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RESEARCH ARTICLE

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Click to Success? The Temporal Effects of Facebook Likes on Crowdfunding

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Abstract

Small and medium-sized businesses as well as individuals are increasingly using online crowdfunding platforms to raise funds in the fintech world. Creators of crowdfunding projects depend heavily on social networks like Facebook to publicize their projects. Social media activities such as "liking" on Facebook bring massive traffic to crowdfunding projects and attract contributions. Using data collected from Facebook and Kickstarter, our empirical tests demonstrate that social media activities significantly and positively impact the likely success of crowdfunding. Our duration model analysis reveals that the impact of social media activities on crowdfunding outcomes follows a J-curve in the temporal space. We explain the J-curve by identifying two important effects of social media activities throughout the crowdfunding process: a quality-signaling effect in the opening period and a herding effect in the closing period. Especially in the "last mile," there is a strong herding effect that helps crowdfunding projects reach their respective fundraising goals. Our results offer useful contributions to the literature and suggestions for practitioners.

Keywords: Herding Effect, Quality-Signaling Effect, Social Media Activities, Temporal Effects, Crowdfunding, Facebook Like

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1 Introduction

Built upon the simple idea of the wisdom of the crowd (Surowiecki, 2005), crowdfunding is an extension of the more general domain of crowdsourcing (Howe, 2006). Crowdfunding (i.e., internet financing), defined as "the financing of a project or a venture by a group of individuals instead of professional parties" (Schwienbacher & Larralde, 2012), has become increasingly popular in the wake of the trending fintech phenomenon (Menat, 2016). Online crowdfunding platforms like Kickstarter enable small and medium-sized businesses, startups, and even individuals to raise funds from the general public. Ranked as one of the top fintech companies by the New York Times,[1] Kickstarter has hosted an average of over 30,000 projects annually in recent years, with a project success rate ranging from 30% to 40%. Given the numerous online crowdfunding platforms available and large numbers of on-going projects competing for limited resources, it is essential that project creators understand how to successfully fund a project. One critical factor is driving more traffic to the project page.

[1]http://www.nytimes.com/interactive/2016/04/07/business/dealbook/The-Fintech-Power-Grab.html

According to a web analytics service provider, about two-thirds of the online traffic to Kickstarter is indirect traffic.[2] The majority of Kickstarter visitors are driven by referrals and social networks, and Facebook accounts for the biggest portion of the traffic. The impact of Facebook has been observed in many successful projects. For example, in 2012, after Pebble Watch, which designs waterproof watches that allow users to communicate with mobile devices, was unable to raise sufficient initial funds through venture capital (Kosner, 2012), the company listed the project on Kickstarter on April 11, 2012, with a fundraising goal of $100,000 and a fundraising duration of 37 days.[3] The project idea immediately attracted high levels of attention from social networks, as Facebook users "liked" and "shared" the project page with their friends. The project was successfully funded within two hours of its listing. As word about the project continued to spread, the Pebble Watch project eventually raised more than US$10 million from over 68,000 funders in 37 days. By the end of the fundraising period, the project had generated over 100,000 online "discussions" on Facebook, including over 30,000 Facebook "likes," more than 40,000 "comments," and over 30,000 "shares."

Naylor, Lamberton, and West (2012) label Facebook "like" features and similar social buttons as "mere virtual presence," which offers a convenient and straightforward way for people to express their preferences and exchange information within their social network circles. Users are driven to participate in social activities mainly through social motivation, that is, to establish and maintain social interaction with others (Salehan, Kim, & Kim, 2017). As a result, large numbers of conversations and word-of-mouth promotions have been generated online. In fact, it has been reported that more than six billion "likes" were clicked each day in December 2013 (Martin, 2014). Successful stories such as the Pebble Watch project exemplify social media's power to positively impact crowdfunding projects. Anecdotal evidence generally seems to suggest the desirability of having more "likes" on a company's social media fan page, prompting a vibrant new business of trading "likes," as reported by NPR (Henn & Chace, 2012) and Huffington Post (Corlon, 2014). Some examples of "like" sellers are boostlikes.com, sociobooster.com, getyourlikes.co.uk, and ozsocial.com.au. On boostlikes.com, 2,000 "likes" can be purchased for US$143, 10,000 "likes" cost US$462 (as of June 2018), and the cost of one "like" is in the range of a few cents. However, marketers also argue that the "like" button does not generate much value for several reasons. For instance, (1) "likes" may be paid for (i.e., generated by computer programs), which is associated with only a very short-term positive effect (Wessel, Thies, & Benlian, 2016); (2) the volume of "likes" may be so large that it trivializes the responses themselves; and (3) individuals may click "like" out of courtesy or habit and doing so may not reflect their true preferences. These possibilities, then, invoke the following questions: Do "likes" and other similar social media activities actually exert an influence on crowdfunding projects? If so, how do they dynamically influence the projects as they progress?

Using data collected from Facebook and Kickstarter, we empirically tested the impact of social media activities on crowdfunding outcomes. Our results reveal that social media activities do have a positive impact on crowdfunding outcomes. More importantly, we show that the impact of social media activities exhibits a nonlinear J-curve pattern in the temporal space. The impact is most notable in the opening period of crowdfunding, resulting from a quality-signaling effect, and in the closing period, because of a herding effect. Especially in the "last mile," social media activities stimulate a persistent acceleration that helps the crowdfunding projects reach their respective fundraising goals.

This paper has both practical and theoretical implications. The J-curve suggests that project creators should adopt different strategies in different crowdfunding periods. Specifically, in the opening period of crowdfunding, project creators should recruit friends and family, incentivize early initiators, and create fan pages to direct more social media traffic to the project page. In the intermediate period, project creators should make greater efforts to collect feedback from users, enhance project design, and update the existing funders with the latest project updates. In the final period, project creators should consider paid "likes" as a means of taking advantage of the strong impact of social media activities.

For platform developers, this study has implications on the design factors of crowdfunding platforms such as the placement of social buttons. For the academic community, our work furthers the understanding of the herd behavior in the online crowdfunding market. Our findings also identify the cross-sectional variations among different categories of crowdfunding projects, as well as the time-varying hazard ratios present during different periods of crowdfunding. To the best of our knowledge, this paper is the first to study the temporal effects of social media activities on reward-based crowdfunding platforms. In sum, the findings of this paper contribute to a growing body of literature on herd behavior and crowdfunding. Our results also shed light on the applications of crowdfunding and plausibly contribute to additional fields such as experimental

[2] https://www.similarweb.com/website/kickstarter.com

[3] https://www.kickstarter.com/projects/597507018/pebble-e-paper-watch-for-iphone-and-android

design, behavioral analysis, incentive mechanisms, and social marketing.

The remainder of this paper is organized as follows. We review relevant crowdfunding literature in Section 2. In Section 3, we lay out the theoretical background for this study and we describe our data collection and data summary in Section 4. We then present our empirical results in Section 5 and conclude with a discussion in Section 6.

2 Literature Review

There are four prevalent types of online crowdfunding platforms currently active in the market: equity-based crowdfunding (investors gain dividends, e.g., CircleUp, AngelList); donation-based crowdfunding (donors make benevolent contributions, e.g., JustGiving, GiveForward); lending-based crowdfunding (lenders earn bonuses or interests, e.g., Prosper, Kiva); and reward-based crowdfunding (funders receive rewards from creators, e.g., Kickstarter, RocketHub). Of these platforms, researchers have increasingly focused on lending-based and reward-based types. Extant literature on lending-based crowdfunding platforms investigates various related issues, such as observed herd behavior among lenders (Herzenstein, Dholakia, & Andrews, 2011; Zhang & Liu, 2012), significant racial discrimination toward borrowers (Pope & Sydnor, 2011), the effectiveness of the different market mechanisms of auction versus posted price (Wei & Lin, 2016), investors' home bias in terms of geographical proximity between lenders and borrowers (Lin & Viswanathan, 2016), and friendship networks that impact the probability of successful funding (Lin, Prabhala, & Viswanathan, 2013). As the context of our paper is Kickstarter, a reward-based crowdfunding platform, we focus our literature review on the reward-based crowdfunding stream. We summarize relevant studies on reward-based crowdfunding and highlight the position of this paper in relation to the extant literature in Table 1.

