Dynamic Strategies for Successful Online Crowdfunding

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Abstract

Crowdfunding is a fast emerging internet fundraising mechanism for soliciting capital from the crowd to support entrepreneurial ventures. This paper empirically investigates the dynamics of investors’ backing behaviors in the presence of network externalities and a finite time window. The proposed model captures how investors dynamically update their expectations on the prospect of a project based on its current funding status and time progress. Model estimation shows that investors are more likely to back a project that has already attracted a critical mass of funding (positive network externalities). For the same amount of achieved funding, the backing propensity declines over time (negative time effects). These two opposing forces give rise to a critical mass of funding the project must attain on time to achieve successful funding by the deadline. Counterfactual simulations show that projects may fail to attain the critical mass because of unfavorable shocks in investor visits at the early stage of the funding cycle. We derive dynamic seeding strategies for project owners to maximize the likelihood of funding success.

Keywords: crowdfunding; group buying; entrepreneurship; network externality; hazards model; Bayesian inference
1 Introduction

Crowdfunding is an emerging internet fundraising mechanism for soliciting capital from the online crowd to support innovative projects. Facing the difficulties and costs of raising early-stage funding from institutional investors (e.g., angel investors, banks, and venture capital funds), entrepreneurs are tapping into the online communities of consumer investors (Economist 2010, Schwienbacher and Larrañaga 2012). Crowdfunding platforms such as Kickstarter.com and IndieGoGo.com allow entrepreneurs to request funding for clearly specified projects from a large number of individual investors (also called “backers”), often vowing future products or certain forms of recognition in return. Crowdfunding has helped new ventures to raise billions of dollars and the volumes and amounts of transactions have continued to increase (Agrawal et al. 2013, Mollick 2014, Burtch et al. 2013). As legalized by the Jumpstart Our Business Startups (JOBS) Act passed in April 2012, crowdfunding efforts may give investors equity stakes in return for their funding in the future.

Contrast to traditional capital sourcing models such as venture capitalists, crowdfunding is characterized by many small investors, collective evaluation of projects, and high transparency of funding status. In addition to the project information provided by entrepreneurs, investors also assess a project’s potential for success based on other investors’ investment decisions, demonstrating typical herding behavior (Zhang and Liu 2012). Besides, major crowdfunding platforms like Kickstarter require entrepreneurs to set a funding target and deadline for any project. Entrepreneurs will receive the funding only if their project successfully reaches the funding target by the deadline. In the presence of the funding target and deadline, investors also assess the project’s prospect of success based on whether it can quickly attract a critical mass of backers. Facing opportunity costs, investors very often do not want to contribute to a project that is unlikely to reach its funding goal. Strong network externalities are critical to the success of a project in this context because the larger the number of backers it attains at the early stage of the funding cycle, the more likely the project will be able to attract more backers and reach its funding goal by the deadline.

Although the value of network externalities has been studied in the literature, the role of network externalities in the presence of a funding target and deadline has not been explored by researchers. A major contribution of this paper is to demonstrate how the dynamic interaction between time-varying network externalities and the deadline gives rise to a critical mass of funding
that a project must achieve on time in order to be successful. The existence of a funding target and
deadline interact with network externalities in an intriguing way. In online crowdfunding, investors
may estimate a project’s chance of success not only from the number of backers the project has
attained, but also from the timing this number was achieved. To illustrate this point, suppose
there are two projects that are identical except that one reaches 50% of its funding goal in 5 days
whereas the other reaches this percentage in 20 days. Since the two projects have attracted the
same number of backers, one would consider the two projects equally appealing if the temporal
information (5 days v.s. 20 days) was not taken into account. However, the temporal information
actually provides essential information for investors to access a project’s prospect and its likelihood
of receiving sufficient funding. The project reaching 50% of its funding goal within 5 days appears
to be a better investment option, as attracting a large number of backers in a short time may
indicate the project’s good prospect of reaching the funding goal by the deadline.

Understanding network externalities under the constraint of a funding target/deadline is an
essential step towards deeper understanding of the online crowdfunding mechanism. The results
from this research have implications for other relevant business problems where agents coordinate
to achieve certain goal by a deadline. For instance, on group-buying platforms like Groupon.com,
sellers may offer products and services at discount prices on the condition that a minimum number
of buyers would make the purchase by the deadline. To our best knowledge, our research is the
first one to investigate the interaction of time and network externalities in the setting of targets
and deadlines and empirically estimated the corresponding critical mass. Specifically, we aim to
answer the following questions:

1. How do investors form and dynamically update their expectations on the prospect of a project
   based on its current funding status (e.g., amount of funding achieved and the length of time left)?
2. What are the seeding and advertising strategies entrepreneurs may use to solicit more funding
   from the crowd?

We model time effects using a hazards model that captures investors’ perceived success prob-
ability of a crowdfunding project. Model estimates provide empirical evidence on how investors
decide whether to contribute to a project based on current funding performance and time progress.
We find that investors are more likely to back a project that has already attracted a critical mass
of funding (positive network externalities). However, with the achieved funding amount fixed,
investors’ backing propensity declines over time as investors’ perceived success probability of a crowdfunding project decreases over time (negative time effects). These two competing forces determine an investor’s overall backing propensity and give rise to a critical mass of funding the project should attain on time in order to achieve successful funding by the deadline.

This research makes several contributions. Existing studies on network externalities have documented that the value of a product/service increases in its network size (see, e.g., Katz and Shapiro 1986, Katz and Shapiro 1992, Brynjolfsson and Kemerer 1996). Our model extends the traditional static view of network externalities (i.e., focusing on the size of the network) to consider its interaction with time (i.e., the timing of achieving a certain network size). We provide a parsimonious yet flexible framework for modeling investor decisions in crowdfunding. Empirical results show that incorporating both network externalities and time effects significantly improves model fit. Ignoring either effect leads to biased parameter estimates.

This research also contributes to the emerging literature on online crowdfunding. Several papers have provided descriptive evidences on why people contribute to online crowdfunding. However, existing studies have not formulated the dynamic crowdfunding process and looked into the interaction between network externalities and a finite funding cycle. This paper provides an economic framework to understand dynamic investor behaviors and provide an intuitive explanation for the time-varying funding patterns. We find that if the negative time effects dominate the positive network externalities, investors become less likely to contribute to a project in later periods. However, if the positive network externalities dominate, investors are more likely to contribute in later periods. Our results shed light on the complex crowdfunding process which has yet to be unraveled to researchers and practitioners.

Our model and results provide important insights for entrepreneurs and crowdfunding platforms. We demonstrate by counterfactual simulations that crowdfunding projects may fail to reach their funding target due to low investor valuation. Advertising on various media to attract more potential investors is a plausible means to achieve successful funding. We evaluate the impact of seeding timing on crowdfunding performance and find that early seeding is more effective. This is due to the direct effect and indirect effect of seeding. Seeding informs a larger number of investors and thus more contributions (direct effect). In additional, a large amount of funding achieved in early periods also boost late-coming investors’ expectation on the prospect of the project, which
increases their backing propensity (indirect effect). As a result, the project will continue to receive more contributions in later periods, even though the project owner has ceased promotion.

