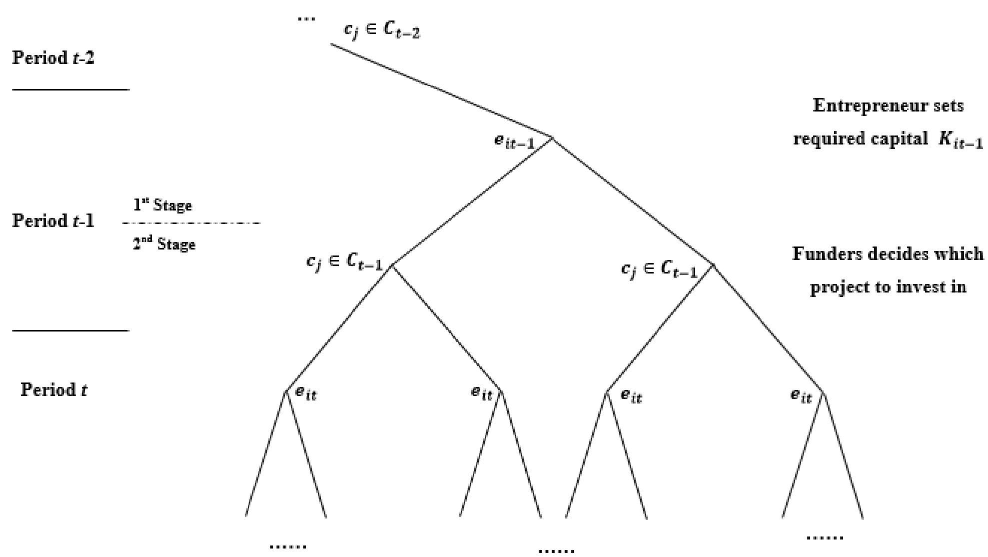

Fig. 1 Decision-Making Sequence

Finally, there are a few points that we need to note about A5 and A6. First, the approach to differentiate for-profit and non-profit projects in our model explains the determinants behind behavior of funders, which is an extension of Mollick's model [2014]. Second, funders can obtain payoff from investing in projects in two ways: pre-ordering and profit sharing. However, we do not differentiate these in our model. This is because our model can incorporate these two forms of payoff and provide results that are more general. Third, to preserve parsimony, we exclude elements, such as funders' search cost, marketing practice of entrepreneurs, and recommendation from the CF platform, so that we can focus on the main characteristics of crowdfunding.

Hence, the dynamic system of crowdfunding, under these assumptions, can be generally represented by a multidimensional nonlinear mapping, which is a combination of equations (2), (4), (8), and the optimization problem.

$$\begin{cases} \gamma_t(c_i) = f[\pi_{t-1}(c_k)] \\ m_t = m_{t-1}(1+\dfrac{|S_{t-1}|}{|A_{t-1}|}) \\ E[\pi_{it}(c_j)] = \dfrac{1}{l}\sum_{q_{jt-1}\in B_{ji}^t}(z_{kt-1}-\theta_{jk}^{t-1}) \\ \max\limits_{K_{it}} |D_i^t| \\ s.t.\ U_{jt-1} \\ \qquad s.t.\ \max\limits_{q_{kt-1}} E[\pi_t(c_j)] \\ \qquad U_{st} \end{cases} \tag{9}$$

Equations (2) and (4) describe the dynamic evolution of participation of potential funders and entrepreneurs under control of the CF platform respectively. The dynamic interaction between funders and entrepreneurs with information asymmetry is characterized by equation (8) and the optimization problem (6).

4. Simulation and Analysis

In order to simulate the dynamics of crowdfunding numerically, we utilize free software called NetLogo5.1.0, which effectively handles various heterogeneity problems [Dickerson 2011]. To illustrate this, we first assign the parameters with the following initial values.

$N = 100{,}000$, $K = 160$, $m_0 = 50$, $\varepsilon = 1.2$, $\beta = 0.6$, $\sigma_f = 0.4$.

Second, we randomly generate an initial 'small-world' network and projects for period $t = 0$.

