Network Externalities in Collaborative Consumption: Theory, Experiment, and Empirical Investigation of Crowdfunding*

Zhuoxin Li

Carroll School of Management, Boston College

140 Commonwealth Ave, Fulton Hall 460, Chestnut Hill, Massachusetts 02467

Phone: (617) 552-2468, Email: zhuoxin.li@bc.edu

Jason A. Duan

McCombs School of Business, The University of Texas at Austin

2110 Speedway Stop B6700, Austin, Texas, 78712

Phone: (512) 232-8323, Email: duanj@mccombs.utexas.edu

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Abstract: Crowdfunding is an emerging internet fundraising mechanism for soliciting capital from the crowd to support entrepreneurial ventures. Entrepreneurs set a funding target and deadline, and investors decide whether to contribute. Investors may estimate a project's chance of funding success not only from the amount of funding the project has attained, but also from the timing that this number was achieved. To illustrate this, 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 (suppose the funding period for both projects is 30 days). The two projects have attracted the same amount of funding, however, the temporal information (5 days *vs.* 20 days) may also provide essential information for investors to evaluate a project's prospect and its chance of reaching the preset funding target by the fixed deadline. The temporal dynamics of network externalities have not been well-understood in the literature.

This paper combines randomized experiments, theoretical modeling, and empirical methods to investigate investors' contribution behaviors in the presence of network externalities and a deadline. The empirical model captures investors' expectation 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 reached a critical mass of funding goal (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. Interestingly, this critical mass changes over the funding period. Simulation studies show that projects may fail to attain the critical mass due to unfavorable shocks at the early stage of the funding cycle. Our model and results shed light on the temporal dynamics of network externalities in collaborative consumption with a target and deadline. We provide actionable promotion strategies and decision support for entrepreneurs to dynamically manage their crowdfunding campaign.

Keywords: crowdfunding; group buying; social media; entrepreneurship; network externality; herding; network effects; 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 Larralde 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 in total and the volume of transactions continues increasing (Agrawal et al. 2013, Mollick 2014, Burtch et al. 2013). 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.

In contrast to traditional capital sourcing models such as venture capital, 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 (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 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 amount of funding 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.

Despite its importance, the role of network externalities in the presence of a funding target and deadline has been under explored in the literature. A major objective of this paper is to demonstrate how time-varying network externalities and the deadline jointly give rise to a critical mass of funding that a project must achieve on time. Investors may estimate a project's chance of success not only from the amount of funding the project has attained, but also from the timing that 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 (suppose the funding period for both projects is 30 days). Since the two projects have attracted the same amount of funding, one would consider the two projects equally appealing if the temporal information (5 days *vs.* 20 days) were not taken into account. However, the temporal information actually provides essential information for investors to evaluate a project's prospect and its probability of receiving sufficient funding. The project reaching 50% of its funding goal within 5 days appears to be a better investment option, for attracting a large percent of funding goal in a short time indicates 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 also provide insights 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, this is the first empirical research that investigates the joint effects of time and network externalities in the setting of targets and deadlines. Specifically, we aim to answer the following questions:

(1) *How do investors form their expectations on the prospect of a project based on its current funding status (e.g., percent of funding goal already achieved and the length of time left)?*

(2) *What are the promotion strategies entrepreneurs may use to increase the probability of funding success?*

Our model captures investors' perceived success probability of a crowdfunding project. The model estimates provide empirical evidence of how investors decide whether to contribute to a project based on current funding performance and the progress in time. We find that investors are more likely to back a project that has already attracted a critical mass of funding (positive network externalities). When the achieved funding amount is 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 which the funding the project needs to 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). We demonstrate that the presence of network externalities and funding deadline jointly leads to a critical mass for funding success, and this critical mass changes over time. 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 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 investors' decision problem during the crowdfunding process. This paper constructs an economic framework to understand dynamic investor behaviors and offers 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. We demonstrate how the presence of network externalities and funding deadline jointly leads to a critical mass for funding success, and how this critical mass changes over time. 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 the timing of the promotion strategy on crowdfunding performance and find that early promotion is more effective. This is due to the direct effect and indirect effect of promotion. Promotion 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 the subsequent-arriving 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 entrepreneur has ceased promotion.

A highly interesting result from our simulation is that high-valuation projects may also fail to attain the critical mass of funding and eventually fizzle out, due to a few unfavorable shocks in investor arrivals 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. We derive dynamic promotion strategies and provide decision support for entrepreneurs 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 on how our model and results provide new insights into the literature on online crowdfunding, followed by some results from an online experiment about crowdfunding in Section 3. We present details of our empirical dataset and provide exploratory evidence on the interaction between network externalities and time effects in Section 4. We then construct our model followed by its estimation method in Section 5. In Section 6, we present the estimation results and their interpretations, followed by the use of counterfactual simulations for managerial analysis in Section 7. We conduct several robustness checks in Section 8 and conclude the paper in Section 9.

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.

Network Externalities and Critical Mass

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). The larger the total number of buyers using compatible products, the greater benefits each buyer receives (Katz and Shapiro 1992). The value of cross-side network externalities is essential to firms in two-sided markets as well (Dubé et al. 2010, Zhang et al. 2012). 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 probability 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. Our model shows that the presence of network externalities and funding deadline jointly leads to a critical mass for funding success, and this critical mass changes over time.

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 analyses complement to 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 owing 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.

Several recent papers have adopted a structural approach to study the emerging crowdfunding mechanism. Kim et al. (2015) find that the observational learning signal, or the number of backers, is not informative. This suggests that potential backers do not take this as a signal of project quality, a similar result found by Kuppuswamy and Bayus (2013). Marwell (2015) studies how different mechanisms affect backers' backing incentives and fundraisers' choice of crowdfunding mechanism. He finds that creators of high quality projects tend to adopt the all-of-nothing mechanism, where entrepreneurs receive the funding only if the funding pledged exceed the pre-set funding goal. Our paper complements to this stream of literature by looking into the joint effect of network externalities and a finite funding cycle. Our model provides an economic framework to understand dynamic investor behaviors and the funding patterns observed in the crowdfunding literature.

3 Observation from a Randomized Experiment

We conducted a randomized experiment on Amazon Mechanical Turk (MTurk) to gain insights into investor behaviors in crowdfunding. MTurk has recently become popular among social scientists as a source of experimental and survey data (Paolacci et al. 2010). We chose online experiments on MTurk over offline lab experiments with student subjects for several reasons. MTurk shares similar features with online crowdfunding platforms, such as crowd-based organizing and a diverse population of subjects (Lowry et al. 2016). These similarities enhance the external validity of the experimental results.

We recruited 200 subjects to participate in the experiment and survey. In the online experiment, participants were shown a crowdfunding project and decided whether they would contribute to the project based on current funding progress:

*Suppose today is Day **5** (**2** days left until the end of the funding period). So far the crowdfunding deal has received in total **$3000** (**75%** of the $4000 goal reached) from **12** buyers.*

Based on the information above, do you think the crowdfunding deal will be able to reach the funding goal of $4000 by the end of Day 7? Please give below your estimate of the chance of reaching the funding goal.

		Percent of Funding Goal Achieved			
		[0%,25%)	[25%,50%)	[50%,75%)	[75%,100%]
Time Elapsed	[0%,25%)	0.389	0.467	0.650	0.833
	[25%,50%)	0.240	0.380	0.500	0.700
	[50%,75%)	0.233	0.322	0.400	0.640
	[75%,100%]	0.217	0.245	0.300	0.464

Table 1: Relationship between Current Funding Progress and Perceived Funding Success

The numbers in bold in the example above (time elapsed, funding received, number of backers) are independent drawn from some uniform distributions. Specifically, the time elapsed (Day 5 with 2 days left in this example) is randomly drawn from the set (2,3,...,6) with equal chance, the cumulative amount funding received ($3800 or 75% of the goal reached in this example) is randomly drawn from (200,400,...,3800), and the number of buyers who have pledged (25 backers in this example) is randomly drawn from (1,2,...,19).

Table 1 shows a clear pattern that participants consider a crowdfunding project to be more likely to be successfully funded if the project has reached a larger fraction of funding goal (positive network externalities) and less time has elapsed, or more time left until the end of the funding period (negative time effects). If a project already reaches more than 3/4 of goal within 1/4 of the funding period, the project's likelihood of funding success is considered high (over 83% of chance). In contrast, if a project raises less than 1/4 of goal when there is less than 1/4 of the funding period left, the project's likelihood of funding success is considered low (less than 22% of chance).

Participants were asked whether they would contribute to the crowdfunding project:

Suppose the smartwatch worth ***$300*** *to you. You can get a smartwatch if the crowdfunding deal reaches its funding goal by the end of the funding period. If the crowdfunding deal fails to reach this goal, you will get full refund (however, it may take several weeks to process your refund). Would you pledge $200 to sign up for the deal?*

A participant's valuation of the product (number in bold, i.e., $300, in the example above) is randomly drawn from the set (250,300,350) with equal chance. Participants chose whether to contribute to the project and provided the reasons for their decision. Among the 200 participants, 106 of them decided to contribute to the project whereas 94 decided not.

Figure 1 summarizes the factors that influence participants' contribution decisions. Participants selected one or more from the list of five reasons for contributing (or not contributing) to the crowdfunding project. The two most frequently mentioned factors are the funding success likelihood and the value of the product. About 66% and 61% of contributors (and 51% and 41% of those who chose not to contribute) indicated funding success likelihood and product valuation, respectively. With pre-set funding goal and fixed funding duration, crowdfunding projects are subject to the uncertainty of funding success. Even investors may get full refund, there is still opportunity cost that discourages investors from contributing to a crowdfunding project.

The controlled online experiment shed light on the dynamic behaviors of crowdfunding investors. To ensure external validity, we complement the controlled experiment a comprehensive empirical study of a leading crowdfunding platform in the United States. In the rest of the paper, we develop a model and conduct empirical analyses to study how real crowdfunding investors make decisions. We discuss how entrepreneurs may use our model to increase the chance of funding success.