A highly interesting result from our simulation is that high-valuation projects may also fail to attain a critical mass of funding and eventually fizzle out, due to a few unfavorable shocks in investor visits at the early stage of the funding cycle. In the presence of network externalities, negative shocks in early periods will carry over to later periods and have permanent negative effects on the final crowdfunding outcome. Therefore, project owners should actively monitor their crowdfunding project, especially at the early stage of the funding cycle. We derive dynamic seeding strategies and provide decision support for project owners to implement real-time control and management of their crowdfunding projects.

The rest of the paper is organized as follows. In the next section, we elaborate upon how our model and results provide new insights into the literature on online crowdfunding. We present details of our dataset and provide exploratory evidence on the interaction between network externalities and time effects in Section 3. We then construct our model followed by its estimation method in Section 4. In Section 5, we present the estimation results and their interpretations, followed by the use of counterfactual simulations for managerial analysis in Section 6. We conclude the paper in Section 7.

2 Related Literature

Our research is related to the literature on product adoption subject to network externalities and the literature on online crowdfunding and group buying. We discuss these two streams of literature below.

Product Adoption Subject to Network Externalities

Existing studies on network externalities have documented that the value of a product/service may increase in its installed base (see, e.g., Katz and Shapiro 1986, Brynjolfsson and Kemerer 1996, Kauffman et al. 2000). Products and services with a larger installed base may provide better compatibility and higher exchange value to users. The larger the total number of buyers using compatible products, the greater benefits each buyer receives (Katz and Shapiro 1992). Gallaugher

In our study of the online crowdfunding setting, network externalities reveal unique characteristics that are absent in the traditional settings studied in the literature. A large number of backers do not necessarily increase the value of the product/service itself. Instead, it increases the likelihood that a crowdfunding project will be successfully funded by the end of the fundraising cycle. Therefore, network externalities play an indirect role in consumers’ backing decisions. Zhang and Liu (2012) investigate the online peer-to-peer lending market and find that well-funded borrower listings tend to attract more funding. However, their paper and other studies of network externalities focus on the size of the network rather than the timing of achieving a certain network size. Our research extends the traditional static view of network externalities to consider its interaction with time. Model estimation shows that both network externalities and time effects influence investors’ backing decisions.

Dynamics of Online Crowdfunding and Group Buying

Our research is also related to several theoretical studies on group buying, where consumers enjoy a discounted group price if they are able to achieve a required group size (see, e.g., Kauffman and Wang 2002, Anand and Aron 2003, Jing and Xie 2011). Hu et al. (2013) study group-buying mechanisms in a two-period game where cohorts of consumers arrive at a deal and make sign-up decisions sequentially. Their theoretical model shows that posting the number of first-period sign-ups to the second-period consumers increases the deal’s success rate. Information about first-period sign-ups help second-period consumers make sign-up decisions by eliminating the uncertainty facing them. Our empirical paper complements these theoretical studies by providing empirical evidence on how investors decide whether to contribute to a project based on current funding performance and time progress.

Several empirical papers have provided descriptive evidence on investor behaviors in online crowdfunding (see, e.g., Agrawal et al. 2013, Mollick 2014, Burtch et al. 2013). Burtch et al. (2013) study donation-based crowdfunding. They find evidence of a crowding-out effect, where
contributors become less likely to contribute to a popular project as additional donations are less important to the recipient. In our study of rewards-based crowdfunding, we find a different effect: investors are more likely to back a project that has already achieved a critical mass of funding. Mollick (2014) offers a description of the underlying dynamics of success and failure among crowdfunding ventures. He finds that projects that are unable to reach its funding goal tend to fail by a large amount, possibly due to the all-or-nothing crowdfunding mechanism. As an exploratory study, Mollick (2014) does not look into the underlying reasons for this funding pattern. Kuppuswamy and Bayus (2013) find that backer contributions are smaller at the middle of the funding cycle. They attribute the dynamic patterns to the bystander effects, where contributors' are likely to back a project when they expect others will contribute.

None of the papers discussed above has formulated the dynamic crowdfunding process and looked into the interaction between network externalities and a finite funding cycle. Our model provides an economic framework to understand dynamic investor behaviors and the funding patterns observed by previous exploratory studies.

3 Data Description and Exploratory Results

3.1 Rewards-Based Crowdfunding

The dataset is obtained from one of leading crowdfunding platforms in the United States. The crowdfunding platform provides rewards-based crowdfunding mechanism (very similar to Kickstarter) where project backers receive future products for their contribution. The dataset covers a sample of crowdfunding projects launched between November 2013 and March 2014. We restrict to projects whose owners are located in the United States. The final sample consists of 577 projects in various categories, including technology, small business, music, and gaming, etc. We supplement the funding performance data with social media data from Facebook and Twitter.

For each project, we observe daily funding status, including the number of visits to the crowdfunding project page, the number of backers, and the accumulative amount of funding received. The dataset also records a project’s daily social media activities including Facebook exposure (number of likes, shares, and comments) and Twitter buzz (number of tweets). Besides the dynamic funding information described above, we also observe static project information such as the funding target,
funding duration, the category of the project, the number of photo demonstrations the project owner provided, whether the project has a video clip, and whether the project is in partnership with a third-party organization, etc. The rich dataset captures the comprehensive dynamics of the crowdfunding process.

Descriptive statistics of the key variables are presented in Table 1. Among all the projects in our sample, only about 23% successfully raised at least the amount of their funding goal by the deadline. In addition, there is large heterogeneity across projects in funding goals and funding performance. The median funding target of the projects in our sample is $8,700, whereas the most ambitious project set the target as high as $10 million. Over one quarter of the projects attracted less than 2 backers, whereas the most successful project received contributions from over 3,000. The average funding duration is 40 days.

3.2 Evidence on Network Externalities and Time Effects

In this section, we provide preliminary empirical evidences on how investors dynamically decide whether to contribute to a project based on current funding performance and time progress. We hypothesize that investors are more likely to back a project that has already attracted a critical mass of funding (positive network externalities). For the same amount of achieved funding, the backing propensity declines over time (negative time effects).

The observed backing rate in period $t$ is defined as the ratio of the number of investors who contributed and the number of investors who visit the crowdfunding page in that period. Figure 1 demonstrates two representative backing patterns observed in our dataset. In Figure 1(a), the crowdfunding project receives some amount of contributions from backers in early periods. However, investors’ backing likelihood decreases in time after period 6 as the project fails to attain a critical mass of funding. The decreasing backing rate can be attributed to the strong negative time effects - investors’ perceived probability that the project will be successfully funded decreases in the length of time left before the funding deadline. Although there are small fluctuations in the amount of funding received from Periods 10 to 20, the positive network externality continues to be dominated by the strong negative time effect. As a result, investors’ backing propensity approaches zero when the project is close to its funding deadline.