Then for each period t $(t > 0)$, we run our simulation following the procedure shown in Table 2.

Table 2: Numerical Simulation Procedure of/for Period t $(t > 0)$

Step 1:	Construct a new network in potential funders based on the network and net utility of funders in period $t-1$, i.e. $\pi_t(c_i)$, $c_i \in C_{t-1}$.
Step 2:	Generate new projects that will be submitted to CF platform according to the success rate in period $t-1$, i.e. τ_{t-1}.
Step 3:	CF platform decides which projects to show.
Step 4:	Entrepreneurs with accepted projects in CF platform decide their required capital; and potential funders decide which project to invest in.
Step 5:	Obtain the results, such as utility of funders and success rate in period t.

Note that entrepreneurs determine their required capital only after their projects are selected by the CF platform in our simulation process. Although this process does not fully capture the reality, it helps to simplify the calculation.

4.1. Success Rate and Control of CF Platform

The success rate, a crucial measure of the CF platform performance, has a significant influence on its sustainability. The CF platform with a higher success rate not only attracts a large number of entrepreneurs, but also enhances the funders' experience through providing them more diverse investment options and higher community benefits. In practice, the success rate is remarkably different across various CF platforms, ranging from 6% (PledgeMusic) to 92% (Sonicangel), with an average value of 64% [Hemer 2011].

Different from previous literature focusing on characteristics of projects and entrepreneurs [Kuppuswamy & Bayus 2014], we investigate how different CF platform control mechanisms impact the success rate. Hence, in this section, we first obtain the simulated success rate over periods, i.e. iterations. Then we discuss how the platform can control success rate through its decision-making.

To obtain the success rate value, we assign values to the following parameters:
$\rho = 0.6$, $\alpha = 0.6$, $\mu = 0.3$, $\gamma = 4$, and $\varphi = 0.8$.

Table 3 illustrates the success rates in both for-profit and non-profit projects in 600 iterations.

Table 3: Success Rate in 600 iterations

Success Rate	For-Profit	Non-Profit	41.22%
	35.23%	65.38%	

Out of 436 submitted applications, the CF platform accepts 131 projects, including 105 for-profit projects and 26 non-profit projects over 600 iterations. There are 37 successfully funded for-profit projects and 17 non-profit projects. Our results in Table 3 support the empirical evidence from the study by Pitschner & Pitschner-Finn [2014] and are consistent with the theoretical research of Belleflamme et al. [2010], that non-profit projects significantly outperform for-profit ones in terms of the success rate.