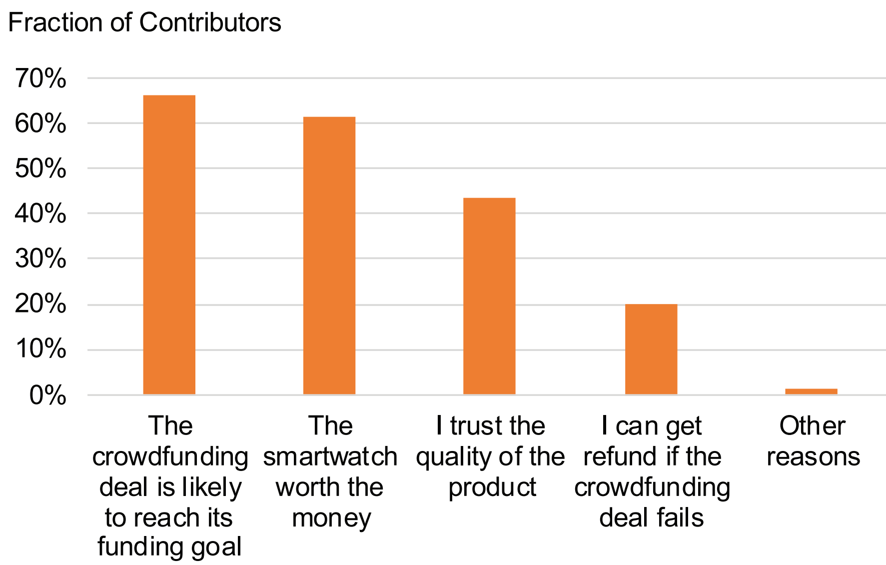
4 Empirical Context and Exploratory Results

4.1 Rewards-Based Crowdfunding

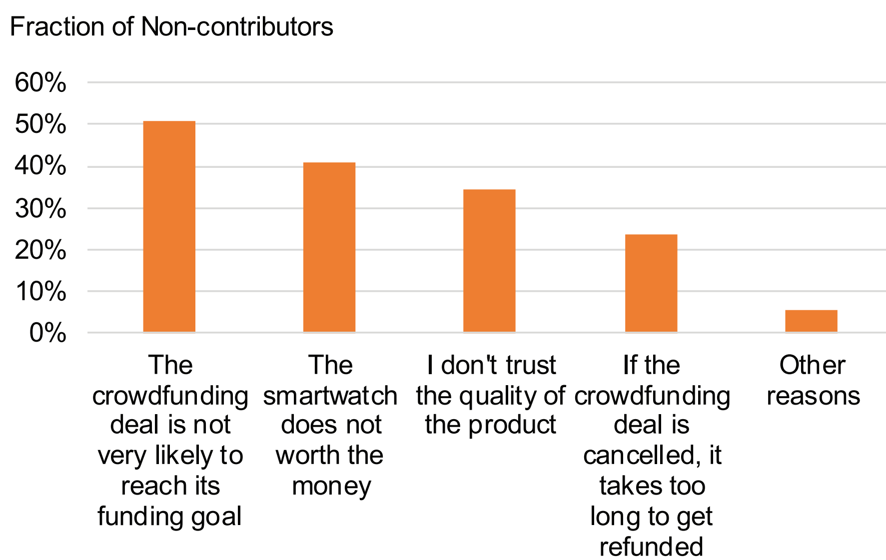
The dataset is obtained from one of leading crowdfunding platforms in the United States. The crowdfunding platform provides rewards-based crowdfunding mechanism (very similar to Kickstarter) where project backers receive future products for their contribution. The platform operates the all-or-nothing crowdfunding mechanism where a project is successfully funded only if the total amount of funding pledged by the deadline exceeds the project's pre-set funding goal. Otherwise, the project is considered to have failed and all the money pledged will be refunded to backers. For successfully funded projects, the platform collects 5% of the funding total as service fee.

The dataset covers a random sample of crowdfunding projects launched between November 2013 and March 2014. We restrict to projects whose owners are located in the United States and with at least one backer (projects received zero pledge provide little information for identification of model parameters). 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 crowd-



(a) Reasons for Contributing ($n = 106$ contributors)



(b) Reasons for Not Contributing ($n = 94$ non-contributors)

Figure 1: Survey of Factors Affecting Contributions to Crowdfunding Projects

funding project page, the number of backers, and the cumulative 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 entrepreneur 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 2. Among all the projects in our sample, only about 23% successfully raised at least the amount of their funding goal by the deadline. In additional, 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.

4.2 Descriptive Evidence of Network Externalities and Time Effects

In this section, we provide preliminary empirical evidences on how investors decide whether to contribute to a project based on current funding performance (percent of funding goal already achieved) and time progress. We hypothesize that investors are more likely to back a project that has already attracted a critical percentage of funding goal (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 2 demonstrates two representative backing patterns observed in our dataset. In Figure 2(a), the crowdfunding project receives some amount of contributions from backers in early periods. However, investors' backing probability 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

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

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

Table 2: Definitions and Summary Statistics of Variables

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 2(b), investors' backing rate is first decreasing but becomes increasing in time after 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.

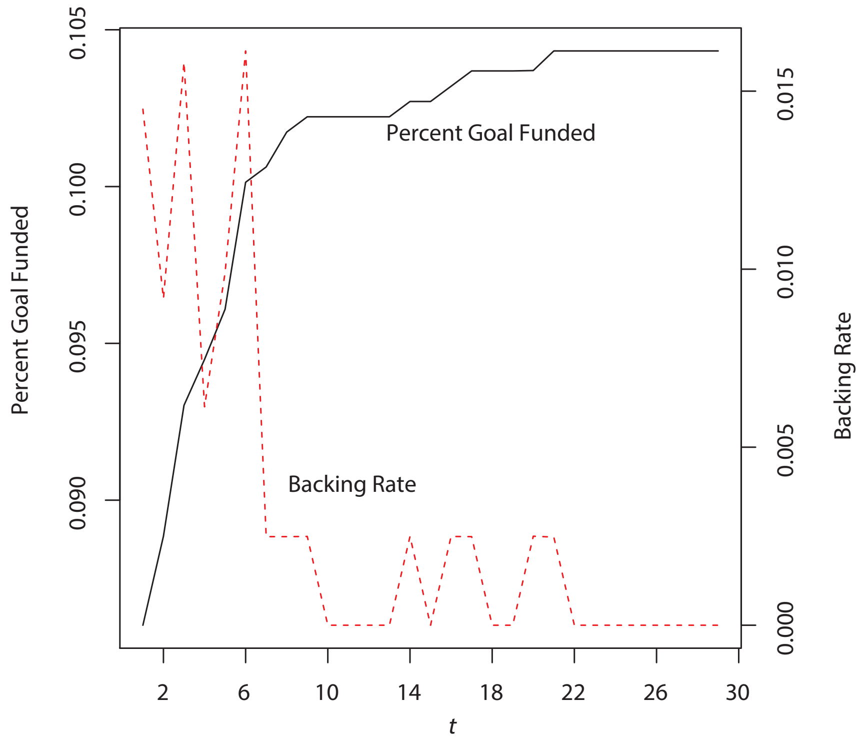
1. Figure 2 highlights the impact of network externalities and time effects on investors' evaluation of a project's success probability. To gain additional insights into the two opposing effects, we create a matrix (see Table 3(a)) to show the relationship between the number of new backers on a given day depends on the percent of funding goal achieved (horizontal direction) and the percent of time elapsed (vertical direction). This matrix clearly shows that investors are more likely to back a project that has already attracted a critical percent of funding. For the same amount of achieved funding, the backing propensity declines over time. Table 3(b) shows a similar matrix for the backing rate, which reveals similar dynamic funding patterns.

4.3 Exploratory Regression Analysis

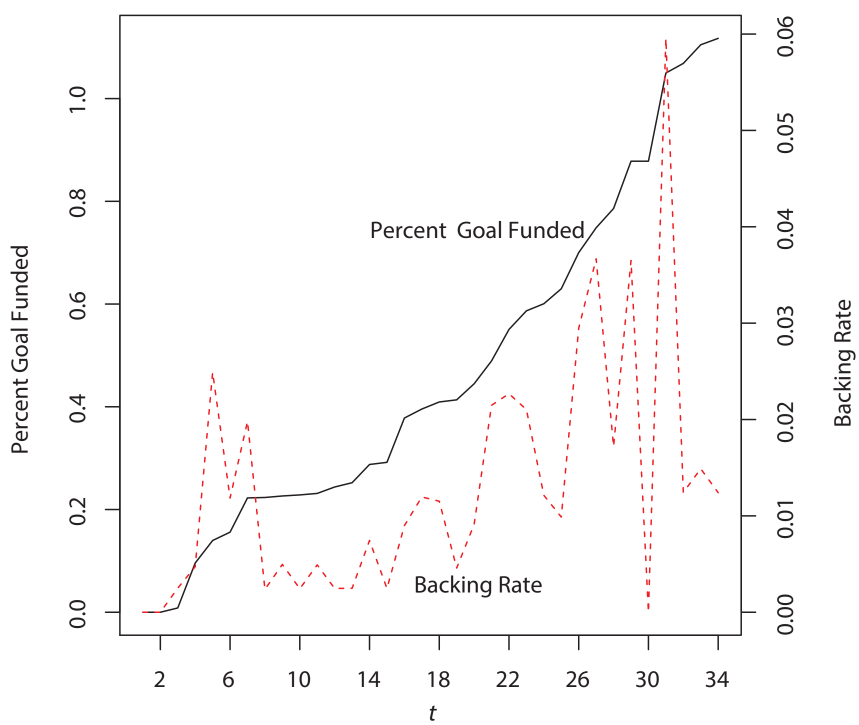
To empirically test the impact of network externalities and time effects on investors' backing propensity, we specify the following linear regression for exploratory analyses,

$$y_{jt} = \beta_1 \log t + \beta_2 \log Q_{jt} + \beta_3 \log t \times \log Q_{jt} + \xi_j + \varepsilon_{jt},$$

where $y_{jt} \equiv \log\left(\frac{N_{jt}}{M_{jt}}\right)$ 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 percent of funding cycle elapsed which captures the time/deadline effect, Q_{jt} is the percent of funding goal attained (i.e., cumulative funding amount divided by the funding goal) by time t which captures network externalities. We measure the number of visitors (potential investors) by the number of clicks (page loads) for each project on a given day. We believe this is a good measure for several reasons. First, the search page only provides



(a) Decreasing Backing Rate



(b) Increasing Backing Rate

Figure 2: Dynamic Backing Behaviors Observed in Online Crowdfunding

		Percent of Funding Goal Achieved			
		[0%,25%)	[25%,50%)	[50%,75%)	[75%,100%]
Time Elapsed	[0%,25%)	0.4851	4.5922	8.0532	5.8085
	[25%,50%)	0.2677	2.0964	3.6184	4.3077
	[50%,75%)	0.1302	1.2374	2.5669	3.2182
	[75%,100%]	0.0990	1.0700	1.7153	3.3415

(a) Daily New Backers

		Percent of Funding Goal Achieved			
		[0%,25%)	[25%,50%)	[50%,75%)	[75%,100%]
Time Elapsed	[0%,25%)	0.0026	0.0200	0.0489	0.0510
	[25%,50%)	0.0015	0.0168	0.0249	0.0365
	[50%,75%)	0.0007	0.0120	0.0251	0.0281
	[75%,100%]	0.0003	0.0086	0.0274	0.0274

(b) Daily Backing Rate

Table 3: Effects of Network Externalities and Deadline

limited information about a project. Second, unlike buying familiar products from a well-known retail store where consumers have prior knowledge, crowdfunding investors are backing innovative projects/products that are mostly not yet available on the market.

Some projects receive zero backer contribution on a given day. In the ordinary least squares (OLS) regression model above, we add 1 to N_{jt} before taking log. As an alternative specification, we also use a Poisson regression model to explicitly address the sparse data issue (some projects receive zero backer contribution on a given day). Table 4 gives the parameter estimates of the network externality and time effect in the exploratory regression. The estimate of network externality is positive, suggesting that investors are more likely to contribute to a project that has attracted a larger percent of funding goal, holding other variables, especially the time effect (Time Elapsed) fixed. The estimate of the time effect is negative, suggesting that investors' backing probability decreases over time, holding the 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.

