CROWDFUNDING CREATIVE IDEAS:
THE DYNAMICS OF PROJECT BACKERS IN *KICKSTARTER*

Venkat Kuppuswamy
Kenan-Flagler Business School
University of North Carolina
CB3490; McColl 4608
Chapel Hill, NC 27599
venkat@UNC.edu

Barry L. Bayus
Kenan-Flagler Business School
University of North Carolina
CB3490; McColl 4521
Chapel Hill, NC 27599
Barry_Bayus@UNC.edu

ABSTRACT

Entrepreneurs are turning to crowdfunding as a way to finance their creative ideas. Crowdfunding involves relatively small contributions of many consumer-investors over a fixed time limit (generally a few weeks). In online crowdfunding communities, potential donors can see the level of support from other project backers as well as its timing before making their own funding decisions, suggesting that social information (i.e., others' funding decisions) will play an important role in the ultimate success of a project. Two years of publicly available panel data on successfully and unsuccessfully funded projects listed on *Kickstarter* is used to empirically study the role of social information in the dynamic behavior of project backers. Building off the well-established social psychology theory around bystander effects, we show that additional backer support is negatively related to its past backer support. Due to a diffusion of responsibility, many potential backers do not contribute to a project that has already received a lot of support because they assume that others will provide the necessary funding. Consistent with the deadline effect widely observed in bargaining and online auctions, we also show that the bystander effects diminish as the project funding cycle approaches its closing date. Moreover, as the project deadline draws near we find that project updates tend to increase as the project creators make a final plea for help to reach their funding goal. Reduced bystander effects, together with the positive influence of project updates, lead to generally increasing project support in the final stages of funding. This is particularly the case for projects that successfully achieve their goals as they are more likely to have an update in the last weeks of funding and generate more excitement from recent backers than projects that fall short.

[Keywords: Innovation, Entrepreneurship, Strategy, Marketing]

February 20a, 2013

1. INTRODUCTION

An important barrier to innovation is the availability of early-stage funding (Cosh, et al. 2009). Given the difficulties that new ventures face in attracting financing from angel investors, banks and venture capital funds, some entrepreneurs are tapping into large, online communities of consumer-investors (Economist 2010; Schwienbacher and Larralde 2012). Called "crowdfunding," this relatively new form of informal venture financing allows entrepreneurs to directly appeal to the general public (i.e., the "crowd") for help in getting their innovative ideas off the ground. As defined by Belleflamme, et al. (2012), crowdfunding involves an open call (through the Internet) for the provision of financial resources either in the form of donation or in exchange for some form of reward in order to support initiatives for specific purposes[1].

Collecting small amounts of money from a large number of people has a rich history in many domains (Ordanini, et al. 2011). For example, Mozart and Beethoven financed concerts and new music compositions with money from interested patrons, the Statue of Liberty in New York was funded by small donations from the American and French people, a human rights organization is trying to raise money in order to buy a communications satellite to provide Internet access to people in third world countries (http://www.buythissatellite.com, accessed November 2, 2012), and President Barak Obama's 2008 election campaign raised most of its funds from small donations over the Web (Hemer 2011). Today, several hundred global intermediaries with online platforms exist to match up consumer investors with initiatives that they wish to help fund. Prominent examples in the popular press include the narrative movie project by Steve Taylor that got almost 4,500 people to contribute nearly $350,000 and Scott Wilson's idea to create a wristband that will convert an iPod nano into a watch raised over $940,000 from over 13,500 individuals (Adler 2011). One of the largest crowdfunded projects to date is Eric Migicovsky's E-Paper Watch that integrates with an Android or iPhone that received donations totaling over $10.2M from well over 65,000 backers (Segall 2012). According to one industry report, crowdfunding platforms raised almost $1.5B and successfully funded more than one million projects in 2011 (Massolution 2012). Given the potential dollars involved, crowdfunding has recently garnered attention from policymakers and regulators as evidenced by the *Jumpstart Our Business Startups Act* (JOBS Act) recently signed into U.S. law (Chasan 2012).

Crowdfunding differs from the traditional financing of new ventures in two important ways. First, funding is provided by the relatively small contributions of many individuals over a fixed time limit (generally a few weeks). Second, potential donors can see the level of support from other project backers as well as its timing before making their own funding decisions, suggesting that social information (i.e., others' funding decisions) will play an important role in the ultimate success of a crowdfunded project. Understanding these effects is important because studies find that social information can lead to "non-rational" behaviors. For example, people often choose music for downloading based on popularity not quality (Salganik, et al. 2006)

---

[1]This is conceptually similar to crowdsourcing in which community members (non-experts) propose new product and service ideas, as well as comment on and vote for the ideas of others (Bayus 2013).

and bidders tend to herd into online auctions with more bids even though this activity is not a signal of higher quality (Simonsohn and Ariely 2008). Many legal scholars and policy makers believe that this kind of irrational herding behavior increases the chances for fraud in crowdfunded projects since consumer investments are not protected by government regulations or oversight (Bradford 2012; Hazen 2012). To date however, there is very little empirical research to definitively support any position.

In general, crowdfunding communities differ in terms of whether the funder's primary motivation for participating is the expectation of a financial return. For example, crowdfunding communities like *SellaBand* and *Wefunder* offer consumer investors an interest in the venture in the form of equity or some sort of profit sharing agreement (Ward and Ramachandran 2010; Agarwal, et al. 2011). Other crowdfunding communities such as *Prosper* and *Zopa* involve peer-to-peer lending in which it is expected that the original principal is repaid, along with some fixed interest (Herzenstein, et al. 2011; Zhang and Liu 2012). Research on these types of equity- and lending-based crowdfunding communities finds evidence for herding behavior, i.e., individuals want to contribute to projects that already have a lot of support from other community members. Because consumer investors in these communities expect a financial return, herding behavior is a "rational" way for individuals to reduce their own risk in the face of uncertainty about the proposed new ventures on these websites. Following the literature on information cascades (Bikhchandani, et al. 1992), these studies argue that an initiative with a lot of community support signals that the project is of high quality.

Unlike the platforms in which participants expect some sort of financial return, other crowdfunding communities involve no monetary compensation for participation. For example, *JustGiving* and *Spot.us* rely on altruistic motivations in which funders voluntarily donate their money with no expectations of any tangible reward (Burtch, et al. 2012; Smith, et al. 2012). Research on these types of donation-based crowdfunding communities draw on the extensive literature involving philanthropy and public goods (Andreoni 2006; Vesterlund 2006). Because the consumption of public goods cannot be withheld from non-contributors, free-riding is a potential issue in which contributions can be crowded-out by the prior funding decisions of others (Bergstrom, et al. 1986). At the same time, there are several models based on social norms that predict a positive effect of others' funding decisions (Sugden 1984; Bernheim 1994). Depending on the perspective taken, some donation-based crowdfunding studies find positive effects for other community members' funding decisions on contributions (Smith, et al. 2012), while others find the opposite (Burtch, et al. 2012).

Unlike existing research that considers crowdfunding communities with tangible financial returns or no tangible rewards at all, our interest is in crowdfunding communities like *Kickstarter* and *Indiegogo* in which project backers do receive tangible, but non-financial, benefits for their financial contributions. These rewards often take the form of tokens of appreciation (thank-you message, artist's autograph, mentioning the crowdfunder's name in the credits, tee-shirt) or the pre-purchasing of products or services (Hemer 2011). Not surprisingly, qualitative studies find that rewards are one of the most important motivations for participating in crowdfunding communities (de Witt 2012; Gerber, et al. 2012; Steinberg 2012). Reward-

based crowdfunding has the largest number of online platforms and is the fastest growing form of crowdfunding (Massolution 2012). With the exception of Mollick's (2012) cross-sectional study, very little research to date has considered reward-based crowdfunding and none has examined the role of social information.

[insert Figure 1 about here]

The empirical setting for our study is one of the oldest and largest reward-based crowdfunding communities on the Web. Since its launch in April 2009, *Kickstarter* has over one million community members who have combined to pledge hundreds of millions of dollars to fund creative ideas in categories like art, film and video, dance, design, and technology (Ricker 2011). Anecdotal cases studies suggest that *Kickstarter* projects tend to get a lot of backer support in the first and last weeks of their funding cycle—friends and family tend to be early project supporters, while strangers, who make up the majority of contributors, often provide funding as a project nears its conclusion (de Witt 2012; Steinberg 2012). As an example, consider the backer support over time for Cody Webb's New CD (a music project supported by 89 backers that successfully achieved funding of $12,701) shown in Figure 1. This "bathtub" shaped pattern of backer support is sharply different than the generally increasing pattern associated with herding observed with equity or lending-based crowdfunding (e.g., Zhang and Liu 2012) or the decreasing pattern found with donation-based crowdfunding (Burtch, et al. 2012). Although this pattern of backer support is well known by reward-based crowdfunding pundits (de Witt 2012; Mod 2010; Steinberg 2012), insights into its drivers are lacking.