The majority of recent studies on reward-based crowdfunding platforms examine factors that contribute to the success of crowdfunding projects. These factors can be generally classified into two main categories: project characteristics and creator attributes (Mollick, 2014; Zvilichovsky, Inbar, & Barzilay, 2015). Project characteristics include project-intrinsic features such as the fundraising goal and duration, specific rewards offered to funders should projects be successfully funded, and the availability of a project's website. Creator attributes describe the traits associated with the project creator, such as trustworthiness, experience, and the number of friends of the creator. Other factors include the performance of past projects (Greenberg et al., 2013), phrases used to describe the projects (Mitra & Gilbert, 2014), and the location of the fundraising city (Kim & Hann, 2013). In their pioneering study, Zvilichovsky et al. (2015) found that if a project creator has backed other projects, then that history has a positive influence on funding success; however, the number of projects previously backed by a project creator has no effect. Koch and Siering (2015) similarly determined that the experience of the project creator, measured by the number of previously created projects on the same platform, has no significant influence on funding success. Also, Koch and Siering (2015) indicate that more comprehensive project information, presented in the form of texts, images, or videos, positively influences funding success.

Table 1. Comparison of Relevant Papers on Reward-Based Crowdfunding

Author	Project characteristics	Creator attributes	Funder's behavior	Social media activities	Temporal effects
Burtch, Ghose, & Wattal, 2013	√			Google Search	
Mollick, 2014	√	√			
Zheng et al., 2014	√	√			
Zvilichovsky et al., 2015	√	√			
Burtch, Ghose, & Wattal, 2016	√		√		
Yuan, Lau, & Xu, 2016	√				
Xiao & Yue, 2018	√		√		
Hong, Hu, & Burtch, 2018	√			Twitter	
This Paper	√	√		Facebook	√

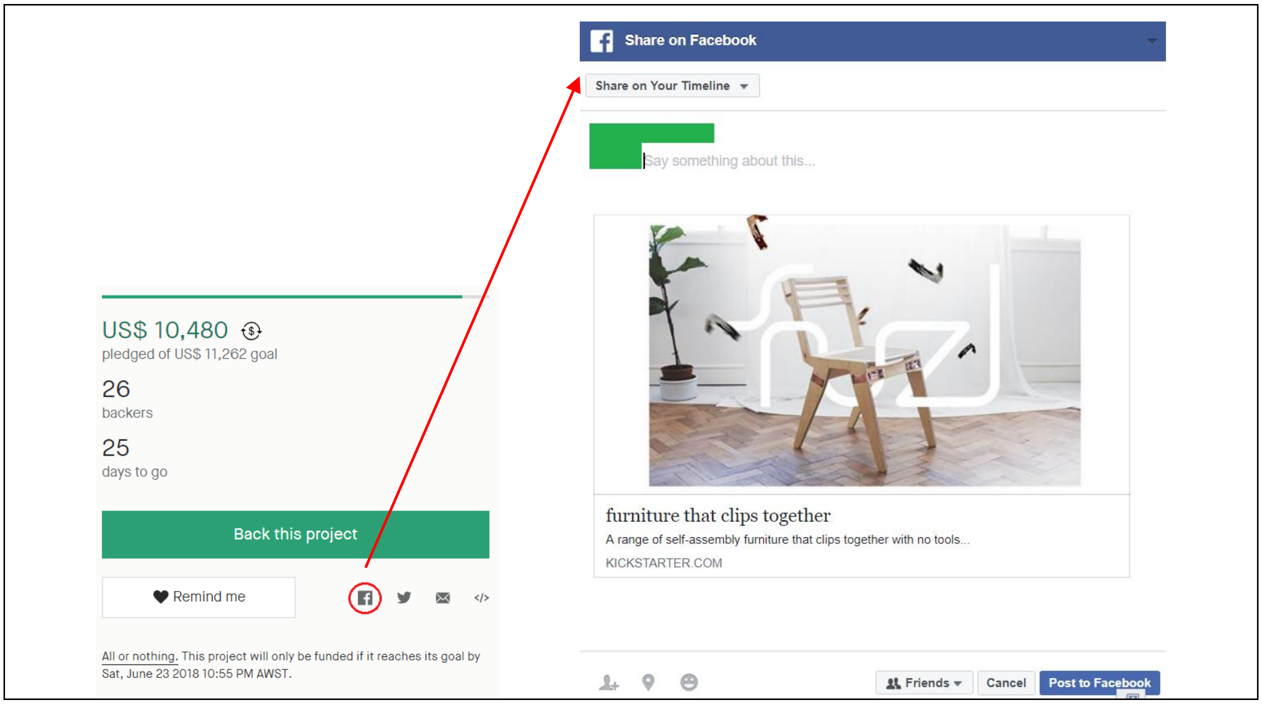
Another stream of reward-based crowdfunding literature examines funding success from the perspective of project funders, as opposed to project creators. Looking at the dynamics of funders of crowdfunding projects, Kuppuswamy and Bayus (2018) discovered that funders who use the Kickstarter platform are more likely to contribute to a project in the first and last week of the funding period rather than in the middle period. Furthermore, they found that this U-shaped pattern of project funding applies to all crowdfunding projects, irrespective of the success or failure of the funding and the size of projects. Agrawal, Catalini, and Goldfarb (2015) offer a different explanation, which suggests that early investment may be largely from local funders (e.g., friends & family), who are less responsive to information about the cumulative funds, while later investment is more likely from distant funders (e.g., total strangers from different regions) actively searching for and reacting to information about the prior funding levels. They discovered interesting patterns regarding who invests at what time throughout the crowdfunding cycle. Li and Duan (2014) developed an analytical model to explain project funders' decisions, based on a project's current status and temporal progress. The estimation of their model reveals both a positive network externalities effect, in which funders are more likely to support a project that has reached a milestone of the funding goal, as well as a negative time effect, where the propensity of funders to support a project declines over time for the same amount of achieved funding. In contrast, Burtch et al. (2013) found evidence supporting a substitution effect, which suggests that prior contributions may crowd out subsequent contributions.

Recent studies have also begun to examine how social media activities, such as Google Search trends (Burtch et al., 2013) and Twitter activities (Hong et al., 2018), impact crowdfunding outcomes. Our work expands the research stream of the influence of social media activities by examining the impact of social media activities on Facebook. Compared to other social media platforms, Facebook has the largest user base, and, more importantly, it focuses on connecting people that a user already knows, such as friends, family, colleagues, and classmates. Facebook's close network creates strong ties and facilitates more personal communication, making it ideal for studying the impact of social media activities. More importantly, as crowdfunding is a dynamic process that typically lasts for several weeks and sometimes longer, focusing solely on crowdfunding outcomes does not tell the full story of reward-based crowdfunding platforms. There is a theoretical and practical need to discern the dynamics of the impact of social media activities throughout the entire crowdfunding process. Our study makes unique contributions to the understanding of reward-based crowdfunding by examining the temporal effects of social media activities across different crowdfunding periods.

3 Kickstarter and Theoretical Background

The Kickstarter platform acts as an intermediary between project creators and potential funders in the fundraising process. The platform profits from drawing a commission from successful projects. Its core business is to assist with fundraising, rather than with the completion or operation of the project. According to Kickstarter, the platform does not guarantee projects or investigate a creator's ability to complete their project. It is solely the funders' responsibility to identify the validity and trustworthiness of the creator/project, and Kickstarter scams have been reported (Knibbs, 2015). The platform adopts an "all-or-nothing" model: the project creators only receive funds if the project is successfully funded on or before the deadline, otherwise no money exchanges hands.[4] The creators of successfully funded projects receive all funds (minus fees) soon after their projects end. To start a crowdfunding project on Kickstarter, a project creator needs to configure a fundraising goal, which is the total monetary amount desired, and a fundraising duration, which is the total time length of the fundraiser. In addition, the project must fit into one of Kickstarter's 13 preset categories, which include design, art, games, film and video, technology, publishing, and so forth. Although creators cannot offer equity or financial incentives to funders, they are advised to reward funders for their support and generosity as a way to incentivize potential funders. In general, a number of pledge levels are devised. Each level represents a different monetary contribution and corresponding reward. A higher pledge level requires a more generous contribution but, assuming project success, also a higher return. If a project fails to reach its fundraising goal, then funders will not be charged; if a project is fully funded before the fundraising closes, then the project will continue to be listed until the deadline.