In Figure 1(b), investors’ backing rate is first decreasing but becomes increasing in time after
<table>
<thead>
<tr>
<th>Variable</th>
<th>Definition</th>
<th>Mean</th>
<th>Std. dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Project Characteristics</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Funding Cycle Length</td>
<td>Duration of the funding cycle (in days)</td>
<td>40</td>
<td>13</td>
<td>8</td>
<td>61</td>
</tr>
<tr>
<td>Funding Goal</td>
<td>The amount of funding the project owner would like to raise</td>
<td>94,352</td>
<td>$6.1 \times 10^5$</td>
<td>500</td>
<td>$1.0 \times 10^7$</td>
</tr>
<tr>
<td>Price</td>
<td>Average amount of money contributed by a backer</td>
<td>78</td>
<td>110</td>
<td>1</td>
<td>1,283</td>
</tr>
<tr>
<td>Team Size</td>
<td>Number of members in the crowdfunding team</td>
<td>1.65</td>
<td>1.35</td>
<td>1</td>
<td>14</td>
</tr>
<tr>
<td>Photo Demos</td>
<td>Number of photo demos provided by the project owner</td>
<td>2.25</td>
<td>4.61</td>
<td>0</td>
<td>44</td>
</tr>
<tr>
<td>Project Social Exposure</td>
<td>Number of places (Facebook, Twitter, YouTube, and company website, etc.) where potential backers can learn more about the project</td>
<td>2.50</td>
<td>1.76</td>
<td>0</td>
<td>10</td>
</tr>
<tr>
<td>Owner Social Exposure</td>
<td>Number of places (Facebook, Twitter, YouTube, and company website, etc.) where potential backers can learn more about the owner</td>
<td>1.48</td>
<td>1.68</td>
<td>0</td>
<td>8</td>
</tr>
<tr>
<td>Owner Has Image</td>
<td>Whether the project owner's profile has a non-default image</td>
<td>0.77</td>
<td>0.42</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Description Length</td>
<td>Number of words in project description</td>
<td>1,543</td>
<td>944</td>
<td>241</td>
<td>7,470</td>
</tr>
<tr>
<td>Links in Description</td>
<td>Number of links in project description</td>
<td>62.48</td>
<td>10.05</td>
<td>48</td>
<td>131</td>
</tr>
<tr>
<td>Images in Description</td>
<td>Number of images in project description</td>
<td>13.06</td>
<td>8.87</td>
<td>7</td>
<td>89</td>
</tr>
<tr>
<td>Has Video</td>
<td>Whether the description has a video</td>
<td>0.68</td>
<td>0.47</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Has Partnership</td>
<td>Whether the project is in partnership with a third-party organization</td>
<td>0.05</td>
<td>0.21</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td><strong>Fundraising Performance</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Daily Page Visits</td>
<td>Number of daily investor visits to the crowdfunding project</td>
<td>417.25</td>
<td>170.86</td>
<td>400</td>
<td>6,482</td>
</tr>
<tr>
<td>Daily Backers</td>
<td>Number of investors who contribute to the project daily</td>
<td>1.31</td>
<td>7.77</td>
<td>0</td>
<td>354</td>
</tr>
<tr>
<td>Daily Facebook Activities</td>
<td>Number of daily Facebook likes, shares, and comments</td>
<td>7</td>
<td>66</td>
<td>0</td>
<td>4,252</td>
</tr>
<tr>
<td>Daily Twitter Activities</td>
<td>Number of daily Twitter tweets</td>
<td>1</td>
<td>10</td>
<td>0</td>
<td>527</td>
</tr>
<tr>
<td>Funding Outcome</td>
<td>Whether the project successfully reaches its funding goal</td>
<td>0.23</td>
<td>0.42</td>
<td>0</td>
<td>1</td>
</tr>
</tbody>
</table>

*Note. No. of projects: 557; No. of observations: 19,557; Time period: November 1, 2013 - March 30, 2014.*

Table 1: Definitions and Summary Statistics of Variables
the project attains a critical mass of funding around Period 15, after that the strong positive network externality dominates the negative time effect despite some fluctuations. We hypothesize that investors’ perceived probability that the project will be successfully funded takes off after the project reaches the critical mass.

Figure 1 highlights the impact of network externalities and time effects on investors’ evaluation of a project’s success likelihood. Investors’ overall backing propensity depends on the relative strength of these two opposing effects. To empirically test the impact of network externalities and time effects on investors’ backing propensity, we specify the following linear regression for exploratory analyses,

\[
y_{jt} = \alpha + \delta \log t + \gamma \log Q_{jt} + X_j \beta + \varepsilon_{jt}
\]

where \(y_{jt}\) is the log backing rate of project \(j\) at time \(t\) (the number of backers \(N_{jt}\) over the number of visitors \(M_{jt}\)), \(t\) is the time elapsed which captures the time effects, \(Q_{jt}\) is the fraction of funding attained by time \(t\) (cumulative funding amount divided by the funding goal) which captures network externalities. We control project characteristics \(X_j\) by including the ones listed in Table 1.

Table 2 gives the parameter estimates of the network externality and time effect in the exploratory regression (to conserve space, we omit the estimates of project characteristics, whose model-based estimation will be discussed in detail in Section 5.2). The estimate of network externality is positive, suggesting that investors are more likely to contribute to a project that already attracted a larger fraction of funding, holding other variables, especially the time effect (Time Elapsed) fixed. The estimate of the time effect is negative, suggesting that investors’ backing likelihood decreases over time, holding other variables, especially the network externality represented by the accumulative amount of funding achieved fixed. These estimates are not only statistically significant, but also large in economic magnitude, indicating the rationale of incorporating both network externalities and time effects into the model of investor decision marking in online crowdfunding.

4 The Model

To capture the dynamic interactions of the network externality and the time effect in investors’ evaluation of a funding project’s success probability, we propose a model in which investors update
Figure 1: Dynamic Backing Behaviors Observed in Online Crowdfunding
their utility over time given the valuation of project and the observed funding status. We also account for heterogeneity across crowdfunding projects, which casts our model in a Bayesian hierarchical framework. In this section, we first discuss the model formulation and then the estimation procedure.

4.1 Model Formulation

An entrepreneur (i.e., project owner) is running a crowdfunding project \( j \) on the crowdfunding website to solicit capital to develop a product. The crowdfunding campaign aims to raise at least the amount of funding \( G_j \) by the deadline \( \bar{T}_j \). In each period \( t, t = 1, 2, \ldots, \bar{T}_j \), a number of investors visit the project on the crowdfunding website and decide whether to back the project. If an investor decides to back the project, she pays a fixed amount of cash \( P_j \) in return for one unit of the future product. This project will only be successfully funded if at least the amount of \( G_j \) is pledged by the deadline. Otherwise, the capital already raised will be refunded to investors and no products will be delivered.

4.1.1 Investor’s Utility Function

Upon visiting project \( j \) at time \( t \), investor \( i \)'s expected utility from backing the project is

\[
U_{ijt} = v_{ijt} \Lambda_{jt} - c
\]

where \( v_{ij} \) is the investor’s valuation of the product, \( \Lambda_{jt} \) is the investor’s expected likelihood that the project will reach its funding goal \( G_j \) by the deadline (we will derive this perceived success likelihood in next subsection), and \( c \) is the opportunity cost of backing the product. The opportunity cost

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficients (Standard Error)</th>
</tr>
</thead>
<tbody>
<tr>
<td>TimeElapsed: ( \log t )</td>
<td>-1.1732*** (0.0283)</td>
</tr>
<tr>
<td>CumulativeFundingAmount: ( \log Q_t )</td>
<td>0.9859*** (0.0133)</td>
</tr>
<tr>
<td>Control of Project Characteristics: ( X )</td>
<td>Yes</td>
</tr>
<tr>
<td>Adjusted ( R^2 )</td>
<td>0.3778</td>
</tr>
</tbody>
</table>

*Note. Standard errors are in parentheses and *\( p<0.10 \), **\( p<0.05 \), ***\( p<0.01 \).*

Table 2: Parameter Estimates of the Exploratory Model
can be associated with the time and effort of evaluating the project, or the investor’s disutility from having her money locked in by the project. The utility function in Equation (1) captures the unique feature of the crowdfunding mechanism which requires a project to at least raise a certain amount of capital before it can be funded. Investors, when facing the opportunity cost, may not want to back a project if they believe the project has little chance of being funded. Investor $i$’s valuation $v_{ij}$ is

$$v_{ijt} = X_j \beta + \varepsilon_{ijt}$$

where $X_j$ is a vector of project characteristics (including the unit price $P_j$) and $\varepsilon_{ijt}$ is idiosyncratic shock which is assumed to be drawn from the Type I extreme value distribution independently across investors, projects, and time periods. In the following sections, we refer to the term $X_j \beta$ as project quality or project valuation.