Two years of publicly available information on successfully and unsuccessfully funded *Kickstarter* projects is used to empirically study the role of social information in the dynamic behavior of project backers. To explain the observed bathtub shaped pattern of backer support over time, we introduce a new theoretical lens. Building off the well-established social psychology theory around bystander effects (Fisher, et al. 2011), we show that backer support for a reward-based crowdfunding project is negatively related to its past backer support. Due to a diffusion of responsibility, many potential backers do not contribute to a project that has already received a lot of support because they assume that others will provide the necessary funding. As a result, initial project excitement is quickly followed by a strong downward trend in backer support. Consistent with the deadline effect widely observed in bargaining and online auctions (Roth, et al. 1988; Ariely and Simonson 2003), we also show that the bystander effects diminish as the project funding cycle approaches its closing date. Moreover, as the project deadline draws near we find that project updates tend to increase as the project creators make a final plea for help to reach their funding goal. Reduced bystander effects, together with the positive influence of project updates, inertia from recent backers and exposure on the *Kickstarter* web site, lead to generally increasing project support in the final stages of funding. This is particularly the case for projects that successfully achieve their goals as they are more likely to have an update

in the last weeks of funding and generate more excitement from recent backers than projects that ultimately fall short.

2. THE THEORETICAL FRAMEWORK

In this section, the theoretical framework that guides our empirical study is discussed. Our interest is in reward-based crowdfunding communities like *Kickstarter* that offer tangible, but non-financial, benefits for the financial contributions of project backers. Given this context, rational herding behavior due to uncertain project quality is unlikely for *Kickstarter* projects because there is no expectation of a financial return. While Burtch, et al. (2012) and Smith, et al. (2012) argue that donation-based crowdfunding involves the provision and consumption of a public good, this is not the case with reward-based crowdfunding. Importantly, the creative ideas posted on *Kickstarter* do not have the properties of being non-excludable and non-rivalrous. Reciprocity (Sugden 1984) and conformity (Bernheim 1994) are also not expected to operate in this environment since donors are anonymous and specific donation amounts are not visible. Moreover, if individuals care mostly about the end result (i.e., provision of the public good), then any crowding-out effects of social information should not vary over time. And, to the extent that individuals in the public goods situation care only about the size of their donation and how it makes them feel, there is no role for social information, i.e., the contributions of donors are unrelated in that one person's donation does not affect the utility someone else receives from giving (Duncan 2004).

Instead, we build off the well-established social psychology theory involving the bystander effect (Fischer, et al. 2011). Studies on the bystander effect demonstrate that an individual's likelihood of helping decreases in the actual or perceived presence of others (Darley and Latane 1968; Latane and Darley 1970; Garcia, et al. 2002). Importantly, the bystander effect is a robust phenomenon that occurs in many experimental and field situations. The original research program on the bystander effect was in response to the very sad real-life case of Catherine Genovese who was raped and murdered in New York while several of her neighbors looked on and did not report the attack to the police (Latane and Nida 1981). Literature reviews by Latane and Nida (1981) and Fisher, et al. (2011) show that the bystander effect operates in many diverse situations, including non-emergencies (e.g., answering the door, helping with a flat tire, leaving a tip). Moreover, the bystander effect occurs for nearly all age groups (except for very young children) as well as for both genders (Latane and Nida 1981). The bystander effect has also been observed with donation behavior (Wiesenthal, et al. 1983).

Latane and Darley (1970) propose a decision model that a bystander must go through before intervening in a critical situation. First, bystanders need to notice the situation. Bystanders must then interpret the situation as one in which action is necessary, and then develop a feeling of personal responsibility (empathy). Next, bystanders need to believe they have the skills and resources to help. Finally, they must decide to actually take action to help. Although presented as a linear sequence, this decision model is meant to be iterative—at any point in this decision model, the bystander can cycle back to a previous

4

decision step. Bystanders can exhibit signs of discomfort over inaction if they find it difficult to reach a decision in any stage of this decision model. In addition, delayed responses will often lead to inaction altogether—the longer bystanders wait to respond, the less likely they are to ever help. Based on anecdotal reports, this general model seems to capture the key decisions made by backers in crowdfunding communities like *Kickstarter* (de Witt 2012; Gerber, et al. 2012; Steinberg 2012).

Latane and Darley (1970) identify three different social psychological processes that can interfere with the completion of this decision sequence. The first process is diffusion of responsibility in which people fail to help because they assume someone else will do so. In this case, the knowledge that others could instead respond reduces their feelings of personal responsibility and thus, inhibits helping. Individuals tend to subjectively divide their own personal responsibility to help by the number of bystanders. This idea is closely related to social loafing ("a reduction in motivation and effort when individuals work collectively compared with when they work individually," Karau and Williams 1993: 681). The diffusion of responsibility predicts that the likelihood of helping is directly related to the size of the bystander group (Forsyth, et al. 2000). The second process is pluralistic ignorance (or social influence) in which people tend to rely on the overt reactions of others when interpreting an ambiguous situation. In this case, individuals look for cues in the environment that can help them determine whether action is necessary. As noted by Cialdini (2001: 100), we "view other behavior as correct in a given situation to the degree that we see others performing it." A strong bystander effect occurs when no one helps because everyone believes that no one else perceives an emergency. The third process is audience inhibition (or evaluation apprehension) in which people feel the risk of embarrassment if the situation is misinterpreted. In other words, individuals are reluctant to help because they are afraid of making mistakes or acting in a way that might be negatively evaluated by onlookers. Given the inherent characteristics of online crowdfunding communities like *Kickstarter* (creators, backers and community members are for the most part anonymous, and the projects are not ambiguous in that they all explicitly ask for financial help), the audience inhibition and pluralistic ignorance processes are not as relevant as the diffusion of responsibility.

Extending the literature which focuses on the bystander effect in face-to-face situations, more recent studies find evidence for the virtual diffusion of responsibility in computer-mediated communication and online communities. For example, Barron and Yechiam (2002) show that the presence of others copied in a private email communication reduces one's willingness to reply to a request for help. Markey (2000) shows that the time it takes to receive help in online chat groups increases with group size. Yechiam and Barron (2003) find that significantly more people that were emailed individually completed an online survey as compared to a general request sent to members of a Listserv. Voelpel, et al. (2008) examine virtual bystander effects in a number of large online communities consisting of Yahoo!Groups members. They show that the likelihood of responding to a help request and the quality of response is significantly related to group size:

small groups are more likely to respond and more likely to have a high quality response than larger groups. In all these studies, perceived group size is negatively related to helping behavior.

To date, the published literature has only considered cross-sectional variation in group size to demonstrate the bystander effect. In the crowdfunding context we study however, time-series variation in group size within a project is of prime interest. Help in the form of financial support can come at any point during a project's funding cycle before it has reached its funding goal. Moreover, perceptions about the number of others that might provide funding will also vary over time. For each time period during the funding cycle, we argue that potential *Kickstarter* backers use the list of publicly displayed backers already supporting a project as an indicator of the size of the group that could provide the remaining funding. This approach of using past project support to gauge future support is consistent with related research (Voelpel, et al. 2008) as well as recommendations on how to plan and manage a *Kickstarter* campaign (Mod 2010; de Witt 2012; Steinberg 2012). Due to a diffusion of responsibility, many prospective backers do not contribute to a project that has already received a lot of support because they assume that someone else will provide the remaining financing. Thus, the bystander effect predicts that project support at any time over its funding cycle is negatively related to the level of support it received prior to that time. The following hypothesis summarizes these arguments.

H₁: *The likelihood a reward-based crowdfunding project receives additional backer support is negatively related to its past backer support.*

According to *Kickstarter* statistics, a lot of backer support comes in the later stages of a project's funding cycle. Matt Haughey, a backer of more than 150 *Kickstarter* projects, sums it up this way (Steinberg 2012: 149):

> *...once you pass 50 percent of your funding, at any point, you have a 95 percent chance of reaching your goal. There's a human psychology element where people go, yeah I'll kick in more, this guy is so close. Only a handful of projects have finished unsuccessfully having reached 85 percent or more of their funding. The people who are at like 60, 70 percent with a week to go, it's gonna be OK!*

This kind of deadline effect in which a lot of action occurs as the end of an experience is approached has been widely observed in many contexts. For example, last minute agreements are common in negotiations (Roth, et al. 1988; Ma and Manove 1993; Zhou 2011) and a large number of bids are made near the end of online auctions (Ariely and Simonson 2003; Ockenfels, et al. 2006). Webb and Weick (1979) cite several unpublished papers that report deadline effects in college applications (more applications are received right before deadline dates), trading on the New York Stock Exchange (trading volume systematically increases two hours before the closing bell), and play calling in the National Football League (total plays executed are highest in the second quarter right before the half time break and fourth quarter right before the end of the game). Similar behaviors have also been observed in rats and pigeons that increase their efforts as the expected end of a fixed reinforcement schedule approaches, even though this behavior does not increase

rewards (Ferster and Skinner 1957). As noted by Ariely and Simonson (2003), unlike the earlier stages, decisions near a deadline are clearly consequential and often irreversible.