[4] https://www.kickstarter.com/help/handbook/funding?ref=handbook_index



Note: the user information in the figure is masked for privacy reasons.

Figure 1. Kickstarter and Facebook

On each project page, Kickstarter offers multiple ways a user can share and spread the word about the project (see in Figure 1). The most widely used option is the Facebook share button. Upon clicking the button, a pop-up window appears, inviting the user to share the project on his or her own Facebook timeline. Once the project is shared on Facebook, it goes public (unless the user sets the privacy setting to private) on the user's timeline and is visible as a notification stating: "Your friend has shared a post" on the newsfeed of the user's friends. Thus, potential funders can observe, in real time, other people's activities (e.g., "likes," "comments," "shares") related to the crowdfunding project. Consequently, they may decide to contribute to the project, subsequently publicizing their approval of the project on Facebook and potentially attracting even more funders to the projects. It creates a cascade of information that passes from early funders to future funders, helping projects reach their fundraising goals.

Clearly, more Facebook activities bring more traffic to crowdfunding projects and positively impact their likelihood of success. The positive impact of Facebook activities has also been explored in contexts such as social commerce (Lee, Lee, & Oh, 2015), web traffic (Rishika et al., 2013), branding (Hoffman & Fodor, 2010; Trattner & Kappe, 2013), and box office sales (Ding et al., 2017). We therefore develop two hypotheses to test the overall impact of Facebook activities in connection with crowdfunding outcomes.

H1a: The higher the number of daily Facebook activities, the higher the success likelihood of crowdfunding projects.

H1b: Regardless of whether the crowdfunding projects are successful or not, the higher the number of daily Facebook activities, the higher the percentage of pledged funds.

In different crowdfunding periods, the impact of Facebook activities has different implications on crowdfunding outcomes. We further analyze the temporal effects of Facebook activities. In the opening period of crowdfunding, potential funders form their prior beliefs about a project primarily based on information posted on the project page (e.g., brief description, video demonstration), which is limited in terms of volume and credibility. Because of information asymmetry, potential funders do not know the true quality of the projects. However, potential funders are likely to instinctively infer quality based on others' opinions and preferences and may update their beliefs about the project quality accordingly. Therefore, observing more Facebook activities during the opening period of crowdfunding should help potential funders reduce their uncertainty regarding quality and incentivize them to make contributions, resulting in a *quality-signaling* effect. Similar phenomena have been explored regarding products and services with great quality uncertainty, i.e., group buying (Li & Wu 2018), video-on-demand (Nam, Manchanda, & Chintagunta, 2010), and wedding services (Tucker & Zhang 2011). We thus hypothesize that the impact of Facebook activities on crowdfunding outcomes in the opening period is strong because of the quality-signaling effect.

By the closing period of crowdfunding, more project updates have been posted and more details (such as reviews) are available on the project page, which should significantly reduce potential funders' uncertainty regarding quality. In other words, at this later stage, there should be less variability in the prior beliefs of potential funders. By observing more Facebook activities in the later periods of crowdfunding, potential funders will likely be incentivized to follow others' actions (either engage in Facebook activities and/or contribute to the project), resulting in a *herding* effect. Herd behavior describes individuals' tendency to imitate the actions of others when making decisions (Banerjee, 1992). Sun (2013) argues that one primary motivator for herd behavior is the observation of others' actions. Individuals observing the actions of others may follow suit because such actions have been "proven right" by other people. This type of behavior is commonly observed in technology adoption (Duan, Gu, & Whinston, 2009; Sun, 2013), financial trading (Admati & Pfleiderer, 1988; Welch, 1992; Dow, 2004), and P2P lending (Herzenstein et al., 2011; Zhang and Liu, 2012). We therefore hypothesize that the impact of Facebook activities on crowdfunding outcomes in the closing period is also strong because of the herding effect.

In the intermediate period, potential funders may be more likely to wait, observing the progress of the project and others' reactions on social media. Hence, we hypothesize that the impact of Facebook activities is relatively weak in the intermediate period. In sum, we develop another three hypotheses to test the temporal effects of Facebook activities.

H2a: In the opening period of crowdfunding, Facebook activities have a strong impact on crowdfunding outcomes.

H2b: In the closing period of crowdfunding, Facebook activities have a strong impact on crowdfunding outcomes.

H2c: In the intermediate period of crowdfunding, Facebook activities have a relatively weak impact on crowdfunding outcomes.

Next, we examine the moderating effect with regard to two important aspects of crowdfunding projects: fundraising goals and project categories. Upon observing these two factors, potential funders form their first impressions of the project scope and their expectations for the product or service proposed by the project creator. Potential funders are likely to be drawn in to read on the details of the project or driven away from the project. Therefore, the impact of Facebook activities may differ in magnitude across different projects.

First, in terms of fundraising goals, it has been shown and explained in previous studies that project size influences funders' expectations and, consequently, their funding decisions (Mollick, 2014; Zheng et. al., 2014). To be successful, projects with higher fundraising goals (hereafter called larger projects) require more attention and contribution from larger crowds than those with lower fundraising goals (hereafter called smaller projects). Smaller projects are generally considered to be less uncertain because their goals are more likely to be achieved and funders are thus more likely to be rewarded by the creator. Hence, we expect the impact of Facebook activities to be more pronounced for smaller projects than for larger projects.

Second, in terms of project categories, projects in private-good categories (such as games, technology, and comics) "aim to produce output that is ultimately sold at a profit" (Hong et al., 2018). The funders of such projects expect to receive tangible rewards such as product prototypes. Their actions are motivated by their personal desires and needs, which potentially vary to a great extent, as does thus their uncertainty about the decision. Projects in public-good categories (such as art, music, film, and theater) "primarily benefit others" (Hong et al., 2018). The crowd contributes to such projects to support some common good cause, thus less variance is expected in individual actions. Therefore, we anticipate the impact of Facebook activities to be more pronounced for projects in public-good categories than in private-good categories. We thus propose our sixth hypothesis to test the moderating effects.

H3: The impact of Facebook activities is more pronounced for projects with lower fundraising goals and projects in public-good categories.

4 Data Collection and Summary Statistics

We collected our data from both Kickstarter and Facebook in 2013. Kickstarter provides relevant data for both project characteristics and creator attributes. Project characteristics data capture the basic information of a project, such as fundraising goals, the category of the project, level of funds raised, and so forth. Creator attributes data contain observable personal characteristics of the creators, such as the number of Facebook friends and the number of other projects the creator has submitted in the past. We also fed project links into the Facebook API (application programming interface) to acquire online Facebook activities related to the project, such as the number of people who have "liked" the project, the number of people who have "shared" the project link, and the number of people who have made "comments" about the project. Table 2 provides an overview of the variables' definitions

Table 2. Definitions of Variables

Project characteristics	
Goal	The level of funds to be raised, preset by the project creator
Duration	Funding period of the project, preset by the project creator
Category	The category the project is labeled
Website	= 1 if the creator sets up a website for this project, 0 otherwise
Updates	Number of times the creator has updated the project page
Levels	Number of pledge levels, preset by the project creator
Min	Lowest pledge level with reward
GoalDaily	Goal / duration
Project outcome	
Success	= 1 if the project is successfully funded, 0 otherwise
Pledged	Amount of funds collected from funders
Funders	Number of people who fund the project
LaunchingDate	The date when the creator posts the project on Kickstarter
FundedDate	The first day the project is fully funded
FundedDuration	Number of days between the launching date and the funded date
PercentageDuration	FundedDuration / (duration + 1)
Feedback	Number of users' feedback on the project page
Creator attributes	
Backed	Number of other people's projects the creator has contributed
Friends	Number of friends the creator has on Facebook
Facebook activity (all projects, up to the fundraising deadline)	
Total	Number of total Facebook activities about the project
Like	Number of Facebook "likes" about the project
Comment	Number of Facebook "comments" about the project
Share	Number of Facebook "shares" of the project
TotalDaily	Daily number of total Facebook activities about the project
LikeDaily	Daily number of Facebook "likes" about the project
CommentDaily	Daily number of Facebook "comments" about the project
ShareDaily	Daily number of Facebook "shares" of the project
Facebook activity (successful projects only, up to the funded date)	
Total2	Number of total Facebook activities about the project
Like2	Number of Facebook "likes" about the project
Comment2	Number of Facebook "comments" about the project
Share2	Number of Facebook "shares" of the project
TotalDaily2	Daily number of total Facebook activities about the project
LikeDaily2	Daily number of Facebook "likes" about the project
CommentDaily2	Daily number of Facebook "comments" about the project
ShareDaily2	Daily number of Facebook "shares" of the project