### 4.1.2 Derivation of Investors’ Perceived Project Success Likelihood

Investors form their expectation on whether the project will reach its funding goal by the deadline based on its current funding status. Intuitively, investors will take into account the funding amount already achieved and the length of the time left before the funding deadline.

We use a hazards model to capture investor expectation. Hazards models have been widely used to model the time that passes before some event occurs (see, e.g., Cox 1972 and Heckman and Singer 1984). Let $T$ be the (random) length of time until the event occurs (i.e., the project reaches its funding goal). At time $t$, the hazard function for this event to occur has the form

$$h(\tau | Q_{jt}) = h_0(\tau; \delta_j) \exp(\gamma_{0j} + \gamma_{1j} Q_{jt})$$

where $h_0(\tau; \delta_j) = \delta_{0j} + \delta_{1j} \tau$ is the baseline hazard and $Q_{jt}$ is the funding percentage achieved by time $t$. As discussed in Section 3, there is large heterogeneity in funding performance across projects. To capture unobserved project heterogeneity, we allow parameters $\delta_j$ and $\gamma_j$ in the hazard function to be project specific. Following the hierarchical Bayes models (see, e.g., Rossi et al. 2005), we assume that project-specific parameters, $\varphi_j \equiv [\delta_j, \gamma_j]$, are drawn from a multivariate normal distribution with mean $\theta_\varphi$ and variance-covariance matrix $\Sigma_\varphi$. 

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At the beginning of the funding period $t_0 = 0$, the probability that the project will reach its goal by the deadline $T_j$ is

$$
\Lambda_{jt_0} = \Pr( T \leq T_j | T \geq t_0 = 0 ) = 1 - S(T_j | Q_{jt_0}), \tag{4}
$$

where the survivor function is defined as $S(t|Q_{jt_0}) = \exp(-H(t|Q_{jt_0}))$ with the cumulative hazard $H(t) = \int_{t_0}^{t} h(\tau|Q_{jt_0}) \, d\tau$. Equation (4) links investors’ expectation on a crowdfunding project’s success probability to the project’s current funding status $Q_{jt_0}$ and time progress $t_0$.

As time progresses and the project has not reached its goal at a given time $t > t_0 = 0$, investors’ perceived success probability in Equation (1) becomes

$$
\Lambda_{jt}(t, Q_{jt}, \bar{T}_j, \gamma_j, \delta_j) = \Pr(T \leq T_j | T \geq t) = \frac{\Pr(t \leq T \leq T_j | T \geq 0)}{\Pr(T \geq t)} = 1 - \exp \left( - \int_{t}^{\bar{T}_j} h(\tau|Q_{jt}) \, d\tau \right).
$$

$$
= 1 - \exp \left( - \exp \left( \gamma_{0j} + \gamma_{1j}Q_{jt} \right) \left( \delta_{0j} (\bar{T}_j - t) + \frac{\delta_{1j}}{2} (\bar{T}_j^2 - t^2) \right) \right), \tag{5}
$$

From Equation (5), we can see that investors’ perceived success probability $\Lambda_{jt}$ increases in the accumulated funding amount $Q_{jt}$ if $\gamma_{1j}$ is positive (positive network externality). In addition, this probability may be increasing, decreasing, or curvilinear in time depending on the sign and magnitude of $\delta_{0j}$ and $\delta_{1j}$. For example, if both $\delta_{0j}$ and $\delta_{1j}$ are positive, then investors’ perceived success probability of the project decreases in $t$, i.e., the time effect is negative. The negative time effect has an intuitive explanation: the shorter the length of time left, the less likely a project will be able to reach its funding goal (holding other factors such as the funding amount already achieved fixed). The hazards model in Equation (3) and the resulting success probability we derived in Equation (5) provide a parsimonious yet flexible framework that captures both network externalities and time effects.

4.1.3 Investor’s Backing Decisions

Investors make binary choices: backing the project or adopting the outside option of “not backing” (investor utility from the outside option is normalized to zero). Investors evaluate the prospect of a project based on her/his valuation of the product and the project’s likelihood of successfully
raising the funding. Specifically, investor $i$ will back the project if and only if the net utility $U_{ijt}$ is greater than that of the outside option, or equivalently,

$$
\varepsilon_{ijt} \geq \frac{c}{\Lambda_{jt}} - X_j \beta.
$$

Let $\varepsilon_{jt}$ be the threshold such that the investor with $\varepsilon_{ijt}$ above this threshold will contribute in period $t$, i.e., the equality above holds. With the Type I extreme value distribution of $\varepsilon_{ijt}$, an individual investor’s backing probability follows

$$
\text{Pr}(\varepsilon_{ijt} \geq \varepsilon_{jt}) = \Psi(t, Q_{jt}, \bar{T}_j, X_j, \beta, c, \gamma_j, \delta_j) = \frac{1}{1 + \exp\left(\frac{c}{\Lambda_{jt}} - X_j \beta\right)}.
$$

(6)

The backing probability in Equation (6) has the same properties as investors’ perceived success probability in Equation (6), i.e., it is increasing in $Q_{jt}$ if $\gamma_j$ is positive, and decreasing in time if $\delta_{0j}$ and $\delta_{1j}$ are positive. In addition, the backing probability is increasing in the project valuation $X_j \beta$.

Let $M_{jt}$ denote the number of visitors to project $j$ in period $t$, then $N_{jt}$, the number of backers who decide to contribute to the project in that period is

$$
N_{jt} = M_{jt} \Psi(t, Q_{jt}, \bar{T}_j, X_j, \beta, c, \gamma_j, \delta_j).
$$

(7)

### 4.1.4 Modeling Investor Visits

We model investors’ visits to the crowdfunding platform by a nonhomogeneous Poisson process. The Poisson process model has proved to be useful in modeling consumer arrivals (see, e.g., Lenk and Rao 1995, Bijwaard et al. 2006). In period $t$, the probability of observing the number of visitors $M_{jt}$ is

$$
\text{Pois}(M_{jt} = m|\lambda_{jt}) = \frac{\exp(-\lambda_{jt})\lambda_{jt}^m}{m!},
$$

(8)

where $\lambda_{jt}$ is the time-varying rate parameter for the mean arrival. A larger value of $\lambda_{jt}$ corresponds to a higher probability of observing a large number of investor visits. In online crowdfunding funding, a project’s exposure on social media may influence investor arrivals. To capture the
impact of social media, we allow the rate parameter to be a function of a project’s social buzz:

$$\lambda_{jt} = \exp (\omega_0 + \omega_1 FB_{jt} + \omega_2 TW_{jt}),$$

(9)

where $$\omega_0$$ is baseline rate while $$\omega_1$$ and $$\omega_2$$ captures the effect of the project’s Facebook ($$FB_{jt}$$) and Twitter ($$TW_{jt}$$) activities (i.e., the number Facebook “share” and Twitter “tweet” in period $$t$$).