In terms of the bystander decision model proposed by Latane and Darley (1970), we argue that perceptions about the number of others that might provide funding are also influenced by the deadline effect. For a recently launched project, there is a lot of time for others to make contributions. Due to a diffusion of responsibility, potential backers feel less personal responsibility for a project in the early stages of its funding cycle and thus are less likely to contribute. For an unfunded project about to end however there is a very real possibility that the necessary funding to reach its goal will not come from others (even though the project may have a high level of past backer support). In this case, potential backers have lower expectations of how much support a project will ultimately receive from others, and consequently they are more likely to contribute. Thus, we expect that the bystander effect is reduced when a deadline is present, i.e., when a deadline to act is looming, people are more likely to help even when others are present. To capture this idea, we propose that the bystander effect in H_1 is moderated by time in the funding cycle, i.e., the bystander effect becomes less negative in the later stages of the funding cycle. This discussion is summarized in the following hypothesis.

H₂: *The effects of past backer support for a reward-based crowdfunding project are moderated by time in the project's funding cycle so that the effect of past backer support for projects in the later stages of funding is larger than that for projects in the earlier stages of funding.*

3. DATA

In this section, we briefly discuss the empirical setting of our study. Based in the U.S., *Kickstarter* is one of the world's largest crowdfunding platforms. By April 2012, *Kickstarter* had raised more than $200 million for 20,000 projects, or about 44 percent of those that sought financing on the site (Wortham 2012). According to their website, "*Kickstarter* is focused on creative projects. We're a great way for artists, filmmakers, musicians, designers, writers, illustrators, explorers, curators, performers, and others to bring their projects, events, and dreams to life." Projects are grouped into thirteen broad categories: Art, Comics, Dance, Design, Fashion, Film and Video, Food, Games, Music, Photography, Publishing, Technology, and Theater. The website defines a project as "something finite with a clear beginning and end. Someone can be held accountable to the framework of a project—a project was either completed or it wasn't—and there are definable expectations that everyone can agree to." Consequently, *Kickstarter* does not accept projects created to solicit donations to causes, charity projects, or general business expenses.

In order to participate, individuals must join the *Kickstarter* community (at no cost) by selecting an anonymous username. Like most online communities, information on demographics and personal characteristics are not collected (the *Kickstarter* community is a large, undefined "crowd"). Community members can propose projects for funding, back a project by financially contributing (with a credit card via

Amazon), and/or comment on projects. *Kickstarter* projects can only be proposed by U.S. residents (for tax purposes); project contributors have no geographic restrictions.

To use *Kickstarter*, an entrepreneur (called "creator" in *Kickstarter*) creates a webpage for the project on the platform explaining the purpose of the project and the specific deliverables that they aim to produce with the contributed funds. Along with an end date for the project funding cycle, the creator also indicates the funding goal of the project, i.e., the amount of money they require to execute the project as specified. Creators can communicate with their supporters by posting private updates as well as potential contributors by posting public updates that everyone can see.

When a potential donor (called "backer" in *Kickstarter*) visits an active project's webpage, they are presented with all the project information initially posted by the creator. Moreover, potential backers are shown the current funding status of the project (i.e., the funds raised thus far), the ultimate funding goal, and the number of days remaining until the project funding cycle expires. A visitor can also see a listing of the other backers that have contributed to the project, as well as the timing of these contributions[2]. Specific donation amounts by backers are not publicly shown on the website. To help potential backers discover projects they want to support, *Kickstarter* has a number of search options. In particular, projects can be sorted based on the first week after their initial launch ("Recently Launched"), last week before the project funding closes ("Ending Soon"), or popularity (based on the number of backers recently added to a project). Occasionally, *Kickstarter* staff mention an active project on their blog.

There are two important features of *Kickstarter* that distinguish it from many other smaller crowdfunding platforms, as well as more traditional forms of entrepreneurial finance. The first is the "all-or-nothing" aspect of fundraising on the platform. A project must be fully funded before its funding cycle concludes or no money pledged by any backer is transferred to the project creator. An over-ambitious funding goal may thus result in the fundraising effort falling short and consequently, raising no funds whatsoever. At the same time, once a project has reached its funding goal, it can continue to receive contributions until its deadline. As a result, funded projects can exceed their original funding goal. We expect that the bystander and deadline effects described in H_1 and H_2 operates before a project has reached its funding goal—backer motivation and behavior during the post-funded phase of a project may be quite different since the project no longer needs financial help.

The second feature of the crowdfunding model that differs from traditional venture capital is the fact that individuals contributing to a project do not receive equity in the project in return for their funds. Specifically, backers do not receive any financial incentives, returns, or repayment in exchange for their contributions. Instead, project creators typically offer more modest "rewards" to contributors which vary by the level of contribution. According to the *Kickstarter* website, the four most common reward types are: (a)

---

[2]Shortly after our data collection in March 2012, *Kickstarter* removed this information in their updated website design.

copies of the thing (e.g., the actual product, an assembled version of a DIY kit); (b) creative collaborations of various kinds (e.g., a backer might appear as a hero in the comic, or she may be painted into the mural); (c) creative experiences (e.g., a visit to the film set, a phone call from the author, dinner with the cast, a concert in the backer's backyard); and (d) creative mementos (e.g., photos sent from filming location, explicit thanks in the closing credits of the movie, etc.).

Data for our study come from publicly available information on the *Kickstarter* web site. We extracted information on all backed projects posted on the platform from its inception in May 2009 through February 2012. We focus on projects with at least one backer since we are interested in the dynamics of backer behavior (projects with zero backers will not contribute any information to our analyses). To allow a time buffer for community activity around a project to stabilize, projects completed after 2011 are dropped from the analysis. In addition, projects started in 2009 are not used in the analysis because the look and feel of the web site underwent several revisions in the first few months after launch. Thus, two years of daily data on 25,058 projects with complete[3] information that began on or after January 1, 2010 and concluded by December 31, 2011 is available for analysis purposes.

[insert Table 1 about here]

Descriptive statistics for these projects are reported in Table 1. The average project[4] has a goal of just over $8,500 but only receives a little more than $4,600 in pledged contributions[5]. Projects tend to last for almost six weeks; a relatively large proportion of backers support a project in the first or last week of its funding cycle. Over eighty percent of the projects include a video. The average project offers more than six reward categories as incentives for their donors and receives almost $75 per backer. Creators generally post a couple of public project updates and infrequently post private updates to their backers. Over ninety percent of creators only propose a single *Kickstarter* project.

[insert Figure 2 about here]

There is a considerable amount of variance in the funding outcomes for *Kickstarter* projects. Figure 2 shows the distribution of project success: projects that reach their funding goal do so by a small margin (almost half of all the successful projects are within ten percent of their original funding goal), while projects that miss their targets do so by a large margin (almost half of all the unsuccessful projects achieved less than ten percent of their goal). Consistent with the earlier quote from Matt Haughey, there are very few unsuccessfully funded projects that reach between fifty and ninety-nine percent of their goal.

---

[3]Forty projects had incomplete or suspect information and were dropped from our sample.
[4]One project had a goal of over $21M (Kickstarter's limit) to help reduce the national debt (http://www.kickstarter.com/projects/2116548608/help-erase-the-national-debt-of-the-usa?ref=search). This project only had 8 backers who pledged $180.
[5]The largest funded project in our sample received a little over $942K. Since our data collection, several projects have received over $1M in funding.

Descriptive statistics by project funding outcome are reported in Table 2. Although these statistics cannot be used to assess causality, this information is useful to better understand the nature of a reward-based crowdfunding community. While unsuccessful projects have a funding goal more than three times as large as successful projects ($14,580 compared to $4,726), these projects receive well less than half of the amount contributed to successful projects ($1,232 compared to $4,743). Successful projects tend to be shorter in duration. All projects receive a relatively large proportion of their backers in the first week—multiplying the total number of backers in the first week by the average contribution per backer, and dividing by the goal indicates that successful projects average almost thirty percent of their goal in the first week (as compared to unsuccessful projects that achieve less than one percent). Successful projects also get a lot of support in the last week of their funding cycle. Not surprisingly, successfully funded projects have significantly more backers than unsuccessful projects, and add more backers each day. Successful projects are generally more likely to have a video and a larger number of reward categories than unsuccessful projects. Successful projects tend to be featured more often (on the *Kickstarter* blog or Most Popular List) and communicate more to the community and their backers by posting updates.

[insert Table 2 and Figure 3 about here]

The average number of backers added to a project over its relative funding cycle is depicted in Figure 3. Consistent with Figure 1 and the descriptive statistics in Tables 1 and 2, projects tend to get a lot of backer support in the first and last weeks of their funding cycle. A high level of initial project support in the first few days is followed by generally decreasing support over most of the funding cycle. As the project approaches the end of its funding cycle, successful projects are likely to have a sharp increase in backer support. To better understand the dynamics of backer funding behaviors and the role of social information, we next turn to an econometric analysis of these data.

4. THE EMPIRICAL STUDY

In this section, we exploit the panel structure of the *Kickstarter* data to investigate the relationship between the additional backer support a project receives and its past backer support (**H₁**), as well as the moderation of this relationship by time in the project funding cycle (**H₂**). Because **H₁** and **H₂** concern the likelihood a project receives additional backer support, an appropriate dependent measure to test these hypotheses is *BackerAdded$_{it}$*, a binary variable where a value of one indicates that project i received a new contribution pledge on day t (0 otherwise). This measure is similar to that used by Simonshon and Ariely (2008) to study online auctions and Herzenstein, et al. (2011) in lending-based crowdfunding.