Table 3. Summary Statistics

Variables	Obs.	Mean	SD	Min	Max
Goal	7289	17960.43	100709.10	1.00	5000000.00
Duration	7289	27.47	8.53	2.00	60.00
GoalDaily	7289	644.16	3198.02	0.03	131579.00
Website	7289	0.84	0.37	0.00	1.00
Updates	7289	2.85	4.99	0.00	101.00
Levels	7289	9.04	5.69	1.00	80.00
Min	7289	8.26	20.01	1.00	599.00
Success	7289	0.45	0.50	0.00	1.00
Pledged	7289	8134.99	51107.92	0.00	2232933.00
Funders	7289	107.14	491.83	0.00	22195.00
FundedDuration	3262	17.33	11.02	0.00	60.00
PercentageDuration	3262	0.65	0.34	0.00	1.00
Feedback	7289	43.40	1533.91	0.00	123624.00
Backed	7289	3.57	11.73	0.00	480.00
Friends	7289	478.09	736.10	0.00	5076.00
Total	7289	335.42	1099.67	0.00	34582.00
Like	7289	177.92	593.65	0.00	18812.00
Comment	7289	54.44	254.61	0.00	8288.00
Share	7289	103.06	337.01	0.00	12767.00
TotalDaily	7289	12.49	41.96	0.00	1824.50
LikeDaily	7289	6.66	23.73	0.00	1100.00
CommentDaily	7289	2.00	8.99	0.00	295.50
ShareDaily	7289	3.83	12.04	0.00	429.00
Total2	3262	447.45	1104.95	0.00	29095.00
Like2	3262	245.28	620.09	0.00	14306.00
Comment2	3262	67.39	226.90	0.00	7888.00
Share2	3262	134.78	326.55	0.00	9848.00
TotalDaily2	3262	16.49	36.74	0.00	969.83
LikeDaily2	3262	9.03	20.73	0.00	461.48
CommentDaily2	3262	2.48	7.61	0.00	262.93
ShareDaily2	3262	4.97	10.79	0.00	328.27

We constructed our sample as follows: (1) We compared the fundraising goal to the amount of funds collected from the funders by the fundraising deadline, so that we could determine whether the project was successful. (2) If the project was successful, we set the funded date as the first day the project was fully funded and calculated the funded duration as the time length between the launching date and funded date. (3) We also calculated the percentage duration of successfully funded projects, defined as the funded duration divided by one plus the fundraising duration. (4) We constructed two samples with Facebook activities: Sample A comprised all projects, we recorded each project's cumulative number of Facebook activities at the fundraising deadline and then divided them by the fundraising duration to obtain the daily average number of Facebook activities; Sample B comprised successful projects only and we recorded their cumulative number of Facebook activities on the date funded and also calculated the daily average during the duration of funding.

There was a total of 7,289 projects in our sample; 3,262 were successful and 4,027 were unsuccessful. As described before, we collected three sets of variables, reflecting projects' characteristics, creators' attributes, and Facebook activities, respectively. Table 3 presents summary statistics of the variables in our sample.

We present the correlation matrix in Table 4. We note that the three Facebook activities (i.e., Variables 4-6) are highly correlated with each other. For example, the coefficient between the number of "likes" and number of "comments" is 0.846. A multicollinearity issue may arise when all three measures are included in the same regression. We thus carefully address the multicollinearity issue in the subsequent analysis. The Facebook activities also correlate with project characteristics and creator attributes; however, the correlations are moderate and small. Correlations among all the control variables (i.e., Variables 7-15) are also moderate and small.

5 Empirical Results

5.1 A Logit Model

We first employed the following simple logistic regression to test H1a:

$$\begin{cases} \Pr(Success = 1|\boldsymbol{X}) = \dfrac{\exp(\boldsymbol{\beta X})}{1+\exp(\boldsymbol{\beta X})} \\ \boldsymbol{\beta X} = \beta_0 + \beta_1 FB + TimeEffect + \\ \qquad + CategoryEffect + \varepsilon \end{cases}$$

The dependent variable $Success$ is a dummy that equals one if the project is successfully funded and zero otherwise. The independent variable FB measures the daily number of Facebook "likes," "shares," and "comments." Since three measures are highly correlated, we further constructed an aggregate measure "total," which is the sum of all three numbers, to indicate the collective online chatter of crowdfunding projects. We then added the time-fixed effect and category-fixed effect to the model to capture the unobserved constant heterogeneity across time and within each project category (Wooldridge, 2010). The time-effect dummy labels a project's launching month, and the category-effect dummy labels a project's category. We also applied both effects in our subsequent tests. The results of the regression are shown in Table 5.

According to Model 1, the coefficient of the number of daily Facebook activities is positive and significant at the 1% level, indicating that they generate a positive impact on the crowdfunding outcome. Models 2 to 4 present the individual effects of daily "likes," daily "shares," and daily "comments." Our empirical results suggest that all three measures are significantly and positively related to the success likelihood, which is consistent with H1a. Moreover, they exhibit substantially different degrees of effects. Daily "comments" had the strongest effect, which may be due to the textual and sentiment-based information contained in the comments. This is more apparent in Model 5, in which we test all three measures simultaneously. Their coefficients are 0.039, 0.226, and 0.075, respectively, and are all significant.

Table 4. Correlation Matrix

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. Success														
2. Pledged	0.655													
3. Total	0.312	0.319												
4. Like	0.303	0.303	0.968											
5. Comment	0.304	0.312	0.923	0.846										
6. Share	0.309	0.324	0.944	0.892	0.883									
7. LogGoal	-0.247	-0.286	0.316	0.3	0.298	0.32								
8. Duration	-0.096	-0.067	0.115	0.104	0.107	0.125	0.238							
9. Website	0.118	0.146	0.112	0.107	0.105	0.118	0.065	0.044						
10. Updates	0.344	0.383	0.421	0.388	0.42	0.451	0.179	0.147	0.146					
11. Levels	0.167	0.223	0.367	0.351	0.344	0.373	0.306	0.103	0.137	0.412				
12. Min	-0.052	-0.13	-0.053	-0.049	-0.05	-0.054	0.032	-0.027	-0.031	-0.075	-0.189			
13. Feedback	0.2	0.231	0.38	0.336	0.457	0.405	0.177	0.092	0.074	0.527	0.248	-0.021		
14. Backed	0.225	0.26	0.198	0.185	0.211	0.2	0.053	0.033	0.108	0.397	0.243	-0.068	0.292	
15. Friends	0.122	0.122	0.167	0.171	0.125	0.168	0.02	0.015	0.101	0.052	0.107	-0.014	-0.04	0.064

Table 5. A Logistic Regression

	Model 1	Model 2	Model 3	Model 4	Model 5
Variables					
TotalDaily	0.072*** (11.213)				
LikeDaily		0.131*** (10.569)			0.039** (2.314)
CommentDaily			0.481*** (10.732)		0.226*** (2.997)
ShareDaily				0.228*** (12.365)	0.075*** (2.896)
Constant	-0.362*** (-3.717)	-0.337*** (-3.485)	-0.371*** (-3.809)	-0.363*** (-3.728)	-0.401*** (-4.117)
Time effect	Yes	Yes	Yes	Yes	Yes
Category effect	Yes	Yes	Yes	Yes	Yes
Observations	7,289	7,289	7,289	7,289	7,289
Pseudo R2	0.139	0.136	0.141	0.136	0.149
Note: Standard errors are in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$					

Since the three Facebook activities are highly correlated, as shown in Table 4, there could be multicollinearity issues in Model 5. To address this issue, we constructed three orthogonal Facebook variables that retained their effects in the model and had zero correlation with each other at the same time (Golub & Van Loan, 2012).[5] We performed logistic regression and OLS regression with these three orthogonal variables and found that all three orthogonal Facebook activity measures still had significant and positive relationships with the outcome of the project.