4.2 Likelihood-Based Estimation

We observe the number of investor visits and contributions in each period. The likelihood for observations data $$j \equiv \{Q_{jt}, \bar{T}_j, X_j, FB_{jt}, TW_{jt}\}$$ from project $$j$$ over the $$T_j$$ periods is

$$L_j (data_j|\beta, c, \omega, \gamma_j, \delta_j) = \prod_{t=1}^{T_j} \left\{ \Psi(t, Q_{jt}, \bar{T}_j, X_j, \beta, c, \gamma_j, \delta_j)^{N_{jt}} \times \left(1 - \Psi(t, Q_{jt}, \bar{T}_j, X_j, \beta, c, \gamma_j, \delta_j)\right)^{M_{jt} - N_{jt}} \times Pois(M_{jt}|\omega, FB_{jt}, TW_{jt}) \right\}.$$ 

Pooling the data from the $$J$$ projects, the likelihood for all observations is

$$L (data|\beta, c, \omega, \gamma, \delta) = \prod_{j=1}^{J} L_j (data_j|\beta, c, \omega, \gamma_j, \delta_j).$$

We estimate the model using Bayesian inference with the Markov Chain Monte Carlo (MCMC) method. Details of the estimation procedure are in Appendix A.

5 Empirical Analysis and Results

We first show the goodness of the proposed model over alternative specifications. Parameter estimates of the proposed model and their implications are then discussed.

5.1 Model Comparison

We estimate the proposed (full) model and two nested models, one without network externalities and the other without time effects. In the nested model without network externalities, we constrain
the parameter $\gamma_{1j}$ in Equation (5) to zero. As a result, investors’ backing probability at time $t$ is not directly related to the accumulative amount of funding achieved by that time. In the nested model without time effects, we remove the two time-effect terms, i.e., removing $\delta_{0j} (\bar{T}_j - t) + \frac{\delta_{1j}}{2} (\bar{T}_j^2 - t^2)$ in Equation (5). In this constrained model, investors' backing likelihood is not directly influenced by the length of time left.

Model comparison results are summarized in Table 3. The deviance information criterion (DIC) of the full model is significantly lower than that of the two nested models, suggesting that the proposed model outperforms the two nested models in goodness of model fit. Ignoring time effects lead to the worst model fit. These model comparison results suggest that network externalities and time effects are two essential dimensions of online crowdfunding. Incorporating both of the effects can greatly improve the model’s predictive power.

### 5.2 Parameter Estimates

Estimation results from the full model are in Table 4. Parameter estimates of investors’ perceived success probability function reveal that the network externality is positive (the estimate in row 5 is positive) whereas the time effect is negative (the estimates in rows 6 and 7 are positive). Holding time fixed, investors are more likely to contribute to a project that already receives a larger fraction of funding. Holding achieved amount of funding fixed, investors are less likely to back a project with fewer days until deadline. In the presence of a funding target and deadline, investors assess the project’s prospect of success based on whether it can quickly attain a critical mass. The larger the number of backers the project attains at the early stage of the funding cycle, the more likely the project will be able to reach its funding goal by the deadline. Investors face significant opportunity cost (see estimate of $c$ in row 2) and may not want to contribute to a project that is not very likely to be successfully.
<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficients (Standard Error)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Opportunity Cost (c)</td>
<td></td>
</tr>
<tr>
<td>Opportunity Cost</td>
<td>1.1484*** (0.0154)</td>
</tr>
<tr>
<td>Success Probability Function - Mean (θφ)</td>
<td></td>
</tr>
<tr>
<td>Intercept</td>
<td>-2.5664*** (0.1185)</td>
</tr>
<tr>
<td>Cumulative Funding Amount: log Qt</td>
<td>10.2602*** (0.5818)</td>
</tr>
<tr>
<td>TimeLeft1: T − t</td>
<td>1.1746*** (0.1674)</td>
</tr>
<tr>
<td>TimeLeft2: T^2 − t^2</td>
<td>0.1902*** (0.0310)</td>
</tr>
<tr>
<td>Success Probability Function - Variance (Σφ)</td>
<td></td>
</tr>
<tr>
<td>Intercept</td>
<td>1.7149*** (0.1779)</td>
</tr>
<tr>
<td>Cumulative Funding Amount: log Qt</td>
<td>71.238*** (5.6978)</td>
</tr>
<tr>
<td>TimeLeft1: T − t</td>
<td>2.0235*** (0.3264)</td>
</tr>
<tr>
<td>TimeLeft2: T^2 − t^2</td>
<td>0.0552*** (0.0103)</td>
</tr>
<tr>
<td>Social Media (ω)</td>
<td></td>
</tr>
<tr>
<td>Intercept</td>
<td>5.9799*** (0.0004)</td>
</tr>
<tr>
<td>Daily Facebook Activities (log)</td>
<td>0.0690*** (0.0003)</td>
</tr>
<tr>
<td>Daily Twitter Activities (log)</td>
<td>0.0353*** (0.0007)</td>
</tr>
<tr>
<td>Control of Project Characteristics (β)</td>
<td></td>
</tr>
<tr>
<td>Funding Cycle Length (log)</td>
<td>-0.6843*** (0.0689)</td>
</tr>
<tr>
<td>Price (log)</td>
<td>-0.7603*** (0.0189)</td>
</tr>
<tr>
<td>Funding Goal (log)</td>
<td>0.5249*** (0.0122)</td>
</tr>
<tr>
<td>Team Size (log)</td>
<td>0.0616*** (0.0173)</td>
</tr>
<tr>
<td>Photo Demos (log)</td>
<td>-0.0122 (0.0218)</td>
</tr>
<tr>
<td>Project Social Exposure (log)</td>
<td>-0.8391*** (0.0391)</td>
</tr>
<tr>
<td>Owner Social Exposure (log)</td>
<td>0.1880*** (0.0179)</td>
</tr>
<tr>
<td>Owner Has Image</td>
<td>0.0600 (0.0558)</td>
</tr>
<tr>
<td>Description Length (log)</td>
<td>-0.2229*** (0.0696)</td>
</tr>
<tr>
<td>Links In Description (log)</td>
<td>-0.6965*** (0.1693)</td>
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<tr>
<td>Images In Description (log)</td>
<td>0.5484*** (0.0237)</td>
</tr>
<tr>
<td>Has Video</td>
<td>0.6053*** (0.0528)</td>
</tr>
<tr>
<td>Has Partnership</td>
<td>0.8866*** (0.0281)</td>
</tr>
<tr>
<td>Category Dummies</td>
<td>Yes</td>
</tr>
</tbody>
</table>

*Note. Standard errors are in parentheses and *p<0.10, **p<0.05, ***p<0.01.*

Table 4: Parameter Estimates of the Dynamic Model
Estimation of investors' perceived success probability above may help explain the two dynamic backing patterns observed in Figure 1. As shown in Equation (5), the positive network externality and the negative time effect are two competing forces that determine an investor’s overall backing propensity. As the funding clock ticks and the project accumulate contributions, the positive network externality increases an investor’s backing propensity. However, as the funding cycle progresses and there is less time left before the funding deadline, the investor’s expectation that the project will reach its funding goal diminishes. The shape of a project’s observed backing pattern (increasing, decreasing, or first decreasing and then increasing) depends on the relative strength of these two opposing effects, which also determine the critical mass of funding the project should attain by on time in order to achieve successful funding by the deadline. Estimation results reveal large heterogeneity in network externalities and time effects across projects (see the estimate of $\Sigma_\varphi$ in rows 9-12). As our model allows for project-specific network externalities and time effects, it can capture various backing patterns observed in the dataset.