To examine **H₁** and **H₂**, we start with the following basic model:

$$BackerAdded_{it} = \beta_1 PastBackerSupport_{it} + \beta_2 FundingTime_{it} + \beta_3 PastBackerSupport_{it} \times FundingTime_{it}$$
$$+ X_{it}\theta + Z_i\lambda + \varepsilon_{it} \quad (1)$$

Here, $t=2,\dots,T_i$ where T_i is the duration of project i and ε_{it} is a random error term with mean zero and constant variance. The control variables that vary over projects and time are captured in X_{it}; the variables

that describe projects but do not vary over time are in Z_i. Cluster-robust standard errors for the estimated coefficients are used for statistical tests due to dependence among the errors over time within a project $(\text{cov}(\varepsilon_{it}, \varepsilon_{it'}) \neq 0)$. Later we will discuss our estimation approach. Table 3 summarizes our variables, their definitions, and reports descriptive statistics.

[insert Table 3 about here]

Because projects have different goals, the total number of backers required to reach a funding goal will differ across projects. Thus, to better facilitate comparisons across projects of different sizes, *PastBackerSupport* is a relative measure defined to be the ratio of the cumulative number of backers supporting project *i* before day *t* to the total number of backers required to reach project *i*'s goal. We estimate the number of required backers as the goal divided by the average pledged contribution (calculated as the ratio of total funds pledged to the total number of backers obtained by the end of the project). Here, total required backers are the same as total backers actually obtained if a project exactly achieves its funding goal. Because *PastBackerSupport* is highly skewed (e.g., Table 3), its log transform is used in the estimations. From equation (1), **H₁** is confirmed if β_1 is negative and significant.

Our second hypothesis predicts that the effect of past backer support will be moderated by project funding phase, and it will be weakest near the project's deadline. To test this hypothesis, we construct a multiplicative interaction term involving past backer support and relative time in the project funding cycle. We define *FundingTime* to be the fraction of elapsed time (in days) in a project's funding cycle (i.e., the ratio of the cumulative number of days that have elapsed for project *i* up to day *t* to the length of project *i*'s funding cycle in days). From equation (1), **H₂** is supported if β_3 is positive.

Several time-varying variables that control for possible effects due to other project or situational factors are included in the analysis. As suggested by Table 2, several projects in our sample exceed their original funding goal. While we expect the negative bystander effect to be present with these projects, the deadline effect is complicated by the fact that all these projects achieve their goal before the funding cycle ends. Even though a project may be approaching its end date, all of the funding uncertainty has been resolved since it has already met its goal. To consider this effect, we include *PostFunded*, defined to be one for each day a project has already been funded (i.e., *PastBackerSupport*≥1), and zero otherwise. To capture any effects due to the "Recently Launched" and "Ending Soon" search options available on *Kickstarter*'s web site, we include *FirstWeek*, defined to be one if a project is in the first week of its funding (0 otherwise), and *LastWeek*, defined to be one if a project is in the last week before its deadline (0 otherwise). Communication effects between project creators and backers are incorporated into our analysis by including information on project updates. There are two types of updates: (a) backer-only updates, which are only visible to those individuals who have previously contributed to the project and (b) public updates, which are visible to anyone visiting the project's webpage. We define *PrivateUpdate* to be one if project *i* has an update posted only to backers during day *t* (0 otherwise) and *PublicUpdate* to be one if project *i* has posted an update visible to

11

everyone during day *t* (0 otherwise). We expect updates to have a positive effect on the likelihood a project adds a new backer. In addition, we include *LagBackers* (defined to be the number of new backers contributing to project *i* in day *t-1*) to control for immediate word-of-mouth effects (Duan, et al. 2009) and general inertia in contribution behavior (Burtch, et al. 2012). Because *LagBackers* is highly skewed, its log transform is used in the estimations. Given that potential backers can sort projects on the *Kickstarter* website based on popularity (in addition to recently launched and ending soon), we include *Popular* in our model. Here, *Popular* is defined to be one if a project is ranked in the top fifty of all active projects in terms of backers added over the prior week (0 otherwise). We also include *BlogPost* (defined to be one if www.kickstarter.com/blog made specific mention of project *i* on day *t*, 0 otherwise) to capture any positive effects related to a mention on the *Kickstarter* blog. Finally, we control for the possibility that pledges concentrate on certain days by including separate dummy variables for day of week and account for any other unobserved time-varying effects by including month-year dummy variables.

We also include several time invariant control variables related to project characteristics. Following Mollick (2012), we control for differences in project *i*'s *Goal* (dollars) and *Duration* (length of the funding cycle in days). Here, the log transform of *Goal* is used in our estimations due to its highly skewed values and a squared term is included to capture any non-linear effects (Mollick 2012). Because a high proportion of successful projects have a video (de Witt 2012; Mollick 2012; Steinberg 2012), we control for whether the creator of project *i* included a video (*Video*=1 if yes, 0 otherwise). In line with the experiences from successful *Kickstarter* projects (de Witt 2012; Mod 2010; Steinberg 2012), we include controls for the number of reward categories (*RewardCategories*) and whether the project creator had previously proposed any other *Kickstarter* projects (*CreatorExperience*=1 if yes, 0 otherwise). Among the hundreds of active projects that are available for funding, one of the most important screening mechanisms used by potential backers is the project title (de Witt 2012; Steinberg 2012). Research involving scientific articles has shown that title length and punctuation are related to subsequent downloads and citations (Jacques and Sebire 2010; Jamali and Nikzad 2011). To account for any of these effects, we also include *TitleLength* (number of words in the title of project *i*) and *Colon* (=1 if the title of project *i* has a colon, 0 otherwise) in our estimations. Finally, we include dummy variables for the self-reported category of project *i* (see Table 3).

Though our primary dependent measure is binary, we follow the existing literature and estimate equation (1) as a linear probability model (Wooldridge 2010; Goldfarb and Tucker 2011; Simcoe and Waguespack 2011). We do this for two reasons. First, the estimated coefficients can easily be interpreted as a change in probabilities. Second, and more important, interpretation of interaction terms in nonlinear models is not straightforward because they are a cross-derivative of the expected value of the dependent variable. As Ai and Norton (2003: 123) note, "the magnitude of the interaction effect in nonlinear models does not equal the marginal effect of the interaction term, can be of opposite sign, and its statistical significance is not calculated by standard software." In line with Wooldridge (2010), we find that there is little qualitative

difference in our results for the linear probability and logit specifications. Moreover, most of our explanatory variables are binary and the predicted probabilities for our model generally lie between zero and one[6], suggesting that there is little bias from the bounded dependent variable in our estimations (Wooldridge 2010).

4.1 Preliminary Analysis of Backer Behavior

We begin with a naïve pooled approach in which equation (1) is estimated by ordinary least squares (OLS) regression. The results are reported in Models 1 and 2 in Table 4. While we do not report the estimation details for day of week, month-year, and category fixed effects to conserve space, we can make a few observations. First, projects are more likely to receive contributions on weekdays compared to weekends, with Monday representing the peak and activity decreasing steadily until Friday. Second, we find that the categories of Dance, Design, and Food have a highest likelihood of contributions while Fashion, Publishing, and Film & Video projects have the lowest likelihood of activity. No significant trends are observed with month-year fixed effects. Consistent with Mollick's (2012) cross-sectional analysis of successful projects, we find that the likelihood of an additional backer supporting a *Kickstarter* project is significantly related to *Goal*, *Duration* and *Video*. Specifically, projects with smaller goals, of shorter duration, and having a video are likely to garner additional backer support. In addition, projects with many reward categories and having a colon in their title tend to attract new backer pledges. The positive and significant coefficient estimates for *FundingTime* indicate that, everything being equal, projects typically add new backers over the funding cycle. Not surprisingly, the negative and significant coefficient estimates for *PostFunded* imply that backers are less likely to support a project after it reaches its funding goal. In addition, featured projects (*BlogPost*, *Popular*, *FirstWeek*, *LastWeek*), as well as those with communications from creators (*PrivateUpdate*, *PublicUpdate*), are more likely to receive additional backer contributions. Word-of-mouth and inertia effects (*LagBackersAdded*) are also positively related to the likelihood a project receives new backer support.

[insert Table 4 about here]

More important, the results in Table 4, Model 2 are not consistent with **H₁**: the coefficient estimate for *PastBackerSupport* is positive and significant. We note however that equation (1) does not control for possible unobserved heterogeneity across projects. In particular, unobserved differences in project quality not accounted for with the included control variables are likely to be present and, importantly, related to the past backer support a project receives. For example, high quality projects are expected to receive backer support over their funding cycles (and thus have a high level of past backer support) and are likely to have additional backer pledges in each time period. Thus, the positive coefficient estimate for *PastBackerSupport* may simply reflect that high quality projects typically have more backers than low quality projects. In this case, the estimated coefficients for *PastBackerSupport* in Table 4, Model 2 are biased due to an omitted variable. We next turn to a model specification that accounts for unobserved heterogeneity across projects.