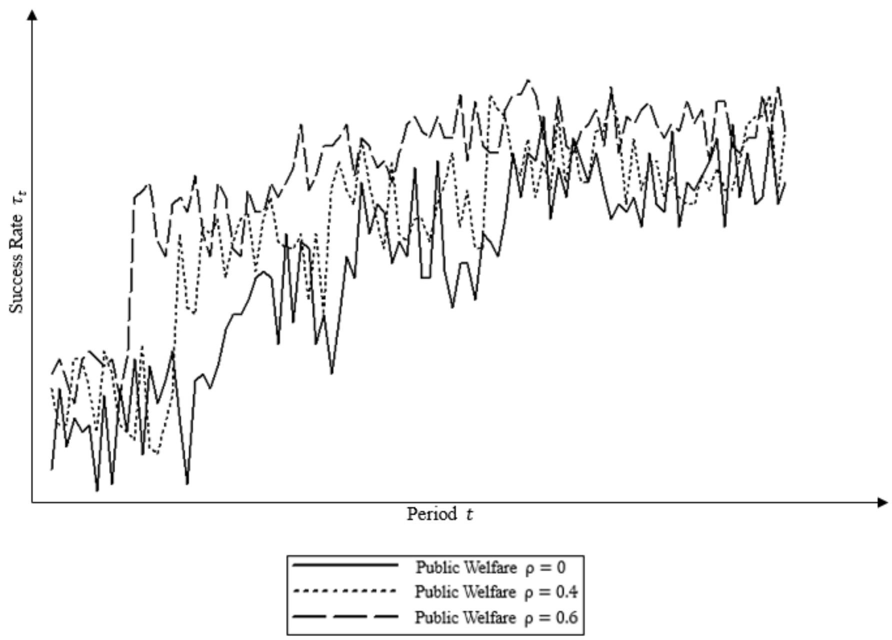

Fig. 2 Success Rate of For-Profit and Non-Profit Projects

Furthermore, if we draw out the success rate over time, two intuitive conclusions can be directly derived from Figure 2. First, generally, the success rate increases if parameter ρ increases/is increased. Second, the difference of success rate between for-profit and non-profit projects is very small and negligible initially, becomes bigger over time/successive periods, and ultimately maintains a certain level. Since ρ measures the level of public welfare, which essentially describes the difference between for-profit and non-profit projects, we show that projects that are more welfare oriented are more attractive in CF platforms. In fact, lower ρ is always accompanied by more seriously distorted information. Higher information asymmetry between funders and entrepreneurs always arises from for-profit projects. Hence, funders, even with risk-neutral preference, tend to support the non-profit projects. Therefore, the simulation results illustrated by Figure 2 may provide an alternative explanation for the observed phenomena in the crowdfunding market. We argue the distorted information may be the main reason why non-profit projects are more likely to reach their funding goals.

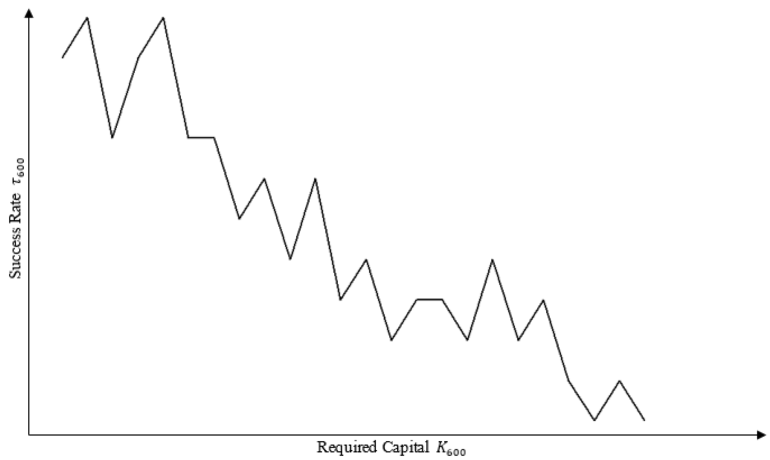

Fig. 3 Kernel Density Estimation for Capital Requirement

In Figure 3, we plot the kernel density estimation for capital requirement K_{it} with success rates in the entire period of our simulation. We see that the projects with smaller capital demand have higher success rates than those with larger funding requirements. This is consistent with Hemer [2011], who argued that the CF platform seems hardly viable for large budgets or capital requirements.

As we mentioned earlier, the success rate is an important measure of performance for the CF platform. Next, we show whether the CF platform can improve the success rate through different control mechanisms. In our model, μ and φ represent the acceptance rate and for-profit project to total project ratio respectively, which are both used as control mechanisms by the CF platform. α is the parameter that represents the diffusion density in the network of potential funders and can be considered as a measurement of CF platform reputation, which is affected by behaviors such as increasing advertising spending and improving quality of service. We investigate the impact of acceptance rate, for-profit project to total project ratio, and diffusion density on success rate one at a time (the two other measures are fixed (for testing)). The results are shown in Figure 4.