We briefly discuss the implications from the parameter estimates of project characteristics in Table 4. Buzz on social media drives more investor visits to a project. Moreover, Facebook buzz is twice as effective as Twitter buzz (see the estimates in rows 15 and 16). Project owners may promote their projects on social media such as Facebook and Twitter to inform more potential investors. Estimation results also indicate that setting a longer funding cycle is a double-edge sword. On one hand, a longer funding cycle may mitigate the negative time effect we have discussed above. On the other hand, investor valuation of a project is negatively associated with the length of the funding cycle (see estimate of $FundingCycleLength$ in row 17).

6 Managerial Analysis and Decision Support

This section discusses how project owners can use our model to manage their crowdfunding projects by counterfactual simulations. We show that project owners of both low-valuation projects and high-valuation projects should actively monitor their crowdfunding campaigns. For simplicity of exposition, we drop the project index $j$. The algorithm used to conduct the managerial analyses in this section is in Appendix B.
6.1 Project Valuation and Seeding

6.1.1 Impact of Investor Valuation

Crowdfunding projects may fail to reach their funding target due to low investor valuation (i.e., $X^\beta$ is small). As low valuation projects are difficult to excite investors, the backing probability is low. Thus, although there are a fair number of investors who are informed about these projects, these projects often fall far away from their funding goal by the end of the funding cycle. To illustrate the impact of investor valuation on a project’s crowdfunding performance, we discuss two representative projects: an average-valuation project with $X^\beta = \bar{X}^\beta$ (where $\bar{X}$ is the mean project characteristics in our dataset), and a high-valuation project with $X^h\beta$ at the top 10% quantile among all projects. The average number of daily visitors to a project page is around 400 in our dataset (if not considering investors who are attracted to a project page from Facebook or Twitter activities, the mean arrival $\lambda_t = \exp(\omega_0) \approx 400$).

Figure 2(a) shows that even the average-valuation project is almost unlikely to reach its funding goal if the project owner does not promote the project. Negative time effect dominates and investors’ backing probability decreases over time as investors believe the crowdfunding project is very likely to be unsuccessful. The high-valuation project is much more likely to attract a critical mass of funding (see Figure 2(b)). The negative time effect slightly dominates the positive network externality in early periods, but the positive network externality quickly gains the upper hand in later periods. As a result, investors’ backing probability first slightly decreases but then increases as favorable funding outcome in early periods boots later investors’ positive belief on the prospect of the project. As a result, funding performance takes off after the project attains the critical mass around Period 5.

6.1.2 Seeding Strategy

For an average-valuation project, advertising on various media to attract more potential investors is a plausible means to achieve successful funding. When designing such promotion campaigns, project owners very often need to decide when they should execute the campaigns and at what promotion level. We use our model to evaluate two seeding strategies: early seeding and late seeding. With early seeding, the project owner conducts informative advertising in early periods
Figure 2: The impact of investor project valuation on funding performance. Panel (a) corresponds to the average-valuation project with $X_a \beta = \bar{X} \beta$; Panel (b) correspond to the high-valuation project with $X_h \beta$ at the top 10% quantile among all projects. Other parameters are at their mean value as in Table 4. Investor arrivals follow $M_t = 400$ in each period.
(Period 1 - Period 10). With late seeding, the project owner attracts additional potential investors in later periods (Period 11 - Period 20).

Figure 3 demonstrates the crowdfunding performance of the average-valuation project under the two alternative seeding strategies. Early seeding is more effective. If seeding early (Periods 1-10), attracting around 2,400 each of the 10 periods is sufficient to achieve successful funding (see Figure 3(a)). However, if seeding later (Periods 11-20), the project owner needs to attract more than 3 times of potential investors to make the crowdfunding successful (see Figure 3(b)). This intriguing result is due to the direct effect and indirect effect of seeding. Seeding informs a larger number of investors and thus more contributions (direct effect). A large amount of funding achieved in early periods also boost investors’ expectation on the prospect of the project, which increases an individual investor’s backing propensity (indirect effect). After attaining the critical mass of funding, the project continues to receive more contributions in later periods, even though the project owner has ceased promotion.

6.2 Exogenous Visitation Shocks and Dynamic Seeding Strategies

6.2.1 Impact of Negative Visitation Shocks

Online crowdfunding is subject to various risks and uncertainty (Agrawal et al. 2013). Descriptive statistics in Table 1 show that there are large fluctuations in daily investor visits to a project. In our dataset, even high-valuation projects may fail to attain a critical mass of funding if the project fails to inform a relatively number of potential investors at the early stage of the funding cycle (e.g., investor visits $M_t$ is too small in early periods).

To reveal the impact of stochastic investor arrivals during the funding cycle, we simulate 1,000 realizations of investor visitation processes $\{M_t\}_{t=1}^T$, where $M_t$ follows a stationary distribution with mean 400 (same level as in the deterministic case in Section 6.1). Details of the simulation algorithm are in Appendix B. Without uncertainty (i.e., standard deviation is zero), the high-valuation project is sure to reach its funding goal, as demonstrated in Figure 2(b). With uncertainty, the project is only able to hit this target in 655 out of 1,000 scenarios (i.e., success rate is 65.5%).

Figure 4 shows two realizations from the simulations. In Periods 1-6, investor arrivals and funding performance are similar in both scenarios. However, in Scenario II, unfavorable shocks
Figure 3: The impact of seeding on funding performance of the average-valuation project.
Figure 4: The impact of exogenous random shocks on funding performance of the high-valuation project. Investor arrivals to the project follow a stationary distribution with mean 400.
occur in Periods 7-15 (see the dashed red curve in Figure 4(a)). There are a small number of visitors and thus a small number of contributions. Although exogenous shocks are stationary, the accumulative funded amount $Q_{jt}$ is path-dependent. A small number of investor arrivals in Periods 7-15 not only result in small contributions in these periods, but also negatively influence later investors’ expectations on the project’s success likelihood. Therefore, even though there are relatively large numbers of investor arrivals in later periods, the backing probability is low and thus the total number of contributions does not recover from the previous negative shocks (see the solid red curve in Figure 4(b)). In Scenario I, however, there are no big negative shocks in early periods so the project is able to reach a critical mass around Period 8 (see the solid black curve in Figure 4(b)). After reaching this critical point, funding performance takes off, despite the unfavorable shocks in later periods. These results show that project owners should actively monitor and plan interventions for their crowdfunding projects.

### 6.2.2 Dynamic Seeding Strategies

The analysis above reveals that crowdfunding projects may fail due to low project valuation and/or unfavorable shocks. Facing negative shocks, project owners may advertise their project to increase the chance of successful funding. However, such promotion efforts are not costless. To increase the return on marketing investment, project owners should know when to execute their promotion campaigns. To help project owners maximize return on marketing investment using our model, we design a dynamic seeding strategy which provides project owners a road map to determine when it is necessary for them to intervene in the funding process.