5.2 Adding Additional Control Variables

We further added two sets of variables in the regression to control for project characteristics and creator attributes. The results are presented in Table 6. The additional two sets of variables exerted a significant influence on the likelihood of success, and our results are consistent with prior studies. For instance, Zvilichovsky et al. (2015) confirmed a positive reciprocity effect, which suggests that a creator's past contributions to the crowdfunding community are positively related to the success likelihood of the creator's project. Previous research has also identified a positive friends and family effect, suggesting that being a creator with a larger social network is positively related to a favorable outcome (Agrawal, Catalini, & Goldfarb, 2011; Mollick, 2014). We mark all the project characteristics and creator attributes as "Controls." When necessary, we include the controls in the subsequent regressions. To focus our discussions on the impact of social media activities, we do not report the estimates of these controls.

In their interviews with project creators and funders, Gerber, Hui, and Kuo (2012) found that one of the key motivations for funders is seeking rewards. Since Kickstarter is a reward-based crowdfunding platform, creators must design the "right" rewards to incentivize potential funders. As mentioned before, the creator generally sets a number of pledge levels, with each pledge level representing a monetary contribution and its corresponding reward. Setting more pledge levels allows potential funders to self-select their respective contribution level, which increases the probability of success. This positive relationship is captured by the coefficient of the variable *Levels*. In addition, the variable *Min* denotes the base (lowest) monetary requirement. One surprising finding is that the coefficient of *Min* is also positive. Since the average base pledge level was $8.26, as shown in Table 3, this finding suggests that project creators should be able to raise the minimum pledge by a few dollars without jeopardizing the crowdfunding outcome.

[5] We use the "orthog" procedure in Stata to construct the three orthogonal Facebook variables.

Table 6. Adding Additional Control Variables

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Variables						
TotalDaily	0.076*** (8.953)					
LikeDaily		0.140*** (8.775)			0.079*** (3.742)	0.011
CommentDaily			0.461*** (8.373)		0.143*** (2.949)	0.020
ShareDaily				0.234*** (10.077)	0.064*** (2.596)	0.009
LogGoalDaily	-0.970*** (-28.817)	-0.974*** (-28.601)	-0.925*** (-28.191)	-0.948*** (-28.797)	-0.988*** (-29.224)	-0.141
Levels	0.352*** (4.201)	0.345*** (4.134)	0.358*** (4.313)	0.331*** (3.991)	0.354*** (4.202)	0.051
Min	0.192*** (12.071)	0.194*** (12.394)	0.204*** (12.848)	0.190*** (11.844)	0.189*** (12.060)	0.027
Website	0.035*** (4.149)	0.036*** (4.228)	0.040*** (4.833)	0.037*** (4.290)	0.034*** (4.007)	0.005
Updates	0.013*** (3.192)	0.012*** (3.055)	0.012*** (3.171)	0.013*** (3.257)	0.013*** (3.200)	0.002
Feedback	0.017*** (3.645)	0.019*** (4.233)	0.014*** (2.969)	0.017*** (3.393)	0.016*** (3.439)	0.002
Backed	0.052*** (6.673)	0.051*** (6.664)	0.051*** (6.538)	0.054*** (6.873)	0.051*** (6.574)	0.007
Friends	0.000* (1.907)	0.000* (1.918)	0.000*** (2.625)	0.000** (2.168)	0.000 (1.626)	0.000
Constant	2.489*** (5.774)	2.493*** (5.784)	2.323*** (5.781)	2.386*** (5.489)	2.557*** (5.869)	
Time effect	Yes	Yes	Yes	Yes	Yes	
Category	Yes	Yes	Yes	Yes	Yes	
Observations	7,289	7,289	7,289	7,289	7,289	
Pseudo R2	0.357	0.359	0.349	0.350	0.364	

Note: Standard errors are in parentheses. ****p* < 0.01, ***p* < 0.05, **p* < 0.1. Model 6 is the marginal effects of Model 5.

Finally, all of the FB coefficients are positive and significant, both individually and collectively. Model 6 presents the marginal effects of Model 5, which implies that an additional daily "like," "comment," or "share" is related to an increase of success likelihood of 0.11%, 0.2%, and 0.09%, respectively. Interestingly, we find that the effect of daily "likes" becomes stronger than the effect of daily "shares," and that the gap between the effect of daily "likes" and that of daily "comments" is smaller than that documented in Table 5. In our preceding analyses, we employed only the success likelihood as the dependent variable to reflect Kickstarter's "all-or-nothing" policy, which allows the project creator to collect the funds given only if the project is fully funded by the deadline. Otherwise, the creator collects nothing, even if the project has reached 99% of its fundraising goal.

To test H1b, we created the percentage of funds pledged with respect to the fundraising goal as the dependent variable, which is represented by $\log\left(1 + \frac{Pledged}{Goal}\right)$. A log transformation was necessary since the percentage values vary from 0 to 665. The resulting relationship between the percentage of pledged funds and the Facebook activities is still positive and significant as indicated in Table 7. H1b is thus supported.

Table 7. Facebook Activities and Percentage of Pledged Funds

	Model 1	Model 2	Model 3	Model 4	Model 5
Variables					
TotalDaily	0.005*** (14.133)				
LikeDaily		0.009*** (13.790)			0.003*** (3.096)
CommentDaily			0.033*** (12.486)		0.016*** (4.136)
ShareDaily				0.017*** (13.693)	0.004** (2.107)
Constant	0.848*** (16.721)	0.846*** (16.748)	0.839*** (16.843)	0.835*** (16.064)	0.850*** (16.862)
Controls	Yes	Yes	Yes	Yes	Yes
Time effect	Yes	Yes	Yes	Yes	Yes
Category effect	Yes	Yes	Yes	Yes	Yes
Observations	7,289	7,289	7,289	7,289	7,289
Adjusted R2	0.456	0.453	0.454	0.453	0.457

Note: Standard errors are in parentheses. ****p* < 0.01, ***p* < 0.05, **p* < 0.1.

Table 8. Moderating Effects

	1. Small vs. large	2. Public vs. private
Variables		
LikeDaily	0.826*** (13.707)	0.095*** (4.343)
LikeDaily*DailyGoal	-0.097*** (-12.701)	
LikeDaily*PublicCategory		0.055** (2.008)
Project characteristics	Yes	Yes
Creator characteristics	Yes	Yes
Time effect	Yes	Yes
SubCategory effect	Yes	Yes
Observations	7,289	4,852
Pseudo R2	0.407	0.322

Notes: Standard errors are in parentheses. ****p* < 0.01, ***p* < 0.05, *p < 0.1

5.3 Moderating Effects

As discussed in Section 3, we hypothesize that the impact of Facebook activities is more pronounced for projects with lower fundraising goals and projects in the public-good categories (H3). We now empirically examine the hypothesis by testing the interaction terms with regard to the fundraising goals and the project categories. We present our results in Table 8.

Model 1 reports the results according to fundraising goals—i.e., large projects vs. small projects. After controlling the daily "like" effect, the coefficient of the interaction term (i.e., *LikeDaily*DailyGoal*) is negative and significant, which suggests that the impact of Facebook "likes" is more pronounced for small crowdfunding projects. Model 2 reports the results according to project categories—public-good vs. private-good projects. Our results show that the projects in the public-good categories achieve a higher aggregate coefficient, which suggests that the impact of Facebook "likes" is more pronounced for projects in the public-good categories. Both results support H3 and provide insights into the cross-section variations among different crowdfunding projects on the Kickstarter platform.