Variable	OLS	OLS	Poisson	Poisson
Time Elapsed: $\log t$	-1.09***(0.03)	-1.64***(0.05)	-1.78***(0.05)	-2.24***(0.09)
PercentFundingGoalAchieved: $\log Q_t$	0.82***(0.04)	0.71***(0.04)	1.75***(0.06)	1.86***(0.01)
Interaction Term: $\log t \times \log Q_t$		-1.15***(0.01)		-0.13***(0.03)
Project Fixed Effects	Yes	Yes	Yes	Yes
Adjusted R^2 / AIC	0.42	0.42	37827	37597

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

Table 4: Parameter Estimates of the Exploratory Model

5 The Model

To capture the dynamic effects of network externalities and time effects in investors' evaluation of a funding project's success probability, we propose a model in which investors decide whether to invest in a project based on their valuation of the 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.

5.1 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, $t = 1, 2, ..., \bar{T}_j$, a number of consumer 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.

In our dataset, we observe aggregate daily activities of each crowdfunding project. In period t, we know the number visitors to the project page, the number of investors who contributed, and the total amount of funding received by time t. Such aggregate level data does not allow us to track each individual investor's activities. Nevertheless, we can still build a model of individual choices that rationalizes the daily aggregate data we observe. In the remainder of this section, we model investor arrivals and backing decisions.

5.2 Investor Arrivals

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). For a nonhomogeneous Poisson process, the probability of observing the number of visitors M_{jt} in a discretized period t has the Poisson distribution

$$Pois\left(M_{jt} = m|\lambda_{jt}\right) = \frac{\exp(-\lambda_{jt})\lambda_{jt}^{m}}{m!}, \tag{1}$$

where λ_{jt} is the time-varying rate parameter for the mean arrival in t. A larger value of λ_{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 (Susarla et al. 2012). To capture the impact of social media, we allow the rate parameter to be a function of a project's social buzz:

$$\lambda_{jt} = \exp\left(\omega_0 + \mathbf{S_{jt}}\omega_1\right), \tag{2}$$

where ω_0 is baseline rate while ω_1 captures the effect of the project's social media exposures $\mathbf{S_{jt}} \equiv (fb_{jt}, tw_{jt})$, including Facebook and Twitter activities (i.e., the number Facebook "share" and Twitter "tweet").

5.3 Investor's Utility Function

Because an investor does not obtain the product immediately after backing the project, we assume investor i's expected utility upon visiting project j at time t from backing the project is

$$U_{ijt} = \upsilon_{ijt}\Lambda_{jt} - c. \tag{3}$$

In this equation, υ_{ijt} is the investor's valuation of the product, which is heterogeneous among investors. We specify an opportunity cost of backing the product, c, to be the investor's disutility from having her money locked in by the project (Hu et al. 2013). Because the value of the product is realized only if the project is successfully funded, we let Λ_{jt} be the investor's expected probability that the project will reach its funding goal G_j by the deadline. Investors visiting the project at time t are assumed to form rational expectations about the success probability and hence they manifest the same Λ_{jt}. In Section 5.4, we will derive the expected success probability and its properties based on a model using backward induction. Inasmuch as the analytical expression of Λ_{jt} cannot be derived form the model, we approximate Λ_{jt} in Section 5.4.3, which induces a tractable expression in a hazard function. Assuming that investors use a hazards model to approximate the funding success probability can be justified by the fact that investors generally apply bounded rationality for the tractability of solving a difficult decision problem. The utility function in Equation (3) captures the unique feature of the crowdfunding mechanism which requires a project to at least raise a predetermined 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 υ_{ijt} is

$$\upsilon_{ijt} = \bar{\upsilon_j} + \varepsilon_{ijt} = \mathbf{X_j}\beta + \varepsilon_{ijt} \tag{4}$$

where $\mathbf{X_j}$ is a vector of project characteristics (including the unit price P_j) and ε_{ijt} is idiosyncratic shock which is assumed to be drawn from the distribution $F(\cdot)$ independently across investors, projects, and time periods. In the following sections, we refer to the term $\mathbf{X_j}\beta$ as project valuation (project "quality"). Notice that investors may contribute different amounts to a project. We rely on the average contribution to the project (P_j) as we do not observe the amount of each individual contribution. We verify the validity of this proxy as a robustness check.

5.4 Investor Expectation on Funding Success

5.4.1 Properties of the Funding Success Probability Λ_{jt}

In Appendix A, we show the funding success probability Λ_{jt} in Equation (3) can be derived recursively from the last period $\bar{T}_j$. Although it is not possible to derive an analytical expression for Λ_{jt}, we can still use the recursive definite of Λ_{jt} to show that: (i) given t, Λ_{jt} is negatively related to g_{jt}, which suggests a higher funding success probability if the additional number of backers needed is smaller and (ii) for a fixed number of remaining target g_{jt}, Λ_{jt} is negatively related to t, which implies a lower funding success probability if there are fewer periods left in the funding cycle. In our empirical model, we define a normalized measure of g_{jt} as $Q_{jt} = 1 - \frac{g_{jt}}{N_{jG}}$, which is the percent of funding goal achieved by time t. We therefore state the conjectures formally below.

Proposition 1. *A project's funding success probability Λ_{jt} has the following properties: (i) it is decreasing in g_{jt} (or equivalently, increasing in Q_{jt}), and (ii) decreasing in t (or equivalently, increasing in $T - t$).*[1]

The proof of Proposition 1 is achieved by mathematical induction using the recursive definition of Λ_t, which is provided in Appendix A. The intuition behind property (i) is that the probability of success funding is higher if a project has achieved a larger percent of funding goal. We refer to this effect as *positive network externality*. Large contributions from early investors increase a project's success probability, which then boosts late arrivals' utility from investing in the project. The intuition behind property (ii) is that the residual market size (i.e., total number of investor arrivals from period t on) is smaller if there are fewer periods left in the funding cycle. We refer to this effect as *negative time effect.* These properties will help us establish an approximation to Λ_t as it cannot be derived in a closed form.

5.4.2 Time-Varying Critical Mass

The presence of positive network externalities and negative time effects may jointly lead to a critical mass for funding success, and this critical mass changes over time. We define a project's time-varying critical mass as follows.

Definition 1. *The time-varying critical mass $Q^*_{jt}(\rho) = 1 - g^*_{jt}/N_{jG}$ is the percentage of funding goal that a project needs to achieve by time t such that the expected funding success probability Λ_{jt} exceeds $1 - \rho$, $0 < \rho < 1$.*

Given that a project has reached Q^*_{jt} of its funding goal at time t, the project's funding success probability is $1 - \rho$, where ρ is the probability that the project eventually fails to reach its funding goal at the end of the funding period. The concept of critical mass is both theoretically interesting and practically important. Entrepreneurs may set a target success probability $1 - \rho$ and use our

[1] In this paper, a function is decreasing (increasing) if it is non-increasing (non-decreasing). A strictly monotone function will be labeled as strictly decreasing or increasing.

model to compute the corresponding critical $Q_{jt}^{*}(\rho)$. In Section 7, we demonstrate how the critical mass Q_{jt}^{*} changes over the funding period and discuss how entrepreneurs may use the concept of critical mass to maximize funding success.

5.4.3 A Hazards Model Approximation of Λ_{jt}

As it is not possible to derive an analytical expression for the success probability Λ_{jt}, we discuss how we can use a flexible hazards model to approximate Λ_{jt}. In Appendix A.2, we discuss how Λ_{jt} implies a hazard function (but not in the closed form) for the event of achieving the funding target before the deadline. In addition to its flexibility, the hazards model is appealing for several other reasons. Data description in Section 4 suggests that there are substantial heterogeneities across crowdfunding projects. Compared to non-parametric approaches, the hazards model is well-suited to capture heterogeneity in network externalities and time effects with project-specific parameters.[2] As we will see in Section 7, project-specific parameter estimates allow entrepreneurs to design project-specific promotion strategies that work best for a particular project.

Investors form their expectation on whether the project will reach its funding goal by the deadline based on its current funding status. We have shown in Section 5.4 investors will take into account the amount already achieved and the length of the time left before the funding deadline. Hence, we use a hazards model with relative risk 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, Heckman and Singer 1984).

Let $\tilde{T}$ 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

$$h\left(\tau|Q_{jt}\right)=h_0\left(\tau;\delta_{\mathbf{j}}\right)\exp\left(\gamma_{0j}+\gamma_{1j}Q_{jt}+\mathbf{S_{jt}}\gamma_{2j}\right) \tag{5}$$

where $h_0\left(\tau;\delta_{\mathbf{j}}\right)=\delta_{0j}+\delta_{1j}\tau$ is the baseline hazard and Q_{jt} is the funding percentage achieved by time t, and $\mathbf{S_{jt}}$ is the vector of the project's social media exposure.[3] As discussed in Section

[2]With a non-parametric approach, we may discretize all state variables that influence funding success (e.g., t, Q, and other factors denoted by $\mathbf{S}$) and estimate the multi-dimensional matrix $\Lambda\left(t,Q,\mathbf{S}\right)$. This non-parametric approach may allow for more flexible patterns of network externalities and time effects. However, it is challenging, if not impossible, to incoporate project heterogeneities into the the success probability matrix.

[3]In Section 4, we find the investor visitation rate is correlated to the social media exposure of the project. Hence

4, there is large heterogeneity in funding performance across projects. To capture unobserved project heterogeneity, we allow parameters $\delta_{\mathbf{j}}$ and $\gamma_{\mathbf{j}}$ 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, $\varphi_{\mathbf{j}} \equiv [\delta_{\mathbf{j}}, \gamma_{\mathbf{j}}]$, are drawn from a multivariate normal distribution with mean θ_φ and variance-covariance matrix Σ_φ.