Observing the current funding status $(t, Q_t)$, project owners may use the simulation procedure we develop in Appendix B to evaluate the success probability of the project. If the success probability is lower than the targeted level, project owners may advertise their project to inform more potential investors. In the heat maps in Figure 5, we compute the minimal seeding level required in order to achieve a success rate of 0.9 for each $(t, Q_t)$ combination. The white color corresponds to the cases where no additional advertising is needed, whereas the darker the red color, the higher the seeding level is required. For example, the average-valuation project owner needs to seed at Level 17 (attracting additional 850 visitors) if the project has achieved less than 8% of its funding goal by Period 10 (see Figure 5(a)). However, the high-valuation project owner only needs to seed the
Figure 5: Given the current project status \((t, Q_t)\), the minimal seeding level (from period \(t + 1\) on) required to achieve a success rate of 0.9. A seeding level of 1 corresponds to attracting additional 50 visitors.
project at Level 2 (attracting additional 100 visitors), as shown in Figure 5(b). These heat maps offer important decision support for project owners to dynamically manage their crowdfunding projects.

7 Conclusion

This research build a dynamic model to study how investors decide whether to contribute to a project based on current funding performance and time progress. We model the time effect using a hazards model that captures the success probability of a crowdfunding project. The proposed model extends the traditional static view of network externalities by incorporating the timing of achieving a certain network size. Model estimation shows that investors are more likely to contribute to a project that has already received a sufficiently large number of backers in a timely manner. Investors are less likely to back a project with little time left to achieve its funding target. Investors face a relative large opportunity cost and may not want to contribute to a project that is not very likely to be successfully funded. These two competing forces (positive network externalities and negative time effects) determine an investor’s overall backing propensity. If the negative time effect dominates the positive network externality, investors become less likely to contribute to a project in later periods. However, if the positive network externality dominates, investors are more likely to contribute in later periods. These two competing forces give rise to a critical mass of funding the project should attain on time in order to achieve successful funding by the deadline. Our results shed light on the complex dynamic mechanism and uncertainty in the crowdfunding process which has yet to be unraveled to researchers and practitioners so far.

This research contributes to the emerging literature on online crowdfunding. None of the existing studies have formulated the dynamic crowdfunding process and looked into the interaction between network externalities and a finite funding cycle. The proposed model provides an economic framework to understand investors’ dynamic decision behaviors and the resulting funding patterns. Our research provides important implications for entrepreneurs and crowdfunding platforms. We demonstrate that crowdfunding projects may fail to reach their funding target due to low investor valuation. High-valuation projects may also fail to attain a critical mass of funding because of unfavorable shocks at the early stage of the funding cycle. Project owners should actively monitor
their crowdfunding campaigns to maximize the likelihood of funding success. Our research provides actionable guidance on how to design a crowdfunding campaign and helps project owners decide when and how much they should promote their project on social media to maximize the return on marketing investment.

This research has great potential for extensions. As our objective is to provide a parsimonious framework for modeling network externalities and time effects, future research can construct more complex model for strategic interactions between investors. On the crowdfunding platform we study in this paper, backers are individual, inexperienced consumers rather than professional, institutional investors. Therefore, our results are robust to strategic investor behaviors. However, if there is empirical evidence that some sophisticated institutional investors may optimally time their backing decisions and make their own decisions to influence others, we can extend our model to incorporate these behaviors. Satisfactory identification of such strategic behaviors will require individual-level investor data on investor characteristics, visit history, and backing time, which are beyond the scope of the current dataset. We hope this paper could stimulate more research in this area and encourage crowdfunding platforms to share individual-level investor data with academic researchers.

References


Appendix

A Estimation Procedure

A.1 Summary of the Bayesian Hierarchical Model

We develop a dynamic model of consumer choices with network externalities and time effects. Given the hierarchical nature of the model, we cast it in the Bayesian hierarchical framework. The full specification of the model is

\[
N_{jt} | t, Q_{jt}, T_j, X_j, \beta, c, \gamma_j, \delta_j, \\
M_{jt} | FB_{jt}, TW_{jt}, \omega,
\]

with the following parameters to be estimated

- \( \beta \sim MVN_{K_\beta}(\theta_\beta, \Sigma_\beta) \),
- \( c \sim Gamma(\bar{a}_c, \bar{b}_c) \),
- \( \omega \sim MVN_{K_\omega}(\theta_\omega, \Sigma_\omega) \),
- \( \varphi_j = [\gamma_j, \delta_j] \sim MVN_{K_\varphi}(\theta_\varphi, \Sigma_\varphi) \),
- \( \theta_\varphi \sim MVN_{K_\varphi}(\bar{\theta}_\varphi, \bar{\Sigma}_\varphi) \),
- \( \Sigma_\varphi \sim IW_{\varphi}(\bar{S}^{-1}, \bar{\nu}) \),

where \( K_\beta \) is the dimension of the vector of project characteristics, \( K_\varphi \) is the dimension of the vector of project-specific parameters in the hazards model, and \( K_\omega \) is the dimension of the vector of social media activities. As illustrated Section 4.1, each of the parameters plays a distinct role in the data-generating process, so the parameters to be estimated should be identified. Estimation with a simulated dataset confirms that the model is identified (results available upon request).

A.2 MCMC Algorithm

We develop an MCMC algorithm to estimate the model.

Step 1. Sample \( \beta \)
We assume the prior distribution of $\beta$ follows $MVN_{K_\beta} (\theta_\beta, \Sigma_\beta)$, where $\theta_\beta = 0$ and $\Sigma_\beta = 10^4 I_{K_\beta}$ ($I_{K_\beta}$ is an $K_\beta \times K_\beta$ identity matrix). We use Metropolis-Hastings sampling with random-walk to generate the next draw $\beta^*$ from a normal distribution, i.e., $\beta_k^* \sim N (\beta_k, \sigma_k^2)$. The accepting probability for $\beta^*$ is

$$
\min \left\{ \frac{L (\beta^*, c, \omega, \varphi | Data) MVN_{K_\beta} (\beta^* | \theta_\beta, \Sigma_\beta)}{L (\beta, c, \omega, \varphi | Data) MVN_{K_\beta} (\beta | \theta_\beta, \Sigma_\beta)}, 1 \right\}
$$

**Step 2. Sample $c$**

We consider the prior distribution of $c$ following $\text{Gamma} (\bar{a}_c, \bar{b}_c)$, where $\bar{a}_c = \frac{1}{2}$ and $\bar{b}_c = \frac{1}{2}$. We use Metropolis-Hastings sampling with random-walk to generate the next draw $c^*$ from a log-normal distribution, i.e., $c^* \sim \log N (\log (c), \bar{\sigma}_c^2)$. Hence, the accepting probability for $c^*$ is

$$
\min \left\{ \frac{L (\beta, c^*, \omega, \varphi | Data) \text{Gamma} (c^* | \bar{a}_c, \bar{b}_c)}{L (\beta, c, \omega, \varphi | Data) \text{Gamma} (c | \bar{a}_c, \bar{b}_c)}, 1 \right\}
$$

where the last terms in the numerator and denominator correspond to the Jacobian in the log-normal proposal function.