5.4 Controlling for Endogeneity

In the current context, the most critical endogeneity concerns are reverse causality and omitted variables. The most common way to address these issues in a cross-sectional framework is to apply the two-stage least square (2SLS) regression (Heckman, 1979; Mayhew and Mihov, 2004). In the first stage, an OLS regression is performed on the endogenous variables using an instrumental variable (IV) and a set of exogenous variables; in the second stage, the predicted values from the first stage are then used to replace the actual values of the endogenous variables, so that an OLS model for the response of interest can be computed. The challenge is to identify an appropriate IV, since a weak IV could lead to a result even more biased than results without any IV at all.

Lewbel (2012) argues that testing endogeneity is equivalent to testing the triangularity of a simultaneous equation system. Specifically, in our study, consider the simultaneous equation systems:

$$\begin{cases} PPF = \gamma_1 FB + X\beta_1 + \epsilon_1 \\ FB = \gamma_2 PPF + X\beta_2 + \epsilon_2 \end{cases}.$$

Again, FB measures the daily number of Facebook "likes," "shares," and "comments." PPF is the percentage of pledged funds, X represents the control variables, and $\epsilon = (\epsilon_1, \epsilon_2)$ is the unobserved error. The system is fully simultaneous (endogenous) if $\gamma_2 \neq 0$, otherwise the system is well identified (triangular). Lewbel (2012) proposes a new class of generated instruments—heteroskedasticity-based instruments—to achieve the identification in the simultaneous equation systems. These instruments are constructed by the model's data and serve to identify structural parameters in regressions with the endogenous or mismeasured regressors. The assumptions in Lewbel (2012) are very general and mild for the constructed instruments and the simultaneous equation systems. The identification scheme requires the additivity of the endogenous regressors and is based on their higher moments, which are likely to be noisy. We construct the generated instruments using the auxiliary equations' residuals, multiplied by each of the included exogenous variables in mean-centered form:

$$Z_j = \left(X_j - \bar{X}\right)\epsilon,$$

where ϵ is the vector of residuals from the "first stage regression." The generated instruments Z_j fulfill the identification requirements, $\text{cov}\left(Z_j, \epsilon_1 \epsilon_2\right) = 0$ and $\text{cov}(X, \epsilon_i^2) \neq 0$, where $i = 1, 2$. For more details, please see Lewbel (2012).

After obtaining the generated instrument variables (IVs), we further applied the second stage to test endogeneity, and we present these results in Table 9. $\widehat{TotalDaily}$, $\widehat{LikeDaily}$, $\widehat{CommentDaily}$, and $\widehat{ShareDaily}$ denote the fitted natural logarithm of the number of daily Facebook activities during the fundraising period. The results demonstrate that all the coefficients are positive at the 1% significance level. In addition, the generated IVs passed several identification tests, indicating that the IVs are valid and appropriate. Therefore, our earlier results do not appear to be driven by reversal causality or omitted variables.

Table 10 presents the model fit indices. Row 1 provides the AIC and BIC from the logistic regression without any Facebook activities. Rows 2 to 6 provide the AICs and BICs from the logistic regressions with Facebook activities individually and together. Including the Facebook activities in the regression largely improved the models. For example, including the "like" measure alone reduced the AIC by 9.82% and BIC by 9.12%. As lower AIC and BIC indicate a better model, our Facebook activity measures largely improved the model of success likelihood.

5.5 A Panel Data Approach

To showcase the changes in Facebook activities over the fundraising period, we chose crowdfunding projects that lasted 30 days, which is about the sample mean. The evolution of the number of "likes" is illustrated in Figure 2. We found that the number of "likes" increased over time but more rapidly in the opening period of crowdfunding. The successful projects (i.e., dashed line) form an S-curve. Put differently, in our study, successful projects generated significant social momentum early on, maintained a slightly lower speed during the main portion of the fundraising period, and then accelerated again toward the end. While the failed projects also received increments of "likes" at the beginning of the fundraising period, the momentum of these "likes" quickly slowed down. Thus, the differences between successful and unsuccessful projects lie not only in the volume of social conversations but also in their speed. We constructed a panel that includes the time-series data of Facebook activities throughout the fundraising period for each project. We also created three additional variables: (1) $FundPCT_{it}$: project i's cumulative funds pledged on day t divided by the project's goal; (2) FB_{it}: project i's cumulative Facebook activities counts on day t; and (3) $Success_{it}$: a dummy that indicates whether the project is successfully funded or not on day t.

Table 9. Controlling for Endogeneity: IV Regression

	Model 1	Model 2	Model 3	Model 4
$\widehat{TotalDaily}$	0.003*** (8.741)			
$\widehat{LikeDaily}$		0.006*** (8.605)		
$\widehat{CommentDaily}$			0.021*** (7.981)	
$\widehat{ShareDaily}$				0.012*** (8.188)
Constant	0.844*** (11.080)	0.837*** (10.951)	0.848*** (11.080)	0.849*** (11.163)
Controls	Yes	Yes	Yes	Yes
Time effect	Yes	Yes	Yes	Yes
Category effect	Yes	Yes	Yes	Yes
Observations	7,289	7,289	7,289	7,289
R2	0.345	0.343	0.342	0.343
Note: Standard errors are in parentheses. ****p* < 0.01, ***p* < 0.05, **p* < 0.1				

Table 10. Model Fit

Models		AIC	BIC	Improvement (AIC)	Improvement (BIC)
1	w/o IVs	7275.452	7758.04		
2	w/ Total	6577.012	7066.495	9.60%	8.91%
3	w/ likes	6561.233	7050.716	9.82%	9.12%
4	w/ comments	6647.622	7137.104	8.63%	8.00%
5	w/ shares	6653.092	7142.575	8.55%	7.93%
6	w/ likes & comments & shares	6508.863	7012.134	10.54%	9.61%

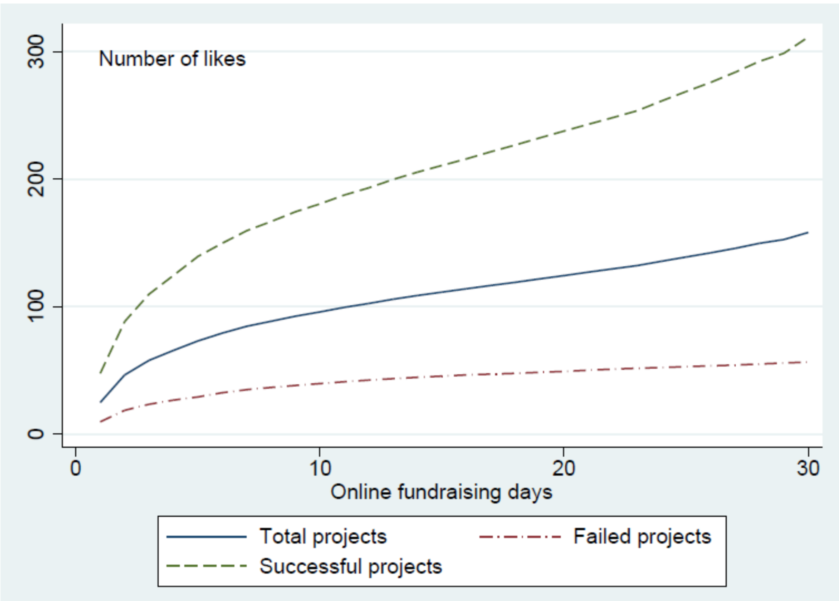


Figure 2. Evolution of Number of “Likes” over a 30-Day Fundraising Period

Table 11. Random Effect Panel Regression

Variables	Coefficients
LogLike_t-1	0.099*** (2.950)
Success_t	0.325*** (5.916)
Controls	Yes
Time effect	Yes
Category effect	Yes
Observations	193,042
Number of projects	7,286
Overall R2 Within R2	0.0060 0.0108
Between R2	0.0063
Note: Standard errors are in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$	

5.5.1 Random effect panel regression

We applied the following regression model to the panel:

$$FundPCT_{it} = \beta_0 + \beta_1 FB_{it-1} + \beta_2\, Success_{it} + Control\ variables_{it-1} + Time\ Effect_t + Category\ Effect_i + \epsilon_{it}.$$

The key explanatory variables are the lagged Facebook activities. Since "likes," "shares," "comments," and "total activities" all show a similar effect, we only present the panel regression with "likes" in this subsection.[6] Control variables include the $Success_{it}$ dummy and additional variables related to project characteristics and creator attributes. We note that some variables are constant throughout time, while others (e.g., *success*, *updates*, *feedbacks*, and *friends*) may be time-variant. Table 11 presents the regression results. The pooled panel data regression shows that our previous results are robust and that Facebook activities have a persistent, positive impact on crowdfunding outcomes.