At the beginning of the funding period $t_0 = 0$, the probability that the project will reach its goal by the deadline $\overline{T}_j$ is

$$\Lambda_{jt_0} = \Pr\left(T \leq \overline{T}_j | T \geq t_0 = 0\right) = 1 - S\left(\overline{T}_j | Q_{jt_0}, \mathbf{S_{jt_0}}\right), \tag{6}$$

where the survivor function is defined as $S\left(t|Q_{jt_0}, \mathbf{S_{jt_0}}\right) = \exp\left(-H\left(t|Q_{jt_0}, \mathbf{S_{jt_0}}\right)\right)$ with the cumulative hazard $H(t) = \int_{t_0=0}^{t} h\left(\tau|Q_{jt_0}, \mathbf{S_{jt_0}}\right) d\tau$. Equation (6) 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 (3) becomes

$$\begin{aligned} \Lambda_{jt}(t, Q_{jt}, \mathbf{S_{jt}}, \bar{T}_j, \gamma_{\mathbf{j}}, \delta_{\mathbf{j}}) &= \Pr\left(T \leq \overline{T}_j | T \geq t\right) = \frac{\Pr\left(t \leq T \leq \overline{T}_j | T \geq 0\right)}{\Pr\left(T \geq t\right)} \\ &= \frac{S\left(t|Q_{jt}, \mathbf{S_{jt}}\right) - S\left(\bar{T}_j|Q_{jt}, \mathbf{S_{jt}}\right)}{S\left(t|Q_{jt}, \mathbf{S_{jt}}\right)} = 1 - \exp\left(-\int_t^{\bar{T}_j} h\left(\tau|Q_{jt}, \mathbf{S_{jt}}\right) d\tau\right) \\ &= 1 - \exp\left(-\exp\left(\gamma_{0j} + \gamma_{1j} Q_{jt} + \mathbf{S_{jt}}\gamma_{2j}\right)\left(\delta_{0j}\left(\bar{T}_j - t\right) + \frac{\delta_{1j}}{2}\left(\bar{T}_j^2 - t^2\right)\right)\right). \end{aligned} \tag{7}$$

From Equation (7), we can see that investors' perceived success probability Λ_{jt} increases in the accumulated funding amount Q_{jt} if γ_{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 δ_{0j} and δ_{1j}. For example, if both δ_{0j} and δ_{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 (5) and the resulting success probability we derived in

we include $\mathbf{S_{jt}}$ in the hazard function.

Equation (7) provide a parsimonious yet flexible framework that captures both network externalities and time effects. If the estimated γ_{1j}, δ_{0j} and δ_{1j} are positive, $\Lambda_{jt}(t, Q_{jt}, \mathbf{S_{jt}}, \bar{T}_j, \gamma_\mathbf{j}, \delta_\mathbf{j})$ derived in equation(7) reflects the same properties of Λ_{jt} defined in Section 5.4. Hence, $\Lambda_{jt}(t, Q_{jt}, \mathbf{S_{jt}}, \bar{T}_j, \gamma_\mathbf{j}, \delta_\mathbf{j})$ can be considered as an approximation to Λ_{jt} in Section 5.4.

5.5 Backing Rate

We assume that ε_{ijt} are drawn from a Type I extreme value distribution $F(\cdot)$ independently across investors, projects, and time periods. The backing rate in period t follows

$$\Psi(t, Q_{jt}, \mathbf{S_{jt}}, \bar{T}_j, \mathbf{X_j}, \beta, c, \gamma_\mathbf{j}, \delta_\mathbf{j}) = 1 - F\left(c/\Lambda_{jt}(t, Q_{jt}, \mathbf{S_{jt}}, \bar{T}_j, \gamma_\mathbf{j}, \delta_\mathbf{j}) - \mathbf{X_j}\beta\right). \quad (8)$$

The backing probability in Equation (8) has the same properties as investors' perceived success probability in Equation (8), i.e., it is increasing in Q_{jt} if γ_{1j} is positive , and decreasing in time if δ_{0j} and δ_{1j} are positive. In addition, the backing probability is increasing in the project valuation $\mathbf{X_j}\beta$. We do not restrict the signs of γ and δ in estimation. Instead, the data will inform us whether positive network externalities and negative time effects exist.

6 Empirical Analysis and Results

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

6.1 Model Comparison

We estimate the proposed (full) model and three nested models, one without network externalities, one without time effects, and one without social media exposures. In the nested model without network externalities, we constrain the parameter γ_{1j} in Equation (7) 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 $\delta_{0j}\left(\bar{T}_j - t\right) + \frac{\delta_{1j}}{2}\left(\bar{T}_j^2 - t^2\right)$ in Equation (7). In this constrained model, investors' backing probability is not directly influenced by the length of time left. In the nested model without social media exposures, we restrict the parameter γ_{1j} in Equation (7) to zero.

Model	Deviance Information Criterion (DIC)
No Network Externalities Q_t	435,661
No Time Effects t	436,293
No Social Media Exposures $\mathbf{S}$	434,226
Full Model	429,168

Table 5: Model Comparison Results

Model comparison results are summarized in Table 5. The deviance information criterion (DIC) of the full model is significantly lower than that of the three nested models, suggesting that the proposed model outperforms the 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.

6.2 Parameter Estimates

Estimation results from the full model are in Table 6. 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.

Estimation of investors' perceived success probability above may help explain the two dynamic backing patterns observed in Figure 2. As shown in Equation (7), 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 a investor's backing propensity. However, as the funding cycle pro-

Variable	Coefficients (Standard Error)	
Opportunity Cost (c)		
Opportunity Cost	1.1484***(0.0154)	0.9951***(0.0125)
Success Probability Function - Mean (θ_φ)		
Intercept	-2.5664***(0.1185)	-2.5913***(0.1315)
PercentFundingGoalAchieved: Q_t	10.2602***(0.5818)	5.5703***(0.4540)
TimeLeft1: $T - t$	1.1746***(0.1674)	0.5059***(0.0817)
TimeLeft2: $T^2 - t^2$	0.1902***(0.0310)	0.1459***(0.0251)
CumulativeFacebookActivities (log)		0.2186***(0.0324)
CumulativeTwitterActivities (log)		0.2068***(0.0643)
Success Probability Function -Variance (Σ_φ)		
Intercept	1.7149***(0.1779)	1.5846***(0.1588)
PercentFundingGoalAchieved: Q_t	71.238***(5.6978)	16.3362***(3.3343)
TimeLeft1: $T - t$	2.0235***(0.3264)	0.5762***(0.0842)
TimeLeft2: $T^2 - t^2$	0.0552***(0.0103)	0.0245***(0.0050)
CumulativeFacebookActivities (log)		0.2165***(0.0242)
CumulativeTwitterActivities (log)		0.7933***(0.0994)
Social Media (ω)		
Intercept	5.9799***(0.0004)	5.9799***(0.0004)
DailyFacebookActivities (log)	0.0690***(0.0003)	0.0690***(0.0003)
DailyTwitterActivities (log)	0.0353***(0.0007)	0.0353***(0.0007)
Control of Project Characteristics (β)		
FundingCycleLength (log)	-0.6843***(0.0689)	-0.5546***(0.0689)
Price (log)	-0.7603***(0.0189)	-0.5593***(0.0189)
FundingGoal (log)	0.5249***(0.0122)	0.6659***(0.0122)
CategoryDummiesAndOtherProjectCharacteristics	Yes	Yes

Table 6: Parameter Estimates of the Dynamic Model

gresses 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. The estimation results reveal large heterogeneity in network externalities and time effects across projects (see the estimate of Σ_φ 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 6. Social media buzz 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). entrepreneurs 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).

For expositional simplicity, we omit parameter estimates for project characteristics that are not interesting in this paper but included are controls in the model (PhotoDemos, ProjectSocialExposure, OwnerSocialExposure, TeamSize, OwnerHasImage DescriptionLength, LinksInDescription, ImagesInDescription, HasVideo, HasPartnership, and Category Dummies).

7 Managerial Implications and Decision Support

This section discusses how entrepreneurs can use our model to manage their crowdfunding projects. With project-specific parameter estimates, our model may help entrepreneurs make informed decisions on, for example, when to promote their project and how much promotion effort they should do. We show that entrepreneurs of both low-valuation projects and high-valuation projects may benefit from dynamically managing their crowdfunding campaign. The algorithm used to conduct the managerial analyses in this section is in Appendix C.

7.1 Project Heterogeneity and Promotion Timing

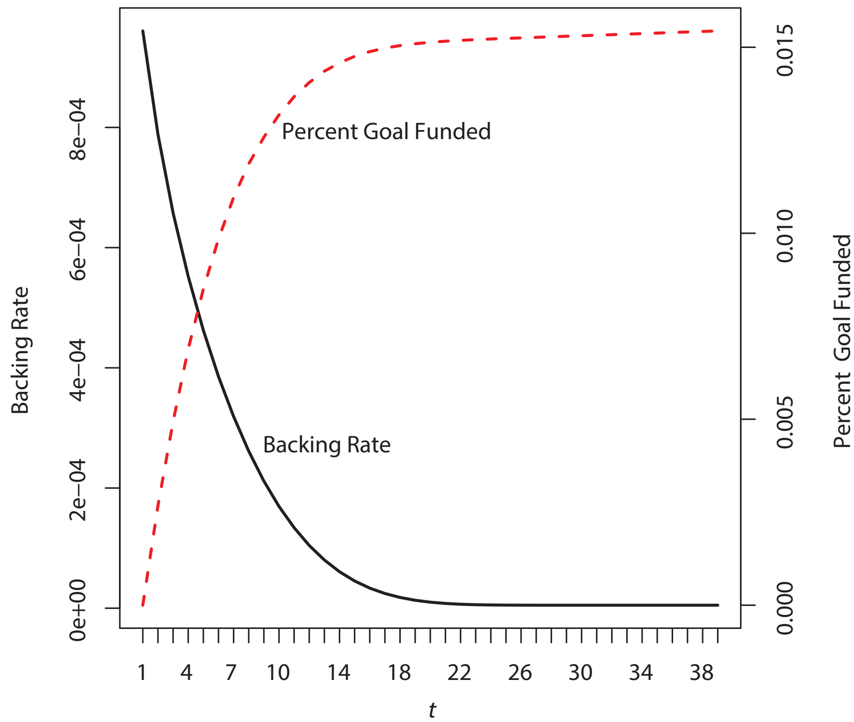
7.1.1 Project Quality: Mean-Valuation Project *vs.* High-Valuation Projcet

Crowdfunding projects may fail to reach their funding target owing to low investor valuation (i.e., $\mathbf{X}\beta$ 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: a mean-valuation project with $\mathbf{X_a}\beta = \bar{\mathbf{X}}\beta$ and $\delta_a = \theta_\varphi$ ($\bar{\mathbf{X}}$ is the mean project characteristics in our dataset and θ_φ is the mean of the parameter estimates), and a high-valuation project with $\mathbf{X_h}\beta$ and δ_h 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 $\lambda_t = \exp(\omega_0) \approx 400$). Other parameters are at their mean value as in Table 6. Investor arrivals follow $M_t = 400$ in each period.