---

[6]Eliminating the very few observations that were outside this range produced essentially the same estimates as reported in our tables.

4.2 Accounting for Unobserved Project Heterogeneity

We extend our basic model (1) by decomposing the error term into two components:

$$BackerAdded_{it} = \beta_1 PastBackerSupport_{it} + \beta_2 FundingTime_{it} + \beta_3 PastBackerSupport_{it} \times FundingTime_{it}$$
$$+ X_{it}\theta + Z_i\lambda + a_i + \varepsilon_{it} \qquad (2)$$

Here, a_i represents all differences between projects (such as quality) that are stable over time and not accounted for by $Z_i\lambda$. Based on a Hausman type test (see Allison 2005), fixed-effects models are preferred over random effects models for the *Kickstarter* data. Here, the unobserved project-level differences a_i are permitted to be correlated with the independent variables. Importantly, a fixed-effects model removes any unobserved, time-invariant heterogeneity across projects since the a_i are differenced out of equation (2). Although the time-invariant characteristics are controlled, a fixed-effects estimation approach will not produce estimates for these variables.

The results from an OLS fixed-effects regression estimation of equation (2) are reported in Table 4, Model 3. As demonstrated in Table 5, Model 3, the coefficient estimates from a conditional fixed-effects logit specification have the same signs[7]. We now find strong support for **H₁** the coefficient estimate for *PastBackerSupport* is negative and significant) and **H₂** (the coefficient estimate for *PastBackerSupport x FundingTime* is positive and significant). As expected, Table 4, Model 4 demonstrates that the bystander effect continues to hold after a project is funded (the sum of the coefficient estimates for ln(*PastBackerSupport*) and ln(*PastBackerSupport*) x *PostFunded* is significantly different than zero; F=6.22, p<0.01), but there is no deadline effect once a project reaches its goal (the sum of the coefficient estimates for ln(*PastBackerSupport*) x *FundingTime* and ln(*PastBackerSupport*) x *FundingTime* x *PostFunded* is zero; F=0.64, p=0.42).

[insert Table 5 about here]

These results clearly indicate the need to account for unobserved project heterogeneity in order to understand the role of social information in the dynamic behavior of backers in crowdfunding communities. After accounting for unobserved project heterogeneity, we find strong evidence for the bystander effect among *Kickstarter* backers. Assuming that others will provide the necessary funding, many potential backers do not contribute to a project that has already received a lot of support. Due to the bystander effect, backer support after a project is launched is generally decreasing over its funding cycle. We also find strong evidence of a deadline effect in that the bystander effects diminish as the project funding cycle approaches its closing date—as the project deadline looms, people are more willing to help by providing funding even when others are present. This effect can be statistically confirmed (from Table 4, Model 3 the sum of the coefficient estimates for ln(*PastBackerSupport*) and ln(*PastBackerSupport*) x *FundingTime* is significantly different than zero; F=23.44, p<0.01).

---

[7]Because the conditional fixed-effects logit model eliminates projects from the estimation that have *BackerAdded*$_{it}$=0 or 1 for all *t*, the number of observations and projects is reduced.

Taken together, these results help us better understand the bathtub shaped pattern of backer support over time depicted in Figure 3. Initial project excitement from being tabbed as "Recently Launched" (*FirstWeek*) is quickly followed by a strong downward trend in backer support due to the bystander effect *(PastBackerSupport)*. As a project approaches its end date, a positive deadline effect begins to reduce the negative bystander effect. In addition to a generally positive upward trend in backer support over the funding cycle (*FundingTime*) and the positive exposure from being tabbed as "Ending Soon" (*LastWeek*), project support near the end of the funding cycle can come from public and private updates, as well as from immediate word-of-mouth and inertia effects related to recent backers (*LagBackersAdded*). This is especially the case for successfully funded projects—as shown in Table 2, successful projects have significantly more public and private updates than unsuccessful projects, and add significantly more backers each day (and during the last week). We can further demonstrate that successfully funded projects are more likely than unsuccessful projects to have a public update in the later stages of its funding cycle.

[insert Table 6 about here]

To do this, we estimate the following model separately for public and private updates:

$$(\textit{Public or Private})Update_{it} = \beta_1 FundingTime_{it} + \beta_2 FundingTime_{it} \times Funded_i + X_{it}\theta + Z_i\lambda + a_i + \varepsilon_{it} \qquad (3)$$

Here, a time-invariant indicator for whether project *i* was eventually funded is included (*Funded$_i$*=1 if yes; 0 otherwise). Because equations (2) and (3) are recursive, independently estimating equation (3) gives unbiased coefficient estimates but is less efficient (coefficient t-statistics are conservative). The results from an OLS fixed-effects regression estimation of equation (3) are reported in Table 6. Not surprisingly, public updates are more likely to be made in early in a project's funding cycle (see the negative and significant coefficient estimate associated with *FundingTime*). The significant and positive coefficient estimates for *FundingTime x Funded* indicate that successful projects are more likely to have a public and/or private update in the later stages of the funding cycle than unsuccessful projects. Thus, we find strong evidence that the creators of successful projects use both public and private updates as the end of their funding cycle approaches to encourage potential backers to make a contribution.

5. DISCUSSION AND IMPLICATIONS

Given the difficulties that new ventures face in attracting financing from traditional sources, many entrepreneurs are directly appealing to the general public for help through large, online communities of consumer-investors. These crowdfunding campaigns involve relatively small contributions of many individuals over a fixed time limit (generally a few weeks). More important, potential donors can see the level of support from other project backers as well as its timing before making their own funding decisions, suggesting that social information (i.e., others' funding decisions) will play an important role in the ultimate success of a crowdfunded project. Understanding these effects is important because studies find that social information can lead to irrational herding behaviors.

15

The empirical setting for our study is *Kickstarter*, one of the oldest and largest reward-based crowdfunding communities on the Web. Two years of publicly available information on successfully and unsuccessfully funded projects is used to empirically study the role of social information in the dynamic behavior of project backers. In sharp contrast to the herding patterns found in equity and lending-based crowdfunding studies (Agarwal, et al. 2011; Zhang and Liu 2012) and crowding-out found in donation-based crowdfunding (Burtch, et al. 2012), backer behavior in reward-based crowdfunding is bathtub shaped (see Figure 3). *Kickstarter* projects typically get a lot of backer support in the first and last weeks of their funding cycle. A high level of initial project interest in the first few days is quickly followed by decreasing support over most of the funding cycle. As the project nears the end of its funding cycle, successful projects are able to generate renewed excitement which results in a rise in backer support.

We propose a new theoretical framework in which to better understand this observed backer behavior and then empirically test it with a panel data set involving daily information on over 25,000 successful and unsuccessful *Kickstarter* projects in the 2010-2011 time period. Taken together, our analyses confirm many of the same time-invariant project characteristics that are associated with successful crowdfunded projects suggested by others (de Witt 2012; Mollick 2012; Steinberg 2012). We extend these previous findings by exploiting the panel structure of our *Kickstarter* data to consider the dynamics of backer funding behaviors and the role of social information. After controlling for all these time-variant project characteristics, as well as any unobserved project differences in quality, we find strong evidence for our hypotheses. Building off the well-established social psychology theory around bystander effects (Fisher, et al. 2011), we find that backer support is negatively related to its past backer support. Due to a diffusion of responsibility, many potential backers do not contribute to a project that has already received a lot of support because they assume that others will provide the necessary funding. Consistent with the deadline effect widely observed in bargaining and online auctions (Roth, et al. 1988; Ariely and Simonson 2003), we also find that the bystander effects diminish as the project funding cycle approaches its closing date.

5.1 Implications for Project Creators

With very few notable exceptions[8], the vast majority of creative ideas on *Kickstarter* involve relatively modest amounts of money (from Table 1, the average project has a goal of $8,500 and from Table 2, successful projects on average receive less than $7,000). Almost by definition, crowdfunding involves small contributions from many people (from Table 1, the average contribution is $75 and from Table 2, no more than 100 backers support the average project). As emphasized in the "how to crowdfund" books (e.g., de Witt 2012; Steinberg 2012), setting appropriate funding goals is paramount to having a successful project. Many project failures set unreasonable funding targets given the scope of their creative idea (from Table 2, the average goal for unsuccessful projects is almost three times the goal for successful projects). Our

---

[8]As of December 29, 2012 only seventeen *Kickstarter* projects had raised over $1M (Shontell and Dickey 2012).

statistical analyses confirm that projects with smaller goals, of shorter duration, and having a video are likely to garner additional backer support, as are projects with many reward categories and having a colon in the title. Not surprisingly, projects featured on *Kickstarter* (blog, "Most Popular," "Recently Launched," "Ending Soon") also are more likely to receive additional backer contributions. In general, potential backers are much less interested in supporting a project after it reaches its funding goal.