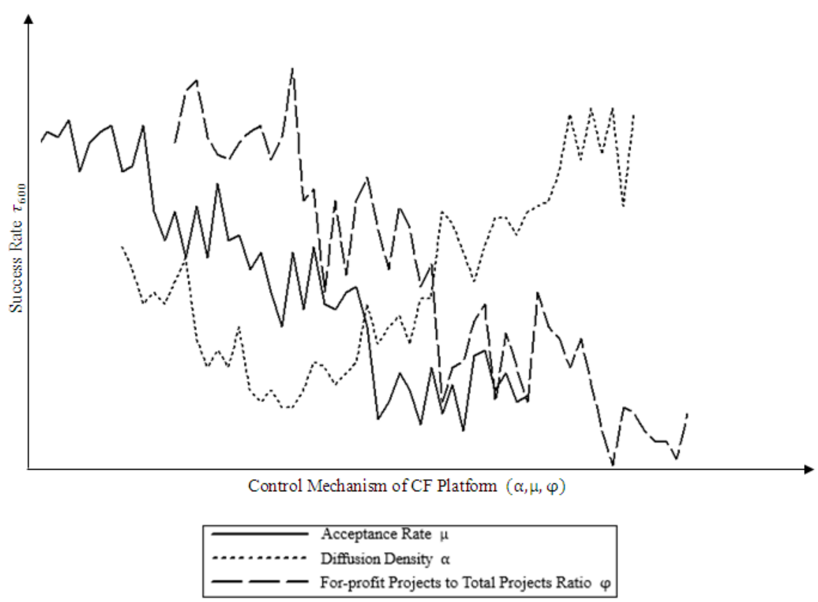

Fig. 4 Control of CF Platform for Success Rate

From Figure 4, we observe a statistically significant negative association between success rate and acceptance rate (*p-value is* 0.0031). The success rate declines, from 60% to 12%, as the acceptance rate increases from 20% to

68%. The intuition behind this is that a smaller acceptance rate leads to higher average value of projects provided to potential funders, and thus increases CF platform success rate.

The U-shaped relationship between the success rate and diffusion density is shown in Figure 4. This may explain capital supply and demand through the CF platform. Initially, the small network of funders cannot provide enough capital to support projects solicited through the CF platform; only a few entrepreneurs can be successfully funded. As α increases, more and more potential funders are attracted to the network and an oversupply of funds occurs in the CF platform when α exceeds a certain threshold, which induces a higher success rate.

From Figure 4, we also see the negative relationship between for-profit project to total project ratio and the success rate (*p-value is* 0.0027), which is consistent with the conclusions of Table 3. Non-profit projects are more likely to be successfully funded due to their relatively lower level of uncertainty. Generally, CF platforms can indeed improve success rate, according to our simulation, by control mechanisms and marketing strategies.

4.2. CF Platform Performance

To make a profit, most CF platforms charge a transaction fee for each successful project, typically from 4% to 5% of the total funding amount [Agrawal et al. 2014]. In our model, the funding amount in period t is derived as $\pi(t)$.

$$\pi(t) = \sum_{i \in S_t} \sum_{j \in D_i^t} \frac{I_j}{\gamma} \tag{10}$$

We can therefore measure the CF platform performance as a function of total funding amount, which is normalized from 0 to 1. Since many CF platforms encourage their funders to invest diversely in order to lower the overall risk, we consider the relationship between performance and investment diversification using the parameter settings from the last section and γ as a variable.

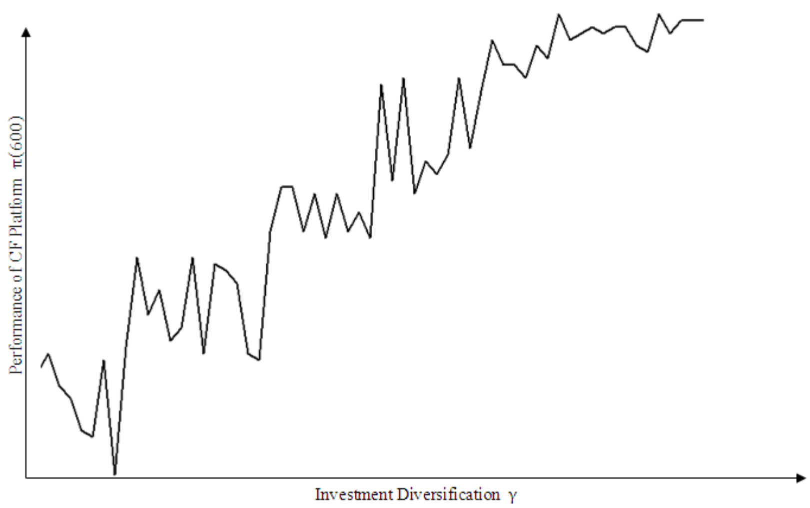

Fig. **5** CF Platform Performance and Investment Diversification

The approximately concave in Figure 5 shows that CF platform performance increases as the level of investment diversification increases. This means that encouraging funders to invest diversely not only benefits funders in terms of reducing risk exposure, but also improves platform performance. One thing worth mentioning is that we cannot conclude the positive relationship between CF platform performance and investment diversification directly from numerical simulation. The better performance may be due to more potential funders attracted by the platform, which leads to improved net utility through investment diversification.