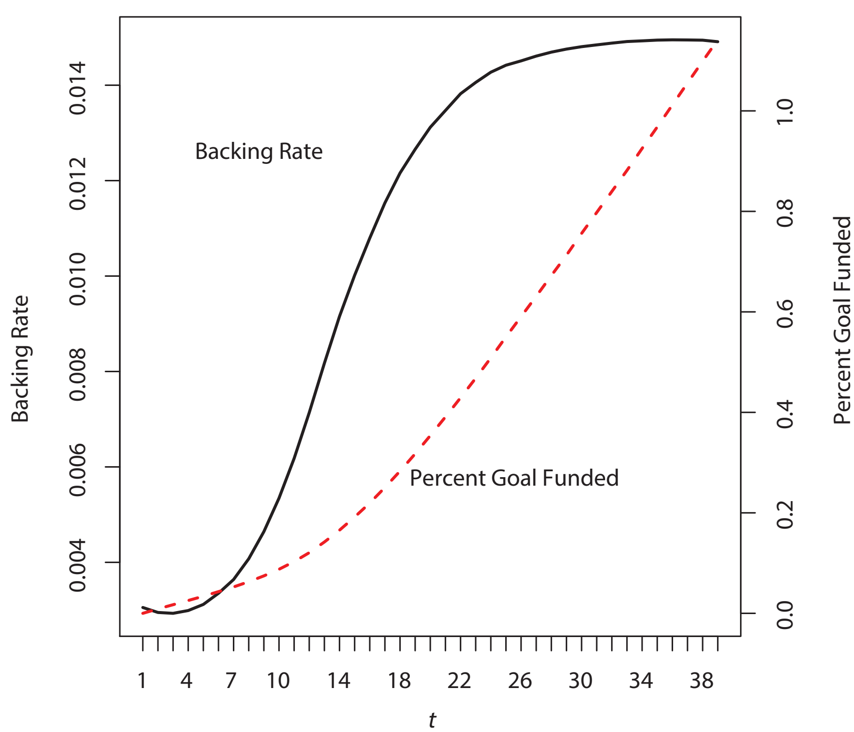
Figure 3(a) shows that even the mean-valuation project is almost unlikely to reach its funding goal if the entrepreneur does not promote the project. Negative time effect dominates and investors' backing probability decreases over time as investors believe the crowdfunding project is very likely to be unsuccessful. The high-valuation project is much more likely to attract a critical mass of funding (see Figure 3(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.

7.1.2 Timing of Promotion: Early Promotion *vs.* Late Promotion

For a mean-valuation project, advertising on various media to attract more potential investors is a plausible means to achieve successful funding. When designing such promotion campaigns, entrepreneurs very often need to decide when they should execute the campaigns and at what



(a) Mean-Valuation Project



(b) High-Valuation Project

Figure 3: Project Valuation on Funding Success

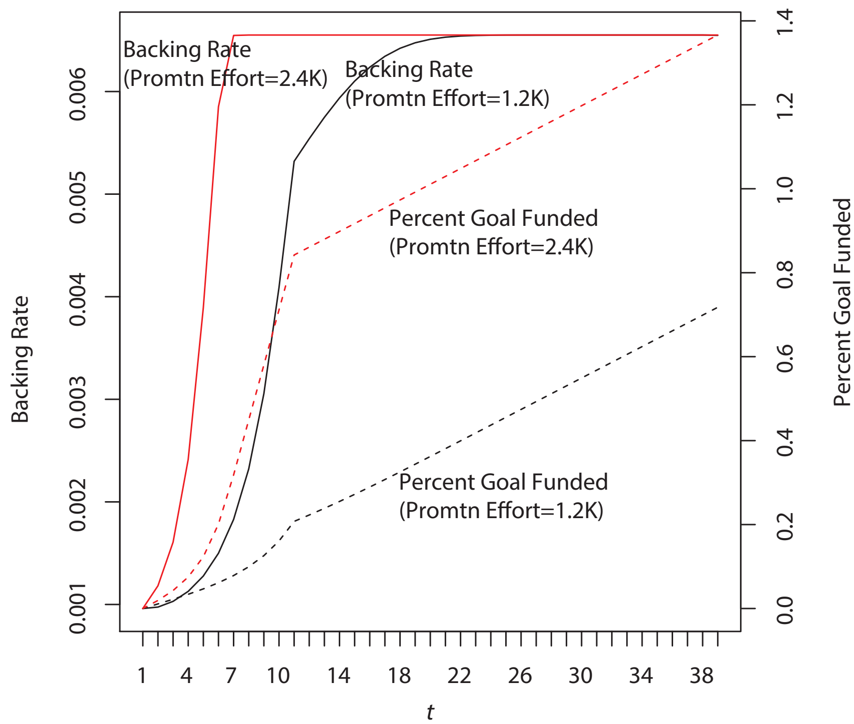
Project Valuation (Quality)	Early Promotion (Periods 1-10)	Late Promotion (Periods 11-20)
90% Quantile Project	0	0
75% Quantile Project	300	925
Mean Project (Figure 4)	2,200	8,300
25% Quantile Project	5.76×10^4	3.77×10^5
10% Quantile Project	6.34×10^5	$> 1.00 \times 10^7$

Table 7: Minimal Promotion Effort for Successful Funding: Promotion Early *vs.* Promotion Late

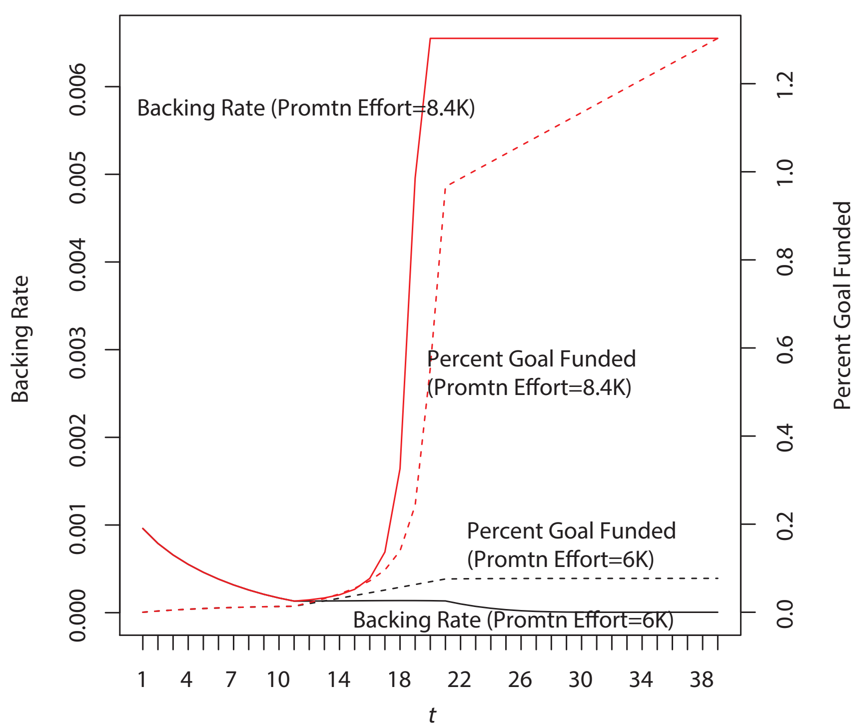
promotion level. We use our model to evaluate two promotion strategies: early promotion and late promotion. With early promotion, the entrepreneur conducts informative advertising in early periods (Period 1 - Period 10). With late promotion, the entrepreneur attracts additional potential investors in later periods (Period 11 - Period 20).

Figure 4 demonstrates the crowdfunding performance of the mean-valuation project under the two alternative promotion strategies. Early promotion is more effective. If promotion early (Periods 1-10), attracting around 2,400 each of the 10 periods is sufficient to achieve successful funding (see Figure 4 (a)). However, if promotion later (Periods 11-20), the entrepreneur needs to attract more than 3 times of potential investors to make the crowdfunding successful (see Figure 4(b)). This intriguing result is due to the direct effect and indirect effect of promotion. Promotion 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 entrepreneur has ceased promotion.

Table 7 summarizes the minimal promotion level required for successful funding for projects of different "quality". We draw these projects from the empirical distribution of project valuation and project-specific parameters (i.e., $\mathbf{X_j}\beta$ and δ_j). The result suggests that the benefit of early promotion is considerable for a variety of projects.



(a) Early Promotion (Periods 1-10)



(b) Late Promotion (Periods 11-20)

Figure 4: Impact of Promotion on Funding Performance of the Mean-Valuation Project

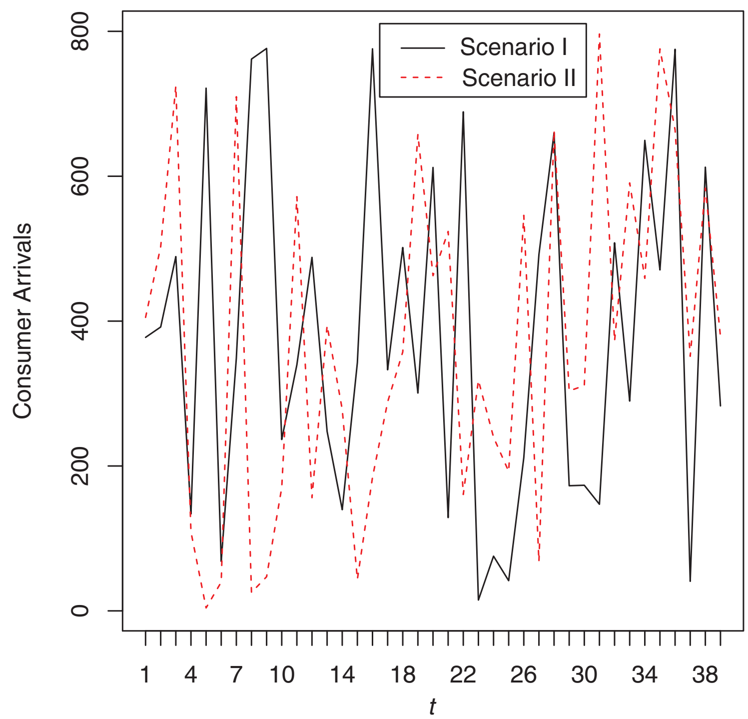
7.2 Funding Uncertainty and Dynamic Promotion

7.2.1 Uncertain Investor Arrivals

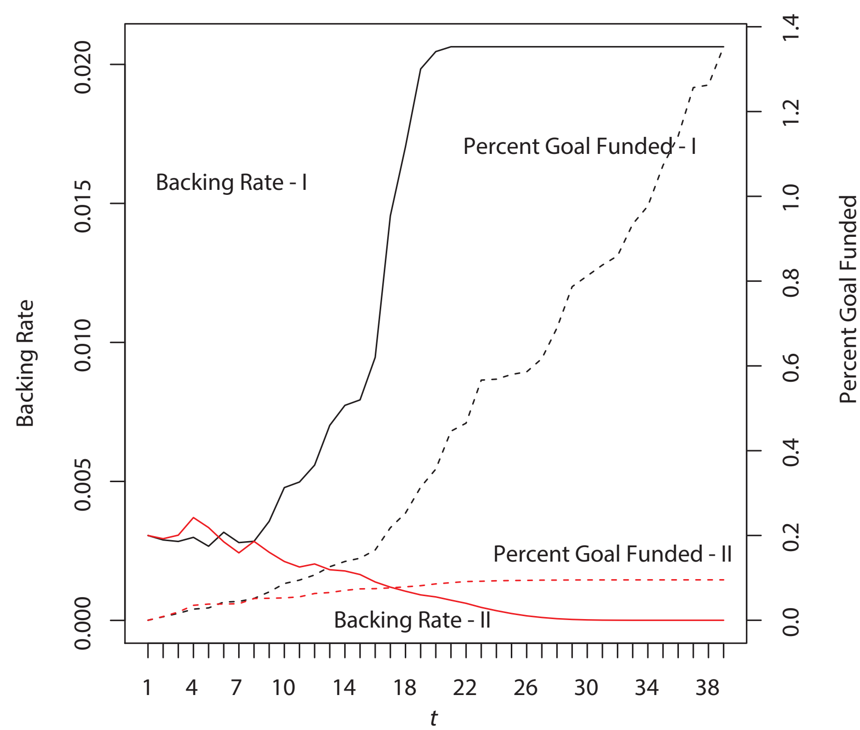
Online crowdfunding is subject to various risks and uncertainty (Agrawal et al. 2013). Descriptive statistics in Table 2 show that there are large fluctuations in daily investor visits to a project. In our dataset, even high-valuation projects may fail to attain a critical mass of funding if the project 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 $\{M_t\}_{t=1}^{\bar{T}}$, where M_t follows a stationary distribution with mean 400 (same level as in the deterministic case in Section 7.1). Details of the simulation algorithm are in Appendix C. Without uncertainty (i.e., standard deviation is zero), the high-valuation project is sure to reach its funding goal, as demonstrated in Figure 3(b). With uncertainty, the project is only able to hit this target in 660 out of 1,000 scenarios (i.e., success rate is 66%).