Very few *Kickstarter* projects achieve at least fifty percent of their goal and are not eventually funded (Figure 2). This suggests that the *Kickstarter* community is generally sympathetic to the creator's plea for help—*Kickstarter* reports an overall success rate of almost 45%. At the same time, our econometric results highlight the difficult challenge facing project creators. Inherent to the *Kickstarter* crowdfunding model is a strong bystander effect, i.e., additional backer contributions are negatively related to the backer support a project has already received (Table 4). Thus, the initial excitement around a new project is quickly followed by a sharp drop in support as potential backers assume that others will provide the requested funding. Project creators need to overcome this bystander effect in order to reach their funding target. While it is important to attract contributors throughout a project's funding cycle, backer support over time is typically bathtub shaped (Figure 3). This means that projects are usually not that active in the middle period of their funding cycle but become much more dynamic in the later stages. Somewhat offsetting the bystander effect, we do find evidence for a deadline effect, i.e., the bystander effect is reduced as a project nears the end of its funding cycle (Table 4). While it is true that successful projects are more likely to receive additional backer support from *Kickstarter* related actions (e.g., blog post, being categorized as "Most Popular" or "Ending Soon"), these positive effects are not directly under the control of a project creator. Instead, project creators need to be proactive by posting public and private updates. We find that successfully funded projects are likely to have a public and/or private update as the end of their funding cycle approaches (Table 6).

This last point about project updates is particularly important since it represents one of the drivers that can be directly influenced by a project creator. Clearly, our analysis of project updates is very basic. Thus, additional research on how product creators might effectively use project updates to overcome any bystander effects is warranted. Further, data limitations prevent us from considering the potential role of other social and online media in generating buzz around a crowdfunding project. Several guidebooks stress the importance of crafting an online marketing campaign and its importance in generating excitement and backer support throughout the funding cycle (de Witt 2012; Steinberg 2012). At this point however, only anecdotal case studies of success stories and their marketing efforts exist, suggesting that further research would be helpful in carefully sorting out the various possible effects.

5.2 Implications for Policy Makers

With the passing of the JOBS Act by the US Congress in 2012, policy makers are persuaded by the potential of crowdfunding to help fund small businesses and entrepreneurs with creative ideas. At the same time however, many pundits have sounded alarms at the potential for fraud associated with unregulated

investing behavior, especially by consumer-investors (the "crowd"). Of particular concern is that project creators with unreasonable ideas will still find funding from naïve investors due to herding behavior (i.e., consumers will simply support projects that others have already supported). In contrast to this perspective, we find no evidence for irrational herding in the *Kickstarter* community. Instead, we demonstrate that a strong bystander effect exists, i.e., others' previous funding decisions are *negatively* related to the likelihood an additional backer will support a project (Table 4). While this bystander effect diminishes over the funding cycle, the overall effect associated with past backers remains negative. Potential backers in this reward-based crowdfunding community seem to be cautious in pledging to ongoing projects, preferring to let others provide the requested funding. Further research is needed to determine if our findings generalize to equity-based crowdfunding communities.

Another possible fear is that project creators propose projects, receive the funding from consumer-investors, and then never complete the project or deliver the promised rewards. Interestingly, Mollick (2012) finds that that most *Kickstarter* project creators in the Technology and Design categories make serious efforts to fulfill their obligations, although the majority deliver the promised rewards later than expected. Although explicitly disclaimed by *Kickstarter*, many consumer-investors believe that the web site is essentially a retail platform in which project creators are pre-selling products. For example, consider the case of Neil Singh (Markowitz 2013). After a searching the web for iPad stands, Singh came across the HanFree iPad Accessory (http://www.kickstarter.com/projects/831303939/hanfree-ipad-accessory-use-the-ipad-hands-free). According to Singh,

> *I didn't know anything about Kickstarter. I was a typical backer like anyone else. I came across this iPad stand. To me, it looked like a cool thing you could buy. 'If you give me $70, I'll send you one of them.' I didn't do any due diligence. I didn't think I had to. I'm not investing. I'm not doing the same sort of things a potential shareholder would do. I'm just buying a product.*

Like Singh, a total of 440 backers liked this product and pledged an average of $80 per person (a total of over $35, 000 was raised, well over the target goal of $10,000). Before listing his idea, Seth Quest, the project creator, had never started a business and had never manufactured a product. Being unable to complete all the required product design and manufacturing planning, Quest posted an update almost eight months after the funding cycle ended explaining that the project had failed. Although Quest initially offered to provide refunds, all of his *Kickstarter* money was gone and he was eventually forced into personal bankruptcy (Markowitz 2013).

To explore the idea of new product pre-orders and the possible effects of product rewards on backer behavior, we split our sample and estimate separate models for Technology, Design and Games projects—categories that typically offer tangible new products as rewards for contributions (Steinberg 2012; see also Mollick 2012)[9]—and projects in any other category. The results from an OLS fixed-effects estimation of

---

[9]We obtain parallel results for each of these three product categories separately.

equation (2) is reported in Table 7. Consistent with our previous results, the coefficient estimates for ln(*PastBackerSupport*) and its interaction with *FundingTime* are in agreement with the bystander (**H₁**) and deadline effects (**H₂**), respectively. However, we find that backer behavior in these two subsamples differs once a project reaches its funding goal. Specifically, the coefficient estimate of the interaction term involving ln(*PastBackerSupport*) and *PostFunded* is positive and significant for Technology, Design and Games projects while it is negative and significant for other projects. Thus, there is strong evidence of herding behavior among backers for successfully funded projects in the Technology, Design and Games categories (the sum of the coefficient estimates for ln(*PastBackerSupport*) and ln(*PastBackerSupport*) *x PostFunded* is significantly different than zero; F=32.65, p<0.01).

[insert Table 7 about here]

These results indicate that funded Technology, Design, and Games projects with a lot of backer support are likely to get even more contributors before their funding cycle ends. Although our data do not allow us to determine if this represents rational or irrational herding behavior, it is interesting to speculate that this herding behavior for successfully funded projects may be responsible for the product rewards delivery delays reported by Mollick (2012). Successfully funded projects may actually be suffering from their own success! This will especially be the case for projects that dramatically exceed their original goal. For example, Eric Migicovsky's Pebble E-Paper Watch, the largest funded *Kickstarter* project to date, received almost 69,000 backers—well over the 1,000 backers expected with their original goal of $100,000. While the promised watch is now shipping more than three months after its promised delivery date, all of their backers (including the authors) will not receive their watch for several more months.

Additional studies are needed to more completely understand the possible herding behavior of consumer-investors in crowdfunding communities. For example, in light of our results in Table 7 an obvious recommendation might be to establish a restriction on the number of additional new backers that can support a project once it reaches its goal. Here, the thinking would be that small startup businesses with limited resources and connections should not be stressed beyond their real capabilities. Such a restriction however, could also change the dynamics of backer behavior so that any bystander effects are minimized. In this case, potential backers may be even more interested in contributing to projects with a lot of past backer support because the project (and its product rewards) may not be available once it meets its target. Thus, herding may be more prevalent if project backers are limited. Further research should tackle these topics more deeply by considering backer motivations and behavior in supporting projects that have already reached their goal.

REFERENCES

Adler, C. (2011), "How Kickstarter Became a Lab for Daring Prototypes and Ingenious Products," *Wired*, March 18, http://www.wired.com/magazine/2011/03/ff_kickstarter/all/1 (accessed May 3, 2012).

Agarwal, A., C. Catalini, and A. Goldfarb (2011), "The Geography of Crowdfunding," available at SSRN: http://ssrn.com/abstract=1770375.

Ai, C. and E. Norton (2003), "Interaction Terms in Logit and Probit Models," *Economics Letters*, 80(1), 123-129.

Allison, P. (2005), *Fixed Effects Regression Methods for Longitudinal Data Using SAS*, Cary, NC: SAS Institute.

Andreoni, J. (1990), "Impure Altruism and Donations to Public Goods: A Theory of Warm Glow Giving," *The Economic Journal*, 100(401), 464-477.

Andreoni, J. (2006), "Philanthropy," in S. Kolm and J. Ythier (eds.), *Handbook of the Economics of Giving, Altruism, and Reciprocity*, North-Holland: Elsevier, 1201-1269.

Ariely, D. and I. Simonson (2003), "Buying, Bidding, Playing, or Competing? Value Assessment and Decision Dynamics in Online Auctions," *Journal of Consumer Psychology*, 13(1&2), 113-123.

Barron, G. and E. Yechiam (2002), "Private E-mail Requests and the Diffusion of Responsibility," *Computers in Human Behavior*, 18, 507-520.

Bayus, B. (2013), "Crowdsourcing New Product Ideas Over Time: An Analysis of the Dell IdeaStorm Community," *Management Science*, 59 (January), 2013, 226-244.

Belleflamme, P., T. Lambert and A. Schwienbacher (2012), "Crowdfunding: Tapping the Right Crowd," available at SSRN: http://ssrn.com/abstract=1836873.

Bergstrom, T., L. Blume, H. Varian (1986), "On the Private Provision of Public Goods," *Journal of Public Economics*, 29(1), 25-49.

Bernheim, D. (1994), "A Theory of Conformity," *Journal of Political Economy*, 102(5), 841-847.

Bikhchandani, S., D. Hirshleifer, and I. Welch (1992), "A Theory of Fads, Fashion, Custom, and Cultural-Change as Informational Cascades," *Journal of Political Economy*, 100(5), 457-486.