We then consider whether the CF platform can improve performance through its control mechanism. We use the parameters shown in the previous section with acceptance rate and for-profit project to total project ratio as variables. The relationship between performance and control mechanism is illustrated in Figure 6.

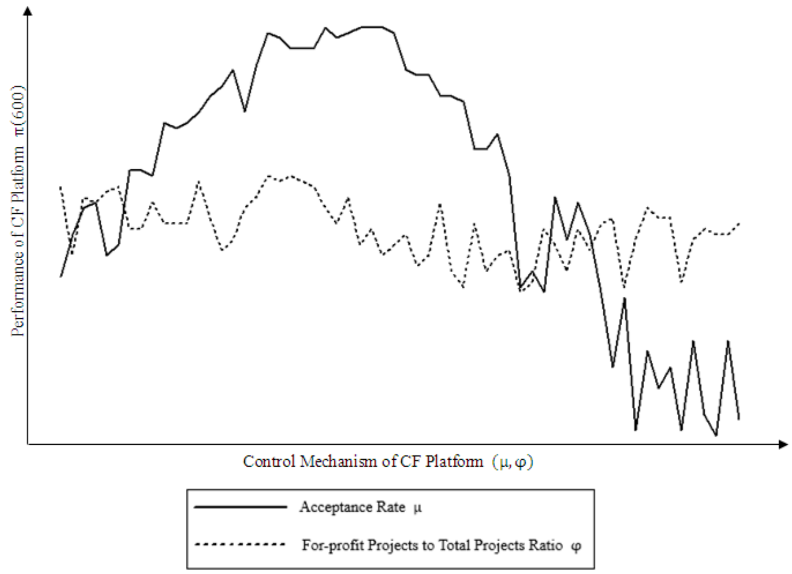

Fig. **6** CF Platform Performance and Control Mechanism (Exogenous Parameter)

According to Figure 6, there is an optimal acceptance rate for the CF platform to reach the best performance. Intuitively, several low-value projects may drag the performance (level) down when the acceptance rate is high. Conversely, if the acceptance rate becomes too low, there are not enough projects to support the performance. Particularly in extreme cases of $\mu = 0$, there is no positive performance. The impact of for-profit project to total project ratio on CF platform is implicit and does not reveal a significant regularity in this figure.

In the aforementioned numerical simulations, the parameter of diffusion density α is always exogenous in our model. However, a higher success rate often increases the CF platform's reputation and thereby helps to attract more potential funders to participate in crowdfunding in practice. Taking this fact into account, we measure the diffusion density α as a function of success rate in the previous period. By choosing two typical function forms, linear function form and logarithmic function form, which are represented as formula (11) and (12) respectively, we discuss the relationship between CF platform performance and control mechanism.