Figure 5 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 occur in Periods 7-15 (see the dashed red curve in Figure 5(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 probability. 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 5(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 5(b)). After reaching this critical point, funding performance takes off, despite the unfavorable shocks in later periods. These results show that entrepreneurs should actively monitor and plan interventions for their crowdfunding projects.



(a) Investor Arrivals



(b) Funding Performance

Figure 5: 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.

7.2.2 Time-Varying Critical Mass and Dynamic Promotion

The analysis above reveals that crowdfunding projects may fail due to low project valuation and/or unfavorable shocks. Facing negative shocks, entrepreneurs 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, entrepreneurs should know when to execute their promotion campaigns. To help entrepreneurs maximize return on marketing investment using our model, we design a dynamic promotion strategy which provides entrepreneurs a road map to determine when it is necessary for they to intervene in the funding process.

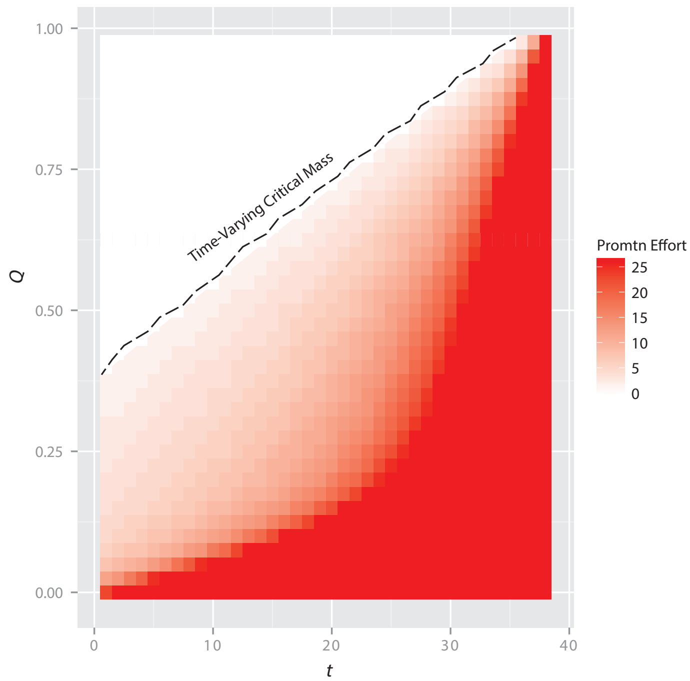
Observing the current funding status (t, Q_t), entrepreneurs may use the simulation procedure we develop in Appendix C to evaluate the success probability of the project. If the success probability is lower than the targeted level, entrepreneurs may advertise their project to inform more potential investors. In the heat maps in Figure 6, we compute the minimal promotion 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 promotion level is required.

The presence of positive network externalities and negative time effects jointly leads to a critical mass for funding success, and this critical mass changes over time. If the funding performance falls below the critical mass, entrepreneurs should promote their project to attract more potential investors. For example, the mean-valuation entrepreneur 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 6(a)). However, the high-valuation entrepreneur only needs to seed the project at Level 2 (attracting additional 100 visitors), as shown in Figure 6(b). These heat maps offer important decision support for entrepreneurs to dynamically manage their crowdfunding projects.

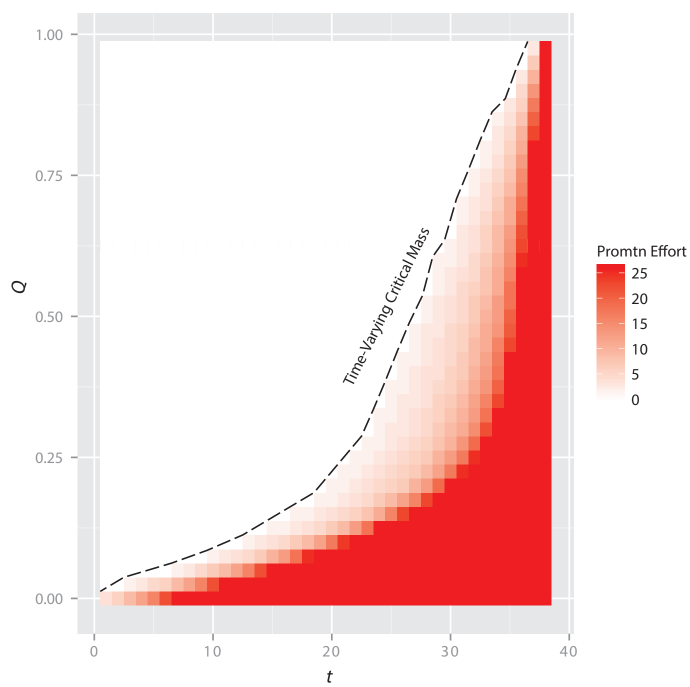
8 Model Robustness Checks

In this section, we conduct several robustness checks to explore the validity of our model of investors' perceived project success probability.

Project Fixed Effects Although we have included rich controls of project characteristics, there might be unobserved heterogeneity not captured by the project valuation function in Equation (4).



(a) Mean-Valuation Project



(b) High-Valuation Project

Figure 6: Given the current project status (t, Q_t), the minimal promotion effort (from period $t+1$ on) required to achieve a success rate of 0.9. A promotion level of 1 corresponds to attracting additional 50 visitors.

Variable	Project Fixed Effects	Excluding First 3 Days	Alternative Q_{jt}
Success Probability - Mean (θ_{φ})			
PercentFundingGoalAchieved: Q_t	4.7161***(0.2239)	4.5049***(0.2843)	4.7143***(0.2849)
TimeLeft1: $T - t$	0.4053***(0.0442)	0.3753***(0.1437)	0.3553***(0.1232)
TimeLeft2: $T^2 - t^2$	0.1259***(0.0089)	0.1763***(0.0270)	0.1663***(0.0282)
CumulativeFacebookActivities (log)	0.3801***(0.0445)	0.2611***(0.0348)	0.2511***(0.0333)
CumulativeTwitterActivities (log)	0.1538* (0.0979)	0.2084***(0.0651)	0.1998***(0.0648)
Success Probability -Variance (Σ_{φ})			
PercentFundingGoalAchieved: Q_t	12.2903***(1.4629)	16.3362***(3.3343)	16.8562***(3.4335)
TimeLeft1: $T - t$	0.4006***(0.0355)	0.5762***(0.0845)	0.5526***(0.0842)
TimeLeft2: $T^2 - t^2$	0.0248***(0.0050)	0.0245***(0.0052)	0.0241***(0.0050)
CumulativeFacebookActivities (log)	0.3131** (0.1520)	0.2165***(0.0242)	0.2065***(0.0237)
CumulativeTwitterActivities (log)	1.1921***(0.3448)	0.7933***(0.0994)	0.7633***(0.0973)

Table 8: Parameter Estimates of the Success Belief Function under Alternative Specifications

To address this, we include project fixed effects and extend the investors' project valuation function as follow:

$$\upsilon_{ijt} = \mathbf{X_j}\beta + \xi_j + \varepsilon_{ijt}.$$

Parameter estimates in the second column of Table 8 show that our main model is robustness to unobserved project heterogeneity.

Friends/Family in Early Stage of Funding It is likely that a entrepreneur's friends and family might play a role in early stage of the funding cycle (Agrawal et al. 2013). Unfortunately, we do not know which backers are friends/family, neither does the owner of crowdfunding platform. Even if we knew which backers were friends/family, it is not clear what their utility function looks like. To alleviate the concern of friends/family in our model estimation, we exclude observations of early backers (all observations in the first 3 days of the funding cycle). The remainder of the observations under this sample would then be more likely to capture the behavior of self-interested backers.

Model estimates, as shown in the third column of Table 8, remain similar to those in our main model. This suggests that friends/family might only account for an insignificant fraction of backers, or they do not behave quite differently from other backers. Similar to Agrawal et al. 2013, we observe in our dataset that a large number of projects raise almost nothing from anyone, including friends and family. This might suggest that backers (including friends/family) may not want to support projects that are unlikely to be successful.

Alternative Measure of Current Funding Status Q_{jt} With our aggregate daily data, we do not observe the exact timing of each investor visit/contribution within a day. We have measured the current funding status Q_{jt} as the percent of funding goal achieved by the end of period $t-1$, which does not allow variation within a given day. This Q_{jt} is likely to be lower than the true funding performance seen by potential investors when they visit the project page (especially for late arrivals). As a robustness check, we use an alternative measure of current funding performance: the average of the percentage of funding goal achieved on day $t-1$ and day t. In contrast to the current measure Q_{jt}, this alternative measure Q'_{jt} is more accurate for late coming visitors on a given day, but less accurate for early coming visitors. The current measure and alternative measure would give the upper and lower bound for the true effect of network externalities. We re-estimate the model and find that the parameter estimates remain very similar. This result is expected as the funding cycle is relatively long (with the mean of 40 days as shown in the descriptive statistics in Table 2) and the number of new backers per day is not very large (with the mean of 1.31).

9 Conclusion

This research builds 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. Our research provides actionable guidance on how to design a crowdfunding campaign and helps entrepreneurs decide when and how much they should promote their project on social media to maximize the return on marketing investment.

This research is not without limitations. As our objective is to provide a parsimonious framework for modeling network externalities and time effects, future research can construct a 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 might not directly apply to other empirical settings such as equity-based crowdfunding. 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, it is possible to 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 (our daily aggregate dataset does not allow us to track an individual investor's dynamic behaviors such as multiple visits to a project). Future research may also look into the behaviors of entrepreneurs in the funding cycle. A flexible model that allows suboptimal strategies will help capture the bounded rationality of entrepreneurs in this empirical setting.

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Appendix

A Analysis of the Funding Success Probability

In this appendix, we first prove the analytical properties of the funding success probability Λ_t. Following the recursive definite of Λ_t, we can prove Proposition 1 by mathematical induction. We then discuss how the funding success probability in Equation (7) is implied by the expected funding success probability of the investors. For expositional simplicity, we drop the project index j.