5.5.2 Fixed Effect Panel Regression

Another major concern is that crowdfunding outcomes may be largely driven by the quality of the project rather than the Facebook activities. Although measuring quality comprehensively remains extremely difficult, we note that the quality of a project is generally determined before a crowdfunding project even starts. Major revisions seldom occur, given the brevity of the fundraising period. Therefore, we assume that the project quality is constant over the period and we tackled this issue with our fixed-effect panel regression, in which the constant project-level characteristics are canceled out. However, this means that we can no longer estimate their coefficients. Table 12 presents the regression results from our fixed effect panel regression. The results show that the coefficient of "likes" is still positive and significant, which indicates that Facebook "likes" do contribute to crowdfunding outcomes. However, we cannot claim a causal relationship if there are still unobservable time-varying variables that affect both the increments of the number of "likes" and the crowdfunding outcome.

5.5.3 Duration Model

To test H2, we applied a time-to-event analysis to examine the dynamic movement of Facebook activities and crowdfunding outcomes. The duration model (or hazard model, see, Van den Berg and Gerard, 2001) takes into account not only *whether* a crowdfunding project is successfully funded but also *when* the project is successfully funded, as the latter point cannot be determined by the logit model. Specifically, we use the Cox proportional hazard model (Cox, 1972) since there are fewer parametric restrictions on this model. The benefit of the Cox model is that it can fit the survival models without specifying the distribution—which may be log-normal, Weibull, or any other parametric distribution. One may also use the likelihood function to estimate the parameters in the survival analysis if the exact distribution is known. In our analysis, we focus on the hazard function (which is similar to the conditional probability of success) with time-varying covariates. The model to be estimated takes the following form:

$$h\big(t, X(t)\big) = h_0(t) \cdot \exp(X(t)\beta'),$$

[6] Note that we also conducted separate tests on "shares" and "comments," and the results are similar.

where $h(t, X(t))$ is the hazard rate at time t for a crowdfunding project with covariates $X(t)$ that include the number of "likes," fundraising goal (in log form), and additional control variables. Based on the above equation, we were able to implement the duration model to study the time-dependent covariates with censoring in the data (Meyer, 1990). For any project (successful or not), the time variable is defined as the ratio of elapsed time length at current time i to the preset fundraising duration. The variable measures the percentage of time already elapsed. Since the variable of interest are time variant, this model examines the effect of differences between projects, as well as changes over time. It helps us understand the effects of "like" clicks in different periods of crowdfunding. $h_0(t)$ is the baseline hazard function and the Cox proportional hazard model does not impose any restrictions on $h_0(t)$. The Cox regression estimates coefficient β using the maximum likelihood method without estimating $h_0(t)$. A positive coefficient implies that a higher X is linked to a higher hazard rate and thus a lower expected duration. $\exp(\beta)$ is the hazard ratio, which measures the extent to which the hazard of the project's success increases if the independent variable is changed by one unit. We report the results in Table 13.

Column 1 of Table 13 reports the estimates of coefficients from the Cox proportional hazard model and Column 2 reports the hazard ratios. We found the lagged number of "likes" to be significantly and positively related to the hazard ratio of a successful crowdfunding outcome. A hazard ratio above 2 means that during the same time period, if the *LogLike_t-1* (log lagged "likes") increases by 1 unit, then the probability of the project being successful more than doubles.

Table 12. Fixed Effect Panel Regression

Variables	**Coefficients**
LogLike_t-1	0.098*** (3.023)
Success_t	0.314*** (5.649)
Controls	Yes
Time effect	Yes
Category effect	Yes
Observations	193,042
Number of projects	7,289
R2	0.011
Note: standard errors are in parentheses. ****p* < 0.01, ***p*<0.05, **p* < 0.1	

Table 13. Cox Proportional Hazard Model

	1. Coefficients	**2. Hazard ratios**
Variables		
LogLike_t-1	0.716*** (39.602)	2.047
LogGoal	-0.800*** (-40.786)	0.449
Controls	Yes	
Time effect	Yes	
Category effect	Yes	
Likelihood ratio test	-24961.2	
No. of successes	4024	
No. of failures	3159	
Observations	159613	
Note: Standard errors are in parentheses. ****p* < 0.01, ***p* < 0.05, **p* < 0.1.		

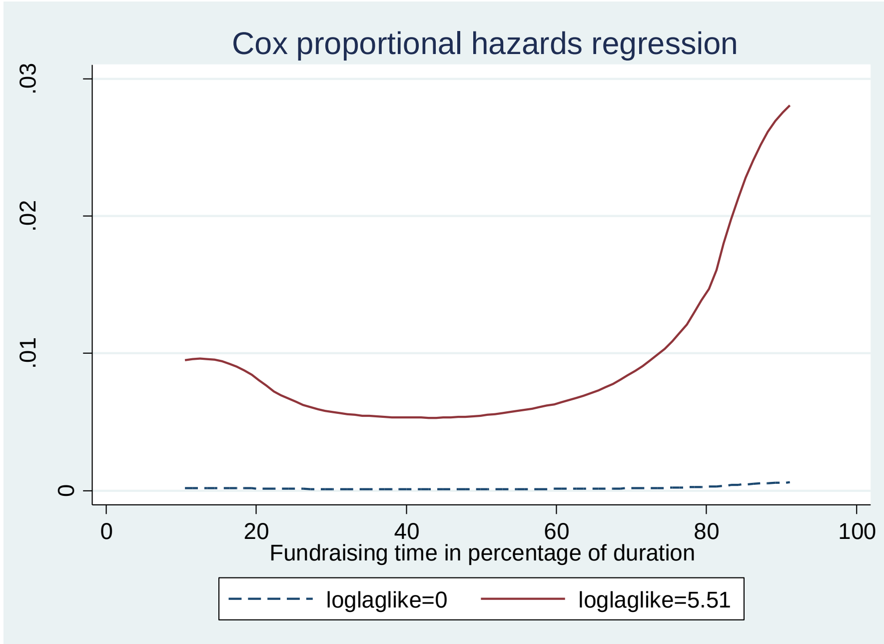


Figure 3. Hazard Ratios of High vs. Low Volumes of Lagged “Likes”

Table 14. Robustness Check

	1. Coefficients	2. Marginal effects
LikeDaily_Beg	0.186*** (7.066)	0.0265*** (7.44)
LikeDaily_Int	0.119*** (4.547)	0.0169*** (4.66)
LikeDaily_End	0.266*** (7.300)	0.0378*** (7.76)
Project characteristics	Yes	
Creator characteristics	Yes	
Time effect	Yes	
SubCategory effect	Yes	
Observations	7,289	
Pseudo R2		
Note: Robust *z*-statistics are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$		

Figure 3 illustrates the economic significance of Facebook activity from our duration model analysis. All the covariates are held at their sample means except for the number of lagged “likes” (in log form), which is differentiated at the tenth (the dashed line in the figure) and ninetieth percentiles (the solid line in the figure), respectively. The hazard ratios are close to zero at all times when the volume of lagged “likes” is very low. When the volume is in the upper region, the hazard ratios are significantly positive. The substantial difference in the hazard functions demonstrates that Facebook “likes” significantly and positively influence successful crowdfunding projects. Interestingly, the temporal effects of Facebook “likes” are neither linear nor constant. Rather, we observe a J-curve hazard function, which suggests that the impact of Facebook “likes” is more notable in the opening and closing periods of crowdfunding. In addition, there is a considerable surge as the crowdfunding process comes close to the end. The findings are consistent with H2. In particular, Facebook activities primarily help signal the true quality of the project in the opening period of crowdfunding, i.e., the quality-signaling effect; in the closing period of crowdfunding, Facebook activities have a herding effect that attracts a surge of traffic to the projects and improves their probability of success. More importantly, our empirical results also reveal that the herding effect in the closing period is even stronger than the quality-signaling effect in the opening period, an intriguing finding that cannot be easily verified or predicted by the theory.