$$\alpha_t = h\tau_{t-1} \tag{11}$$

$$\alpha_t = h\ln(\tau_{t-1} + 1) \tag{12}$$

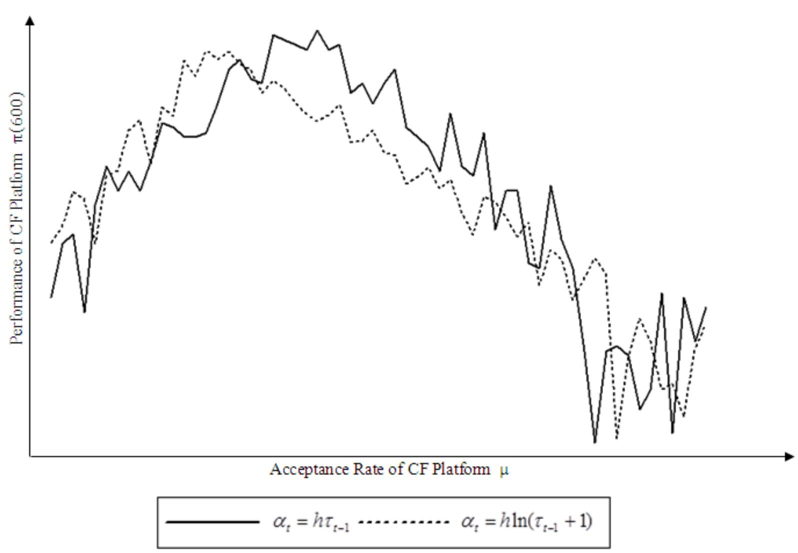

Fig. **7** CF Platform Performance and Acceptance Rate (Endogenous Parameter)

Simply setting the coefficient $h = 1$, Figure 7 illustrates the relationship between the acceptance rate and performance in both function forms of diffusion density. The inverted U-shaped curve shown in this figure, which is similar to the curve in Figure 6, indicates that there is an optimal acceptance for the CF platform so that its performance can reach the maximum value regardless of the specific function form for endogenous diffusion density.

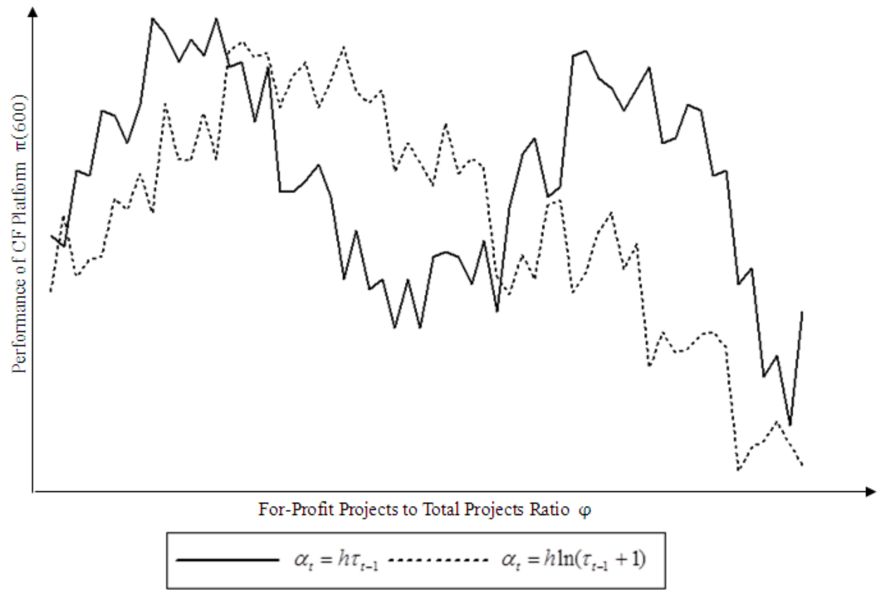

Fig. **8** CF Platform Performance and For-Profit Project to Total Project Ratio (Endogenous Parameter)

However, the role of the control mechanism and for-profit project to total project ratio become explicit in improving the performance of CF platform compared with the exogenous setting, as shown in Figure 8. According to this figure, the inverted U-shaped curve represents the relationship between performance and for-profit projects to total projects ratio when the diffusion density is expressed as a linear function of success rate in the previous period. Moreover, if we consider the logarithmic function form of diffusion density, a bimodal curve can be observed. In this case, two extreme performance values can be reached given other parameters. To sum up, whatever function form we choose in the endogenous setting, the CF platform can choose the optimal mechanism to maintain its best performance. Particularly in the case of linear function form, we argue that the appropriate control mechanism (μ, φ), which is approximately (0.32, 0.63) in our model, can help the platform achieve the best performance.