A.1 Recursive Definition of Λ_t and the Proof of Its Properties

We can divide the entire funding period into a large number of intervals, $t = 1, \ldots, \bar{T}$, such that the number of the random arrival of potential investors in period t, M_{jt} can either be one or zero. This is a property of the Poisson process model for investor visitation in Section 5.2. When the time interval t is small enough, the probability of having more than one investors arriving in t approaches zero. In reality, if we divide the entire funding cycle into many small time periods, we will only observe at most one arrival of a potential investor in a period (Marwell 2015).

We use a recursive approach and derive Λ_{jt} by backward induction (Stokey et al. 1989). Suppose there are a finite number of periods $t = 1, \ldots, \bar{T}$. The project is successfully funded if the total number of backers in the total $\bar{T}$ periods exceed a target number N_{jG} (or equivalently, the total amount of funding pledged exceed the funding goal $G_j = N_{jG} \cdot P_j$). Let g_{jt} the additional number of backers needed to reach the goal N_{jG}.

In the last period $\bar{T}$, we can derive $\Lambda_{j\bar{T}}$ as follows:

1) if $g_{j\bar{T}} \leq 0$, then the project is already successfully funded, i.e., $\Lambda_{j\bar{T}} = 1$;

2) if $g_{j\bar{T}} > 1$, then the project is unlikely to be successfully funded, i.e., $\Lambda_{j\bar{T}} = 0$;

3) if $g_{j\bar{T}} = 1$, then the project will be successfully funded if a consumer arrives AND decides to invest. This happens with probability

$$\Phi_{j\bar{T}} = \Pr\left(M_{j\bar{T}} = 1\right) \Pr\left(\varepsilon_{ij\bar{T}} \geq c - \bar{v}_j\right),$$

where $\Pr\left(M_{j\bar{T}} = 1\right)$ the probability that an investor arrives in period $\bar{T}$ and $\Pr\left(\varepsilon_{ij\bar{T}} \geq c - \bar{v}_j\right)$ the probability that the investor invests in the project.

In summary, we have in period $\bar{T}$,

$$\Lambda_{j\bar{T}}\left(g_{j\bar{T}}\right)=\begin{cases}1, & \text{if } g_{j\bar{T}}\leq 0,\\ \Phi_{j\bar{T}}\left(g_{j\bar{T}}\right), & \text{if } 1\leq g_{j\bar{T}}<0,\\ 0, & \text{if } g_{j\bar{T}}>1.\end{cases}$$

In period $\bar{T}-1$, we can derive $\Lambda_{j(\bar{T}-1)}\left(g_{j(\bar{T}-1)}\right)$ given $\Lambda_{j\bar{T}}\left(g_{j\bar{T}}\right)$ as follows:

1) if $g_{j(\bar{T}-1)}\leq 0$, then the project is already successfully funded, i.e., $\Lambda_{j(\bar{T}-1)}=1$;

2) if $g_{j(\bar{T}-1)}>2$, then the project is unlikely to be successfully funded, i.e., $\Lambda_{j(\bar{T}-1)}=0$;

3) if $2\geq g_{j(\bar{T}-1)}>0$, then the funding success probability is

$$\begin{aligned}\Phi_{j(\bar{T}-1)}\left(g_{j(\bar{T}-1)}\right) \quad = \quad & \left[\Pr\left(M_{j(\bar{T}-1)}=0\right)+\Pr\left(M_{j(\bar{T}-1)}=1\right)\Pr\left(\varepsilon_{ij(\bar{T}-1)}<c/\Lambda_{j\bar{T}}\left(g_{j(\bar{T}-1)}-1\right)-\bar{v}_j\right)\right]\Lambda_{j\bar{T}}\left(g_{j(\bar{T}-1)}\right)\\ & +\Pr\left(M_{j(\bar{T}-1)}=1\right)\Pr\left(\varepsilon_{ij(\bar{T}-1)}\geq c/\Lambda_{j\bar{T}}\left(g_{j(\bar{T}-1)}-1\right)-\bar{v}_j\right)\Lambda_{j\bar{T}}\left(g_{j(\bar{T}-1)}-1\right),\end{aligned}$$

where $\Pr\left(M_{j(\bar{T}-1)}=0\right)$ is the probability that an investor does not arrives,

$$\Pr\left(M_{j(\bar{T}-1)}=1\right)\Pr\left(\varepsilon_{ij(\bar{T}-1)}<c/\Lambda_{j\bar{T}}\left(g_{j(\bar{T}-1)}-1\right)-\bar{v}_j\right)$$

is the probability that an investor arrives but chooses not to invest, and

$$\Pr\left(M_{j(\bar{T}-1)}=1\right)\Pr\left(\varepsilon_{ij(\bar{T}-1)}\geq c/\Lambda_{j\bar{T}}\left(g_{j(\bar{T}-1)}-1\right)-\bar{v}_j\right)$$

is the probability that an investor arrives and invests, which reduces the remaining funding target by 1 to $g_{j(\bar{T}-1)}-1$.

In summary, we have in period $\bar{T}-1$,

$$\Lambda_{j(\bar{T}-1)}\left(g_{j(T-1)}\right)=\begin{cases}1, & \text{if } g_{j(\bar{T}-1)}\leq 0,\\ \Phi_{j(\bar{T}-1)}\left(g_{j(\bar{T}-1)}\right), & \text{if } 2\geq g_{j(\bar{T}-1)}>0,\\ 0, & \text{if } g_{j(\bar{T}-1)}>2.\end{cases} \tag{9}$$

Therefore, for any general period $1\leq t-1\leq\bar{T}$, given $\Lambda_{jt}\left(g_{jt}\right)$ of the following period, we have

$$\Lambda_{j(t-1)}\left(g_{j(t-1)}\right)=\begin{cases}1, & \text{if } g_{j(t-1)}\leq 0,\\ \Phi_{j(t-1)}, & \text{if } \bar{T}-t+1\leq g_{j(t-1)}<0,\\ 0, & \text{if } g_{j(t-1)}>\bar{T}-t+1,\end{cases} \tag{10}$$

where

$$\begin{aligned}\Phi_{j(t-1)}\left(g_{j(t-1)}\right) &= \left[\Pr\left(M_{j(t-1)}=0\right)+\Pr\left(M_{j(t-1)}=1\right)\Pr\left(\varepsilon_{ij(t-1)}<c/\Lambda_{jt}\left(g_{j(t-1)}-1\right)-\bar{v}_j\right)\right]\Lambda_{jt}\left(g_{j(t-1)}\right)\\ &\quad+\Pr\left(M_{j(t-1)}=1\right)\Pr\left(\varepsilon_{ij(t-1)}\geq c/\Lambda_{jt}\left(g_{j(t-1)}-1\right)-\bar{v}_j\right)\Lambda_{jt}\left(g_{j(t-1)}-1\right).\end{aligned}$$

Proof of Proposition 1

Proof.

(i) We first show that Λ_t is decreasing in g by induction.

For $t=\bar{T}$, it is obvious that $\Lambda_{\bar{T}}(g)-\Lambda_{\bar{T}}(g-1)\leq 0$, i.e., $\Lambda_{\bar{T}}$ is (weakly) decreasing in g.

Suppose $\Lambda_{t+1}(g)$ is decreasing in g. We would like to show that $\Lambda_t(g)$ is also decreasing in g. This is obvious if $g\leq 0$ and $g\geq\bar{T}-t$. Thus, we only need to show that $\Lambda_t(g)$ is also decreasing in g for $0<g<\bar{T}-t$. Note that

$$\begin{aligned}\Lambda_t(g) &= \Pr(M_t=0)\Lambda_{t+1}(g) \\ &\quad+\Pr(M_t=1)\Pr\left(\varepsilon_{it}<\frac{c}{\Lambda_{t+1}(g-1)}-\bar{v}\right)\Lambda_{t+1}(g)+\Pr(M_t=1)Pr\left(\varepsilon_{it}\geq\frac{c}{\Lambda_{t+1}(g-1)}-\bar{v}\right)\Lambda_{t+1}(g-1)\\ &\leq \Pr(M_t=0)\Lambda_{t+1}(g)\\ &\quad+\Pr(M_t=1)\Pr\left(\varepsilon_{it}<\frac{c}{\Lambda_{t+1}(g-1)}-\bar{v}\right)\Lambda_{t+1}(g-1)+\Pr(M_t=1)\Pr\left(\varepsilon_{it}\geq\frac{c}{\Lambda_{t+1}(g-1)}-\bar{v}\right)\Lambda_{t+1}(g-1)\\ &= \Pr(M_t=0)\Lambda_{t+1}(g)+\Pr(M_t=1)\Lambda_{t+1}(g-1)\end{aligned} \tag{11}$$

and

$$\begin{aligned}\Lambda_t(g-1) &= \Pr(M_t=0)\Lambda_{t+1}(g-1)\\ &\quad+\Pr(M_t=1)\Pr\left(\varepsilon_{it}<\frac{c}{\Lambda_{t+1}(g-2)}-\bar{v}\right)\Lambda_{t+1}(g-1)+\Pr(M_t=1)\Pr\left(\varepsilon_{it}\geq\frac{c}{\Lambda_{t+1}(g-2)}-\bar{v}\right)\Lambda_{t+1}(g-2)\\ &\geq \Pr(M_t=0)\Lambda_{t+1}(g-1)\\ &\quad+\Pr(M_t=1)\Pr\left(\varepsilon_{it}<\frac{c}{\Lambda_{t+1}(g-2)}-\bar{v}\right)\Lambda_{t+1}(g-1)+\Pr(M_t=1)\Pr\left(\varepsilon_{it}\geq\frac{c}{\Lambda_{t+1}(g-2)}-\bar{v}\right)\Lambda_{t+1}(g-1)\\ &= \Pr(M_t=0)\Lambda_{t+1}(g-1)+\Pr(M_t=1)\Lambda_{t+1}(g-1)\\ &\geq \Pr(M_t=0)\Lambda_{t+1}(g)+\Pr(M_t=1)\Lambda_{t+1}(g-1).\end{aligned} \tag{12}$$

Therefore, we have $\Lambda_t(g)\leq\Lambda_t(g-1)$, i.e., $\Lambda_t(g)$ is decreasing in g.