**Step 3. Sample $\omega$**

We assume the prior distribution of $\omega$ follows $MVN_{K_\omega} (\theta_\omega, \Sigma_\omega)$, where $\theta_\omega = 0$ and $\Sigma_\omega = 10^4 I_{K_\omega}$ ($I_{K_\omega}$ is an $K_\omega \times K_\omega$ identity matrix). We use Metropolis-Hastings sampling with random-walk to generate the next draw $\omega^*$ from a normal distribution, i.e., $\omega_k^* \sim N (\beta_k, \sigma_k^2)$. The accepting probability for $\omega^*$ is

$$
\min \left\{ \frac{L (\beta, c, \omega^*, \varphi | Data) MVN_{K_\omega} (\omega^* | \theta_\omega, \Sigma_\omega)}{L (\beta, c, \omega, \varphi | Data) MVN_{K_\omega} (\omega | \theta_\omega, \Sigma_\omega)}, 1 \right\}
$$

**Step 4. Sample $\varphi_j \equiv [\delta_j, \gamma_j]$**

We consider the prior distribution of $\varphi_j$ following $MVN_{K_\varphi} (\theta_\varphi, \Sigma_\varphi)$. We use Metropolis-Hastings sampling with random-walk to generate the next draw $\varphi^*$ from a normal distribution, i.e., $\varphi_{jk}^* \sim N (\varphi_{jk}, \sigma_k^2)$. The accepting probability for $\varphi_j^*$ is

$$
\min \left\{ \frac{L (\beta, c, \omega, \varphi_j^* | Data) MVN_{K_\varphi} (\varphi_j^* | \theta_\varphi, \Sigma_\varphi)}{L (\beta, c, \omega, \varphi_j | Data) MVN_{K_\varphi} (\varphi_j | \theta_\varphi, \Sigma_\varphi)}, 1 \right\}
$$

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Step 5. Sample $\theta_\varphi$

We consider the conjugate prior distribution for $\theta_\varphi$ following $MVN_{K_\varphi}(\bar{\theta}_\varphi, \Sigma_\varphi)$, where $\bar{\theta}_\varphi = 0$ and $\Sigma_\varphi = 10^4 I_{K_\varphi}$. The next draw $\theta_\varphi^*$ is drawn from a multivariate normal distribution

$$
\theta_\varphi^* \sim MVN_{K_\varphi}(A, B),
$$

where

$$
A = B' \left( \left( \sum_{j=1}^{J} \varphi_j \right)' \Sigma_\varphi^{-1} + \bar{\theta}_\varphi \Sigma_\varphi^{-1} \right)',
$$

$$
B = (I \Sigma_\varphi^{-1} + \Sigma_\varphi^{-1})^{-1}.
$$

Step 6. Sample $\Sigma_\varphi$

We consider the conjugate prior distribution for $\Sigma_\varphi$ following an inverse Wishart distribution $IW_{K_\varphi}(\bar{S}^{-1}, \bar{\nu})$, where $\bar{S} = I_{K_\varphi}$ and $\bar{\nu} = 1$. The next draw $\Sigma_\varphi^*$ is drawn from an inverse Wishart distribution

$$
\Sigma_\varphi^* \sim IW_{K_\varphi} \left( \left( \sum_{j=1}^{J} (\varphi_j - \theta_\varphi) (\varphi_j - \theta_\varphi)' + \bar{S} \right)^{-1}, I + \bar{\nu} \right).
$$

B Simulation Algorithm

We first present a general algorithm used to simulate investor behaviors and backing decisions, followed by additional details on how we conduct each of the managerial analyses in Section 6. For simplicity of exposition, we drop the project index $j$.

The investor valuation of the project is $\upsilon_{it} = X \beta + \varepsilon_{it}$, where $\varepsilon_{it}$ follow a Type I extreme value distribution. The algorithm uses the analytical expression in Equation (6) to compute investors’ backing probability. The mean investor arrival $\lambda_t = \exp (\omega_0 + \eta_t)$, where $\eta_t$ are visitation shocks drawn from a normal distribution $N(0, \sigma^2)$. Parameters $\{c, \omega_0, \gamma, \delta\}$ are at their estimated mean value in Table 4. Alternatively, we can draw parameter value from their posterior distribution, which is computationally more demanding. Suppose the current funding status is $(t, Q_t)$, the general algorithm simulate the impact of seeding at amount $s$ from periods $t+1$ to $\bar{T}$ (i.e., the end the funding cycle).
Simulation Algorithm

1. Simulate $R$ ($R = 1,000$) realizations of investor visits $\{M_{r'}\}_{r'=1}^{\bar{T}}$ for the remainder of $\bar{T}'$ periods ($\bar{T}' = \bar{T} - t$), where $M_{r'} \sim \text{Pois}(\lambda_t)$. The mean arrival $\lambda_t = \exp(\omega_0 + \eta_t)$, where $\eta_t$ is drawn from a normal distribution $N(0, \sigma^2)$.

2. For each realization of investor visits $r := 1 : R$
   2.1 For each period $t' := (t + 1) : \bar{T}$
      2.1.1 Compute the backing probability
      $$\Psi_{r'} = \frac{1}{1 + \exp\left(\frac{c}{\Lambda_{t',Q_{r'-1},T,\gamma,\delta}} - X\beta\right)}.$$
      2.1.2 If seeding of $s_{t'}$ is conducted in period $t'$, then
      $$M_{r'} = M_{r'} + s_{t'}.$$
      2.1.3 Compute the number of backers in period $t'$
      $$N_{r'} = M_{r'} \Psi_{r'}.$$
      2.1.4. Update the fraction of funding achieved up to time $t'$
      $$Q_{r'} = Q_{r'-1} + \frac{N_{r'}P}{G}.$$

3. Compute the success rate of the crowdfunding project as the fraction of the $R$ scenarios where the final achieved funding amount is greater than 1, i.e.,
   $$\text{SuccessRate} = \frac{\#\{Q_{\bar{T}} \geq 1, r = 1, 2, ..., R\}}{R}.$$

We now provide additional details on how we adapt the general algorithm above to do each of the managerial analyses in Section 6. In investigation of the impact of project valuation (Figure 2), the starting funding status is the initiate stage of the project, i.e., $(t = 0, Q_0 = 0)$. There are no exogenous shocks ($\sigma = 0$) and no seeding ($s_{t'} = 0$) for $t' = 1, 2, ..., \bar{T}$. In evaluation of the impact
of seeding, the seeding amount is as described in the caption of Figure 3.

In evaluation of the impact of exogenous shocks (Figure 4), the starting funding status is set as the initiate stage of a project, i.e., \((t = 0, Q_0 = 0)\). Standard deviation of the shocks computed from the investor visitation data is \(\sigma = 1\). There is no seeding \((s_{t'} = 0)\) for \(t' = 1, 2, ..., \bar{T}\). In creating the heat maps in Figure 5, we repeat the simulation for each combination of \((t, Q)\), \(t = 1, 2, ..., \bar{T}\) and \(Q = 0, 0.025, ..., 1\). For each combination, we search for the minimal seeding level needed to achieve the targeted success rate (e.g., 0.9). This is done by starting at seeding level 0 (i.e., \(s_{t'} = 0\)) and increasing this level until the success rate exceeds the targeted one.