5. Discussion and Conclusions

Crowdfunding, an alternative source for entrepreneurs soliciting external funding, has become increasingly popular in recent years. However, previous studies have not produced an integral framework that explained the dynamic processes of this phenomenon. In this study, we proposed a dynamic model of crowdfunding that incorporates interaction among heterogeneous entrepreneurs, funders, and the CF platform, and investgated the evolution of crowdfunding processes. This system not only takes account of heterogeneity of funders and entrepreneurs, including preference, investment budgets, and amount of required capital, but also captures the important characteristics of evolving processes of crowdfunding in reality, such as information asymmetry and CF platform control mechanisms.

Through simulation, our results show some interesting findings. First, it is easier to successfully fund small projects than projects requiring a relatively large amount of capital. Second, information asymmetry leads to different success rates for non-profit projects and for-profit projects. Due to lower variance of value, the success rate of non-profit projects is higher than that of for-profit projects. Third, the success rate of CF platforms can be affected by their control mechanism. We show monotonic relationships between acceptance rate and for-profit projects to total projects ratio with the CF platform success rate, and a convex curve between diffusion density and the success rate. Therefore, appropriate control mechanisms, such as diligence, consulting, and marketing strategies, associated with project status can significantly improve the success rate. In addition, a diversified investment can benefit both funders and CF platform performance. Last, we further show a nonlinear relationship between the control mechanism and the performance of a CF platform when considering the diffusion density as an endogenous parameter. The influence of the acceptance rate on performance still shows an inverted U-shaped curve, while the impact of for-profit projects to total projects ratio becomes explicit.

Our results make important theoretical contributions to the crowdfunding literature. This study is among the first to address the dynamic process of crowdfunding from the complex system perspective. Compared with previous research, the model we proposed in this study is more comprehensive and systematic, and can be used to explain more macroscopic phenomena of crowdfunding markets. Apart from the convenience of multi-agent simulation, this model is not limited to strategy analysis and decision optimization for a specific funder or entrepreneur and is easy to extend to a variety of complex situations. The simulation results of this study also contribute to previous literature. First, our simulation results are consistent with the statistical analysis by Mollick [2014] that CF platforms are more viable for entrepreneurs with small-scale capital requirements. Projects with a large capital requirement are rarely successfully funded. Then, we provide an alternative theoretical explanation for the empirical results of Ghatak and Mueller [2011], Read [2013], and Pitschner and Pitschner-Finn [2014] from the information perspective. We argue that information asymmetry determines why the success rate of non-profit projects is higher than for-profit ones in CF platforms. Last, the CF platform performance and control mechanisms, which are little studied, are discussed in the case of exogenous and endogenous parameter setting respectively.

Our findings also provide useful practical implications for CF platforms. First, CF platforms should encourage funders to diversify their investment because this benefits both funders and the platform performance. Second, CF platforms can significantly improve the success rate of projects by adjusting the acceptance rate for submitted projects, conducting appropriate marketing strategies to attract potential funders, or decreasing the for-profit project to total project ratio. Third, when/if the diffusion density is considered as an endogenous parameter, a platform can always achieve the best performance utilizing appropriate control mechanisms, such as adjusting the acceptance rate. In addition, for regulatory authorities, we argue that the regulatory measures associated with traditional financial institutions, such as reserve requirement, are not applicable here. Because CF platforms, the financial intermediary, still have a significant impact on funder protection, it is necessary to limit the scope of CF platform operations. However, the existing regulatory measures are inadequate and induce a lot of controversy pertaining to their effectiveness. This study provides an alternative form of dynamic regulation that stems from operation of the CF platform to decrease its operational risk and thus protect potential funders.

One limitation of this study is that we assume funders are homogeneous in terms of investment diversification. Although it indeed simplified the model, it limits the generalizability of our results. Future studies may relax this assumption to capture more characteristics in reality. Furthermore, the difference between for-profit projects and non-profit ones is considered in our dynamic system. However, we omit the motivation of entrepreneurs with different types of projects. Combining this trait in the model may produce more interesting conclusions. Finally, the description of the game between entrepreneurs and funders is static, in which the decisions of both players only depend on information from the last period. But in practice, due to market incomplete, all historical information, not only from the previous period, is valuable and often used to support decisions of entrepreneurs and funders. We will extend our model in future studies to reveal information evolution in the crowdfunding context.

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