This J-curve finding suggests to the project creators that there could be two deceptive periods during the crowdfunding process even if there is good momentum on Facebook. The first period occurs at the very beginning of crowdfunding, when the seemingly quick inflow of funding appears to indicate the quality of the project. The second one happens after some time, when the speed of the funding influx drops gradually and persistently. At this point, it seems like the project is going to fail after all, which may be viewed as a big disappointment that may discourage the project creator from continuing social marketing efforts. However, our results indicate that project creators should continue their efforts in such a situation—as long as the corresponding cumulative social media activities have been persistently increasing, there is a good chance of success in the final fundraising period based on a strong herding effect.

5.5.4 Robustness Check

To check the robustness of the temporal effects, we decomposed the total number of daily "likes" into three timespans over the fundraising duration and reexamined the impact of Facebook "likes." Table 14 reports our empirical results. Model 1 presents the coefficients of variables from the logit regression on crowdfunding success, and Model 2 describes the marginal effects of these variables. *LikeDaily_Beg* is the total number of daily "likes" in the first quarter of crowdfunding, *LikeDaily_Int* is the total number of "likes" from the second to the third quarter, and *LikeDaily_End* is the total number of "likes" in the fourth (also the last) quarter. Control variables, time effect, and subcategory effect are the same as those in Table 6. Both the coefficients in Column 1 and the marginal effects in Column 2 support our J-curve finding. The impact of Facebook "likes" on the likelihood of crowdfunding success is stronger in both the opening and closing periods of fundraising, whereas the impact is much weaker in the intermediate period. Comparing the opening and closing periods, Facebook "likes" have a higher impact in the closing period.

6 Conclusions and Implications

6.1 Concluding Remarks

Small and medium-sized businesses as well as individuals are increasingly using online crowdfunding platforms to raise funds in the fintech world. Creators of crowdfunding projects depend heavily on social networks such as Facebook to publicize their projects in order to locate sufficient numbers of potential funders and meet their fundraising goals. Such exposure is made possible primarily by social buttons such as the Facebook "like" button. The sheer size of "likes" may be highly impactful if they accumulate the right momentum. Not surprisingly, crowdfunding has triggered a new type of business that packages and sells Facebook "likes" and similar social media activities. However, some studies suggest that these activities may fail to generate much value for a business. To fully explore this issue, our study examines the significance of the impact of social media activities and, more importantly, investigate the temporal effects of the impact of social media activities in the context of reward-based crowdfunding platforms.

Our research quantitatively confirms that social media activities are significantly related to crowdfunding outcomes. The resulting impact may be immediate and very effective in the online world due to tremendous progress in transparency. Furthermore, our duration model analysis reveals that the impact of social media activities on crowdfunding outcomes follows a J-curve in the temporal space, a key contribution that distinguishes our study from prior literature. We offer an explanation of the J-curve by identifying two important effects of social media activities throughout the crowdfunding process: a quality-signaling effect in the opening period and a herding effect in the closing period. Especially in the "last mile" of crowdfunding, there is a strong herding effect that generates a persistent acceleration that helps crowdfunding projects reach their respective fundraising goals. Accordingly, the implications for project creators differ in different crowdfunding periods. Lastly, we examine the moderating effects with regard to two important aspects of crowdfunding projects, that is, fundraising goals and project categories. We show that the impact of social media activities is more pronounced for small crowdfunding projects and projects in public-good categories.

Despite our best efforts to address endogeneity issues and control for necessary variables in our dataset, there is plausible room for improvement. For instance, project quality is a great indicator that can be used to measure crowdfunding outcomes; however, we were not able to quantify quality scores, given the complex nature of crowdfunding projects. Moreover, influencers (e.g., celebrities) likely strongly impact certain crowdfunding projects. Unfortunately, we were unable to tease out that assumption. Furthermore, we were unable to determine whether a project had also been promoted outside of Kickstarter. Finally, because this paper focuses specifically on crowdfunding, which requires a crowd and a short fundraising cycle, our results may not be applicable to other fields.

6.2 Implications for the Project Creators

The J-curve we identified suggests that the impact of social media activities is relatively strong at the beginning of a crowdfunding effort because of a quality-signaling effect. Thus, obtaining a good starting momentum would send a positive quality signal to potential funders. Specifically, we have the following suggestions to project creators in the early period. First, we recommend recruiting friends and family to spread the word on social media sites such as Facebook. Since it is challenging to generate the desired level of social media activity shortly after a project is posted, getting help and support from close contacts can be an effective way to make it through the early period of crowdfunding. Friends and family could help by sharing the project on Facebook and recommending the project to their own friends. Second, we suggest that project creators provide incentives for users to "share" and "like" the project. As Kickstarter is a reward-based crowdfunding platform, project creators could design substantial rewards for early initiators. For instance, creators could offer substantial discounts on future product consumption to the first 100 users who "share" and "like" the project on Facebook. Third, we recommend creating a fan page on Facebook. A fan page not only helps create a fan base community, but also consolidates resources and information. Having an official presence on Facebook can be useful for identifying potential funders, releasing project-related updates, engaging with online users, exploring opportunities to promote the project, and, most importantly, driving social media traffic.

During the crowdfunding process, the impact of social media activities gradually weakens. A possible explanation is that people are uncertain about the project's outcome so they wait to see whether the support for the project increases. During this period, people are less impacted by "shares" and "likes"; hence, we suggest that the creators make greater efforts to collect feedback from users, enhance project design, and update the existing funders with the latest project news.

In the final period of crowdfunding, the aggregate social media activities become substantially stronger, indicating that people are significantly impacted by others through the herding effect. At this point, we would make the somewhat surprising recommendation that project creators should consider purchasing Facebook "likes" from "like" sellers such as the ones mentioned in the Introduction. Based on our empirical results, this unexpected recommendation may be an effective means to achieve fundraising goals in later periods. Purchasing "likes" would rapidly expand the number of "likes" at relatively low cost. In addition, the paid "likes" (generated by computer programs) are not differentiable from the unpaid "likes" (the actual "likes" clicked by a person) from the online users' point of view. Nevertheless, we also clarify that the recommendation of purchasing "likes" is only made in the context of reward-based crowdfunding from a very practical perspective. The discussion of ethical and legal issues is outside the scope of this paper.

6.3 Implication for Crowdfunding Platforms such as Kickstarter

The results of this study also have implications for the design of crowdfunding platforms. Since the main source of revenue for crowdfunding platforms is commission fees charged to successfully funded projects, the platform has every incentive to assist the project creators in achieving their fundraising goals. One type of such assistance concerns the design of the platform's project page. For example, platform developers could enable better use of the social buttons so that the creators could achieve the desired level of social media impact. We make the following concrete recommendations to platform developers concerning the design factors of crowdfunding platforms.

First, we suggest that platform developers embed social buttons such as Facebook "likes" and "shares" in the source code of each project page so that they are visible and clickable on the page. Facebook provides a straightforward way for developers to configure the buttons on webpages. Second, optimal placement of the social buttons would attract more clicks. We suggest that platform developers place the social buttons on the project page in a way that is readily noticeable to users—for example, next to project titles. Generally speaking, "sharing" and "commenting" require the user's input of written comments, which may hinder the user's willingness to click the social buttons. Hence, we suggest that developers create a list of default comments that the user could choose from and easily use. For instance, "I find this Kickstarter project very innovative" and "Check out my favorite project on Kickstarter." Furthermore, platforms should explicitly illustrate the strength of the social media impact. For example, by displaying the number of social button clicks on the project page. Such numbers offer users good signals of quality and social media impact. In addition, we suggest that platforms allow users to rank projects according to number of social button clicks.

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