Bradford, C. (2012), "Crowdfunding and the Federal Securities Laws," *Columbia Business Law Review*, 1, 1-150.

Burtch, G., A. Ghose, and S. Wattal (2012), "An Empirical Examination of the Antecedents and Consequences of Investment Patterns in Crowd-Funded Markets," available at SSRN: http://ssrn.com/abstract=1928168, forthcoming in *Information Systems Research*.

Chasan, E. (2012), "Crowd-Funding Industry Braces for Regulation," *Wall Street Journal*, April 5, http://online.wsj.com/article/SB10001424052702303302504577326200304117034.html (accessed April 16, 2012).

Cialdini, R. (2001), *Influence: Science and Practice*, Needham Heights, IL: Allyn and Bacon.

Cosh, A., D. Cumming, and A. Hughes (2009), "Outside Entrepreneurial Capital," *The Economic Journal*, 119(540), 1494-1533.

Darley, J. and B. Latane (1968), "Bystander Intervention in Emergencies: Diffusion of Responsibility," *Journal of Personality and Social Psychology*, 8(4), 377-383.

de Witt, N. (2012), *A Kickstarter's Guide to Kickstarter*, http://kickstarterguide.com/files/2012/07/A-Kickstarters-Guide.pdf (accessed November 15, 2012).

Duan, W., B. Gu, and A. Whinston (2009), "Informational Cascades and Software Adoption on the Internet: An Empirical Investigation," *MIS Quarterly*, **33**(1), 23-48.

Duncan, B. (2004), "A Theory of Impact Philanthropy," *Journal of Public Economics*, 88(9-10), 2159-2180.

Economist (2010), "Putting Your Money Where Your Mouse Is," September 2, http://www.economist.com/node/16909869?story_id=16909869 (accessed March 10, 2012).

Ferster, C. and B. Skinner (1957), *Schedules of Reinforcement*, New York: Appleton-Century-Crofts.

Fisher, P., J. Kruegar, T. Greitemeyer, C. Vogrincic, A. Kastenmuller, Dieter Frey, M. Heene, M. Wicher, and M. Kambacher (2011), "The Bystander-Effect: A Meta-Analytic Review on Bystander Intervention in Dangerous and Non-Dangerous Emergencies," *Psychological Bulletin*, 137(4), 517-537.

Forsyth, D., L. Zyzniewski, and C. Giammanco (2002), "Responsibility Diffusion in Cooperative Collections," *Personality and Social Psychology Bulletin*, 28(1), 54-65.

Garcia, S., K. Weaver, G. Moskowitz, and J. Darley (2002), "Crowded Minds: The Implicit Bystander Effect," *Journal of Personality and Social Psychology*, 83(4), 843-853.

Gerber, E., J. Hui, and P. Kuo (2012), "Crowdfunding: Why People are Motivated to Post and Fund Projects on Crowdfunding Platforms," Design, Influence, and Social Technologies Workshop at Computer Supported Cooperative Work, http://distworkshop.files.wordpress.com/2012/01/dist2012_submission_11.pdf (accessed October 7, 2012).

Goldfarb, A. and C. Tucker (2011), "Privacy Regulation and Online Advertising," *Management Science*, 57(1), 57-71.

Hazen, T. (2012), "Social Networks and the Law: Crowdfunding or Fraudfunding? Social Networks and the Securities Laws—Why the Specially Tailored Exemption Must be Conditioned on Meaningful Disclosure," *North Carolina Law Review*, 90, 1735-1807.

Herzenstein, M., U. Dholakia, and R. Andrews (2011), "Strategic Herding Behaviors in Peer-to-Peer Loan Auctions," *Journal of Interactive Marketing*, 25(1), 27-36.

Hemer, J. (2011), "A Snapshot on Crowdfunding," Fraunhofer ISI Working Paper, http://isi.fraunhofer.de/isimedia/docs/p/arbpap_unternehmen_region/ap_r2_2011.pdf?WSESSIONID=71 fbeb093ebe9de0c0b8d0b9db7cda95 (accessed February 23, 2012).

Jacques, T. and N. Sebire (2010), "The Impact of Article Titles on Citation Hits: An Analysis of General and Specialist Medical Journals," *Journal of the Royal Society of Medicine Short Reports*, 1(2), 1-5.

Jamali, H. and M. Nikzad (2011), "Article Title Type and Its Relation with the Number of Downloads and Citations," *Scientometrics*, 88(2), 653-661.

Karau, S. and K. Williams (1993), "Social Loafing: A Meta-Analytic Review and Theoretical Integration," *Journal of Personality and Social Psychology*, 65(4), 681-706.

Latane, B. and J. Darley (1970), *The Unresponsive Bystander: Why Doesn't He Help?* New York: Appleton-Cnetury-Crofts.

Latane, B. and S. Nida (1981), "Ten Years of Research on Group Size and Helping," *Psychological Bulletin*, 89(2), 308-324.

Ma, C. and M. Manove (1993), "Bargaining with Deadlines and Imperfect Player Control," *Econometrica*, 61(6), 1313-1339.

Markey, P. (2000), "Bystander Intervention in Computer-Mediated Communication," *Computers in Human Behavior*, 16, 183-188.

Markowitz, E. (2013), "When Kickstarter Investors Want Their Money Back," *Inc.*, Jan 10, http://www.inc.com/eric-markowitz/when-kickstarter-investors-want-their-money-back.html (accessed January 15, 2013).

Massolution (2012), "Crowdfunding Industry Report," May, http://www.marketwire.com/press-release/crowdfunding-platforms-raise-15-billion-successfully-fund-one-million-campaigns-2011-1654020.htm (accessed May 8, 2012).

Mod, C. (2010), "Kickstartup: Successful Fund Raising with Kickstarter.com," http://craigmod.com/journal/kickstartup/ (accessed August 15, 2012).

Mollick, E. (2012), "The Dynamics of Crowdfunding: Determinants of Success and Failure," available at SSRN: http://ssrn.com/abstract=2088298.

Ockenfels, A., D. Riley, and A. Sadrieh (2006), "Online Auctions," in T. Hendershott (ed.), *Handbook in Information Systems*, North Holland: Elsevier Science, 571-628.

Ordanini, A., L. Miceli, M. Pizzetti, and A. Parasuraman (2011), "Crowd-Funding: Transforming Customers into Investors through Innovative Service Platforms," *Journal of Service Management*, 22(4), 443-470.

Ricker, T. (2011), "Kickstarted: How One Company is Revolutionizing Product Development," *The Verge*, December 20, http://www.theverge.com/2011/12/20/2644358/kickstarter-success-product-development-revolution (accessed April 16, 2012).

Roth, A., J. Murnighan, and F. Schoumaker (1988), "The Deadline Effect in Bargaining: Some Experimental Evidence," *American Economic Review*, 78(4), 806-823.

Salganik, M., P. Dodds, and D. Watts (2006), "Experimental Study of Inequality and Unpredictability in an Artificial Cultural Market," *Science*, 311(854), 854-856.

Schwienbacher, A. and B. Larralde (2012), "Crowdfunding of Entrepreneurial Ventures," in D. Cumming (ed.), *The Oxford Handbook of Entrepreneurial Finance*, Oxford, UK: Oxford University Press.

Segall, L. (2012), "$7 Million Pebble Watch Shatters Kickstarter Records," *Money*, May 2, http://money.cnn.com/2012/05/02/technology/startups/pebble-kickstarter-watch/index.htm (accessed May 8, 2012).

Shontell, A. and M. Dickey (2012), "17 New Ideas That Are Actually Worth Millions," *Business Insider*, http://www.businessinsider.com/17-million-dollar-ideas-on-kickstarter-2012-12?op=1 (accessed February 18, 2012).

Simcoe, T. and D. Waguespack (2011), "Status, Quality, and Attention: What's in a (Missing) Name?" *Management Science*, 57(2), 274-290.

Simonsohn, U. and D. Ariely (2008), "When Rational Sellers Face Nonrational Buyers: Evidence from Herding on eBay," *Management Science*, 54(9), 1624-1637.

Smith, S., F. Windmeijer, and E. Wright (2012), "The Effect of Social Information on Charitable Donations: Evidence from the (Running) Field," University of Bristol Working Paper, http://www.bristol.ac.uk/cmpo/events/2012/charitablegiving/smith.pdf (accessed May 3, 2012).

Steinberg, D. (2012), *The Kickstarter Handbook*, Philadelphia, PA: Quirk Books.

Sugden, R. (1984), "Reciprocity: The Supply of Public Goods through Voluntary Contributions," *The Economic Journal*, 94(376), 772-787.

Vesterlund, L. (2006), "Why Do People Give?" in W. Powell and R. Steinberg (eds.), *The Nonprofit Sector: A Research Handbook*, New Haven, CT: Yale University Press, 568-590.

Voepel, S., R. Eckhoff, and J. Forster (2008), "David against Goliath? Group Size and Bystander Effects in Virtual Knowledge Sharing," *Human Relations*, 61(2), 271-295.

Ward, C. and V. Ramachandran (2010), "Crowdfunding the Next Hit: Microfunding Online Experience Goods," University of Massachusetts Working Paper, http://people.cs.umass.edu/~wallach/workshops/nips2010css/papers/ward.pdf (accessed January 16, 2012).