(ii) We now show that Λ_t is decreasing in t. This is obvious if $g \leq 0$ and $g \geq \bar{T} - t$. Thus, we only need to show that $\Lambda_t(g)$ is also decreasing in t for $0 < g < \bar{T} - t$. From Equation (10), we have for any $1 \leq t \leq \bar{T} - 1$,

$$\begin{aligned}
\Lambda_t(g) &= \Pr(M_t = 0)\Lambda_{t+1}(g) \qquad (13)\\
&\quad + \Pr(M_t = 1)\Pr\left(\varepsilon_{it} < \frac{c}{\Lambda_{t+1}(g-1)} - \bar{v}\right)\Lambda_{t+1}(g) + \Pr(M_t = 1)\Pr\left(\varepsilon_{it} \geq \frac{c}{\Lambda_{t+1}(g-1)} - \bar{v}\right)\Lambda_{t+1}(g-1)\\
&\geq \Pr(M_t = 0)\Lambda_{t+1}(g)\\
&\quad + \Pr(M_t = 1)\Pr\left(\varepsilon_{it} < \frac{c}{\Lambda_{t+1}(g-1)} - \bar{v}\right)\Lambda_{t+1}(g) + \Pr(M_t = 1)\Pr\left(\varepsilon_{it} \geq \frac{c}{\Lambda_{t+1}(g-1)} - \bar{v}\right)\Lambda_{t+1}(g)\\
&= \Pr(M_t = 0)\Lambda_{t+1}(g) + \Pr(M_t = 1)\Lambda_{t+1}(g)\\
&= \Lambda_{t+1}(g).
\end{aligned}$$

The inequality holds because $\Lambda_{t+1}(g-1) \geq \Lambda_{t+1}(g)$ as shown in part (i). Therefore, we have $\Lambda_t(g) \geq \Lambda_{t+1}(g)$, i.e., Λ_t is decreasing in t . □

A.2 A Hazards Model Approximation

In this section, we show how Λ_t implies a hazard function which inherits the properties of Λ_t. Though the proportional hazards model in Section 5.4.3 is not the analytical solution from Λ_t from Equation (10), it is a good approximation that captures the properties of the problem.

For mathematical clarity, we write $\Lambda_t(g_t)$ as $\Lambda(t, g_t)$ and treat t as a continuous variable (when the number of periods approaches infinity and the time interval in each period becomes infinitesimally small, we may treat t as a continuous variable). $\Lambda(t, g_t)$ will have the same properties of Λ_t because the proof in Appendix 1 is true for any number of $\bar{T}$ periods. Let T be the random time when the project is 100% successfully funded, i.e., when $g_T = 0$. In this fashion, $\Lambda(t, g_t)$ can be written as

$$\begin{aligned}
\Lambda(t, g_t) &= \Pr\left(t < T \leq \bar{T} | \bar{T} \geq t, g_t\right) = \frac{\Pr\left(t < T \leq \bar{T} | g_t\right)}{\Pr(T > t | g_t)}\\
&= \frac{\Pr(T > t | g_t) - \Pr\left(T > \bar{T} | g_t\right)}{\Pr(T > t | g_t)} = 1 - \frac{\Pr\left(T > \bar{T} | g_t\right)}{\Pr(T > t | g_t)}.
\end{aligned}$$

Therefore, we have

$$\Pr(T > t | g_t) = \frac{\Pr\left(T > \bar{T} | g_t\right)}{1 - \Lambda(t, g_t)}.$$

If we treat $\Pr(T > t|g_t)$ as a survivor function, we can let

$$\begin{aligned} h(t, g_t) &= -\frac{\partial \Pr(T > t|g_t)/\partial t}{\Pr\left(\tilde{T} > t|g_t\right)} = -\frac{\partial \log(\Pr(T > t|g_t))}{\partial t} \\ &= \frac{\partial \log(1 - \Lambda(t, g_t))}{\partial t}. \end{aligned}$$

Because we have shown that $\Lambda(t, g_t)$ is decreasing in t, it is straightforward to show that $h(t, g_t) \geq 0$, which can be construed as a hazard function. However, we do not have a closed-form solution for $\Lambda(t, g_t)$. As a result, we approximate $h(t, g_t)$ using a proportional hazard function

$$h(t, g_t) = h_0(t; \delta) \exp(\gamma_0 + \gamma_1 g_t),$$

which will lead to the same properties of $\Lambda(t, g_t)$ if $\gamma_1 > 0$.

B Estimation Procedure

B.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

$$\begin{aligned} &N_{jt}|t, Q_{jt}, \mathbf{S_{jt}}, \bar{T}_j, \mathbf{X_j}, \beta, c, \gamma_\mathbf{j}, \delta_\mathbf{j}, \\ &M_{jt}|\mathbf{s_{jt}}, , \omega, \end{aligned}$$

with the following parameters to be estimated

$$
\begin{aligned}
&\beta \sim MVN_{K_\beta}\left(\theta_\beta, \Sigma_\beta\right), \\
&c \sim Gamma\left(\bar{a}_c, \bar{b}_c\right), \\
&\omega \sim MVN_{K_\omega}\left(\theta_\omega, \Sigma_\omega\right), \\
&\varphi_{\mathbf{j}} = [\gamma_{\mathbf{j}}, \delta_{\mathbf{j}}] \sim MVN_{K_\varphi}\left(\theta_\varphi, \Sigma_\varphi\right), \\
&\theta_\varphi \sim MVN_{K_\varphi}\left(\bar{\theta}_\varphi, \bar{\Sigma}_\varphi\right), \\
&\Sigma_\varphi \sim IW_\varphi\left(\bar{S}^{-1}, \bar{\nu}\right),
\end{aligned}
$$

where K_β is the dimension of the vector of project characteristics, K_φ is the dimension of the vector of project-specific parameters in the hazards model, and K_ω is the dimension of the vector of social media activities. As illustrated Section 5.1, 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).

B.2 Likelihood-Based Estimation

We observe the number of investor visits and contributions in each period. 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

$$
N_{jt} = M_{jt}\Psi(t, Q_{jt}, \mathbf{S_{jt}}, \bar{T}_j, \mathbf{X_j}, \beta, c, \gamma_{\mathbf{j}}, \delta_{\mathbf{j}}). \tag{14}
$$

The likelihood for observations $data_j \equiv \{Q_{jt}, \bar{T}_j, \mathbf{X_j}, \mathbf{S_{jt}}\}$ from project j over the $\overline{T}_j$ periods is

$$
\begin{aligned}
L_j\left(data_j | \beta, c, \omega, \gamma_{\mathbf{j}}, \delta_{\mathbf{j}}\right) \quad = \quad \prod_{t=1}^{\overline{T}_j} \Big\{ & \Psi(t, Q_{jt}, \mathbf{S_{jt}}, \bar{T}_j, \mathbf{X_j}, \beta, c, \gamma_{\mathbf{j}}, \delta_{\mathbf{j}})^{N_{jt}} \\
& \times \Big(1 - \Psi(t, Q_{jt}, \mathbf{S_{jt}}, \bar{T}_j, \mathbf{X_j}, \beta, c, \gamma_{\mathbf{j}}, \delta_{\mathbf{j}})\Big)^{M_{jt}-N_{jt}} \\
& \times Pois\left(M_{jt} | \omega, \mathbf{S_{jt}}\right) \Big\}.
\end{aligned}
$$

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

$$L\left(data|\beta, c, \omega, \gamma, \delta\right) \quad = \prod_{j=1}^{J} \quad L_j\left(data_j|\beta, c, \omega, \gamma_{\mathbf{j}}, \delta_{\mathbf{j}}\right).$$

Identification of the parameters comes from the rich variations in the panel dataset. The variations in investor arrival rates across projects help identify ω, the overall funding performance across projects help identify β, and the variations of time-varying funding patterns across projects helps identify δ, γ, and c. We estimate the model using Bayesian inference with the Markov Chain Monte Carlo (MCMC) method as follows.

Step 1. Sample β

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

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

Step 2. Sample c

We consider the prior distribution of c following $Gamma\left(\bar{a}_c, \bar{b}_c\right)$, 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., $c^* \sim \log -N\left(\log\left(c\right), \bar{\sigma}_c^2\right)$. Hence, the accepting probability for c^* is

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

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

Step 3. Sample ω

We assume the prior distribution of ω follows $MVN_{K_\omega}\left(\theta_\omega, \Sigma_\omega\right)$, where $\theta_\omega = 0$ and $\Sigma_\omega = 10^4 I_{K_\omega}$ (I_{K_ω} is an $K_\omega \times K_\omega$ identity matrix). We use Metropolis-Hastings sampling with random-walk to generate the next draw ω^* from a normal distribution, i.e., $\omega_k^* \sim N\left(\beta_k, \bar{\sigma}_k^2\right)$. The accepting probability for ω^* 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 $\varphi_{\mathbf{j}} \equiv [\delta_{\mathbf{j}}, \gamma_{\mathbf{j}}]$

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

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

As there are not enough observations for projects with only one backer, we pool these projects such that they share the same project-specific parameters $\varphi_{\mathbf{j}}$.

Step 5. Sample θ_φ

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

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

where

$$\begin{aligned} A &= B'\left(\left(\sum_{j=1}^{J} \varphi_{\mathbf{j}}\right)' \Sigma_\varphi^{-1} + \bar{\theta}'_\varphi \bar{\Sigma}_\varphi^{-1}\right)', \\ B &= \left(I\Sigma_\varphi^{-1} + \bar{\Sigma}_\varphi^{-1}\right)^{-1}. \end{aligned}$$

Step 6. Sample Σ_φ

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

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

C 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 7. For simplicity of exposition, we drop the project index j.

The investor valuation of the project is $\upsilon_{it} = \bar{\upsilon} + \varepsilon_{it}$, where ε_{it} follow a Type I extreme value distribution. The algorithm uses the analytical expression in Equation (8) to compute investors' backing probability. The mean investor arrival $\lambda_t = \exp(\omega_0 + \eta_t)$, where η_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 6. 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 promotion 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 $\{M_{t'}\}_{t'=t+1}^{\bar{T}}$ for the remainder of $\bar{T}'$ periods ($\bar{T}' = \bar{T} - t$), where $M_{t'} \sim Pois(\lambda_t)$. The mean arrival $\lambda_t = \exp(\omega_0 + \eta_t)$, where η_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*

$$\Psi_{t'}^{r} = \frac{1}{1 + \exp\left(\frac{c}{\Lambda_t(t', Q_{t'-1}^{r}, \bar{T}, \gamma, \delta)} - \mathbf{X}\beta\right)}.$$

    2.1.2 *If promotion level of $s_{t'}$ is conducted in period t', then*

$$M_{t'}^{r} = M_{t'}^{r} + s_{t'}.$$

    2.1.3 *Compute the number of backers in period t'*

$$N_{t'}^{r} = M_{t'}^{r} \Psi_{t'}^{r}.$$

2.1.4. *Update the fraction of funding achieved up to time t'*

$$Q^r_{t'} = Q^r_{t'-1} + \frac{N^r_{t'} P}{G}.$$

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.,*

$$SuccessRate = \frac{\#\{Q^r_{\bar{T}} \geq 1, r = 1, 2, ..., R\}}{R}.$$

We now provide additional details on how we adapt the general algorithm above to do each of the managerial analyses in Section 7. In investigation of the impact of project valuation (Figure 3), 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 promotion $(s_{t'} = 0)$ for $t' = 1, 2, .., \bar{T}$. In evaluation of the impact of promotion, the promotion level is as described in the caption of Figure 4.

In evaluation of the impact of exogenous shocks (Figure 5), 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 promotion $(s_{t'} = 0)$ for $t' = 1, 2, .., \bar{T}$. In creating the heat maps in Figure 6, 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 promotion level needed to achieve the targeted success rate (e.g., 0.9). This is done by starting at promotion level 0 (i.e., $s_{t'} = 0$) and increasing this level until the success rate exceeds the targeted one.