Webb, E. and K. Weick (1979), "Unobtrusive Measures in Organizational Theory: A Reminder," *Administrative Science Quarterly*, 24(4), 650-659.

Wiesenthal, D., D. Austrom, and I. Silverman (1983), "Diffusion of Responsibility in Charitable Donations," *Basic and Applied Social Psychology*, 4(1), 17-27.

Wooldridge, J (2010), *Econometric Analysis of Cross Section and Panel Data*, Cambridge, MA: MIT Press.

Wortham, J. (2012), "Start-Ups Look to the Crowd," *New York Times*, April 29, http://www.nytimes.com/2012/04/30/technology/kickstarter-sets-off-financing-rush-for-a-watch-not-yet-made.html?_r=1 (accessed April 29, 2012).

Yechiam, E. and G. Barron (2003), "Learning to Ignore Online Help Requests," *Computational and Mathematical Organization Theory*, 9, 327-339.

Zhang, J. and P. Liu (2012), "Rational Herding in Microloan Markets," *Management Science*, 58(5), 892-912.

Zhou, J. (2011), "The Timing of Out-of-Court Settlements Revisited: Theory and Cross-Sectional Evidence from Texas since 1988," available at SSRN: http://ssrn.com/abstract=1790543.

Table 1
Summary Statistics for All *Kickstarter* Projects 2010-2011
(N=25,058)

Variable	Mean	Std. Dev.	Min	Max
Funded (1=yes)	0.63	0.48	0	1
Goal ($)	8509.83	139093.10	1	21474836
Total Amount Pledged ($)	4633.17	13759.15	1	942578
Percent of Goal Funded	93.22	179.94	0	15454.20
Duration (days)	41.37	18.52	1	93
Total Number of Backers	62.59	189.54	1	13364
Total Number of Backers in First Week	19.31	69.73	1	4683
Total Number of Backers in Last Week	15.93	58.68	1	3535
Number of Backers Added per Day	1.51	8.52	0	2212
Average Contribution per Backer ($)	73.64	70.08	1	1679.67
Number of Reward Categories	7.89	3.50	1	31
Maximum Reward Claimed ($)	504.37	964.50	1	10000
Has Video (1=yes)	0.81	0.39	0	1
Number of Words in Title	6.37	2.87	1	19
Title has Colon (1=yes)	0.21	0.40	0	1
Number of Blog Posts by *Kickstarter*	0.02	0.15	0	4
Number of Days on Top 50 Most Popular List	1.41	4.96	0	75
Total Number of Public Updates	2.65	4.09	0	83
Total Number of Private Updates Only to Backers	0.44	1.28	0	49
Proposed by a Serial Creator (1=yes)	0.08	0.26	0	1

Table 2

Mean Values for All *Kickstarter* Projects 2010-2011 by Funding Outcome
(N=25,058)

Variable	Funding Level Achieved			t-statistics		
	(1) **<100% of Goal** **(N=9,307)**	**(2)** **100% of Goal** **(N=1,912)**	**(3)** **>100% of Goal** **(N=13,839)**	**(1)-(2)**	**(1)-(3)**	**(2)-(3)**
Goal ($)	14587.01	4726.40	4950.20	3.54***	3.97***	8.32***
Total Amount Pledged ($)	1232.15	4742.84	6905.27	-50.50***	-27.32***	-7.56***
Percent of Goal Funded	15.85	100.26	144.28	-459.37***	-51.16***	-20.68***
Duration (days)	44.26	40.25	39.59	11.68***	20.23***	8.27***
Total Number of Backers	17.56	42.84	95.61	-53.50***	-29.31***	-13.85***
Total Number of Backers in First Week	7.12	11.18	28.64	-36.30***	-24.04***	-15.46***
Total Number of Backers in Last Week	2.57	14.11	25.14	-47.28***	-25.18***	-6.81***
Number of Backers Added per Day	0.40	1.06	2.41	-173.23***	-110.34***	-51.95***
Average Contribution per Backer ($)	59.35	118.68	77.02	-31.14***	-10.92***	23.19***
Number of Reward Categories	7.57	8.05	8.16	-9.04***	-10.23***	-1.15
Maximum Reward Claimed ($)	257.07	608.67	618.50	-30.02***	-27.52***	3.27**
Has Video (1=yes)	0.77	0.79	0.83	-9.90***	-8.62***	1.32
Number of Words in Title	6.31	6.38	6.40	-2.04*	-2.16*	-0.08
Title has Colon (1=yes)	0.20	0.20	0.21	-0.85	-3.16**	-2.19*
Number of Blog Posts by *Kickstarter*	0.01	0.01	0.03	-6.62***	-12.60***	-6.27***
Number of Days on Top 50 Most Popular List	0.15	0.52	2.39	-23.53***	-37.99***	-20.12***
Total Number of Public Updates	1.61	2.43	3.39	-26.45***	-30.89***	-3.76***
Total Number of Private Updates Only to Backers	0.23	0.37	0.59	-16.85***	-20.06***	-4.13***
Proposed by a Serial Creator (1=yes)	0.06	0.09	0.08	-4.50***	-6.30***	-1.68

*significant at 0.05 level; **significant at 0.01 level; ***significant at 0.001 level

Variable	Definition	Mean	Std. Dev.	Min	Max
BackerAdded	=1 if project *i* received a new contribution pledge on day *t* (0=otherwise)	0.39	0.49	0	1
PastBackerSupport	Ratio of the cumulative number of backers supporting project *i* before day *t* to the total number of backers required to reach project *i*'s goal	0.49	1.08	0	154.54
FundingTime	Ratio of the cumulative number of days that have elapsed for project *i* up to day *t* to the length of project *i*'s funding cycle in days	0.52	0.28	0.02	1
FirstWeek	=1 if project *i* is in the first week of its funding cycle on day *t* (0 otherwise)	0.15	0.36	0	1
LastWeek	=1 if project *i* is in the final week of its funding cycle on day *t* (0 otherwise)	0.17	0.38	0	1
PrivateUpdate	=1 if project *i* has posted an update visible to only prior backers during day *t* (0 otherwise)	0.01	0.10	0	1
PublicUpdate	=1 if project *i* has posted an update visible to everyone during day *t* (0 otherwise)	0.06	0.23	0	1
LagBackers	Number of new backers contributing to project *i* in day *t-1*	1.49	8.25	0	2212
Popular	=1 if project *i* is ranked in the top fifty of all active projects in terms of backers added over the prior week (0 otherwise)	0.04	0.18	0	1

con't on next page

Variable	Definition	Mean	Std. Dev.	Min	Max
BlogPost	=1 if the *Kickstarter* blog mentioned project *i* on day *t* (0 otherwise)	0.00	0.02	0	1
Goal	Goal for project *i* ($)	10685.02	201512.60	1	21474836
Duration	Length of the funding cycle for project *i* (days)	49.87	20.66	2	93
Video	=1 if project *i* has a video (0 otherwise)	0.81	0.39	0	1
RewardCategories	Number of reward categories for project *i*	8.04	3.53	1	31
CreatorExperience	=1 if the creator for project *i* created at least one previous *Kickstarter* project (0 otherwise)	0.07	0.25	0	1
TitleLength	Number of words in the title of project *i*	6.41	2.90	1	19
Colon	=1 if there is a colon in the title of project *i* (0 otherwise)	0.21	0.41	0	1
Project Category	Dummy variables for the category in which project *i* is classified: Art, Comics, Dance, Design, Fashion, Film & Video, Food, Games, Music, Photography, Publishing, Technology, Theater	-	-	0	1

Table 4

Panel OLS Estimation Results for Additional Project Backers

(cluster-robust standard errors; t-statistics in parentheses)

Variable	Model 1	Model 2	Model 3	Model 4
ln(*PastBackerSupport*)		0.06 (75.99)***	-0.06 (-29.94)***	-0.07 (-32.72)***
ln(*PaetBackerSupport*) x *FundingTime*		0.05 (38.57)***	0.05 (40.97)***	0.06 (42.96)***
ln(*PastBackerSupport*) x *PostFunded*				0.03 (1.54)
ln(*PastBackerSupport*) x *FundingTime* x *PostFunded*				-0.07 (-5.13)***
Time-Varying Control Variables				
FundingTime	-0.06 (-20.51)***	-0.05 (-15.08)***	0.09 (18.47)***	0.12 (23.35)***
PostFunded	0.02 (6.94)***	-0.12 (-47.73)***	-0.17 (-64.85)***	-0.09 (-13.06)***
FundingTime x *PostFunded*				-0.12 (-14.26)***
FirstWeek	0.04 (28.12)***	0.10 (60.05)***	0.06 (33.52)***	0.06 (33.30)***
LastWeek	0.04 (25.90)***	0.06 (42.15)***	0.07 (44.88)***	0.08 (47.75)***
Popular	0.03 (6.71)***	0.01 (1.85)	0.05 (15.87)***	0.05 (15.09)***
BlogPost	0.14 (6.76)***	0.13 (6.66)***	0.08 (4.81)***	0.08 (4.77)***
PrivateUpdate	0.14 (28.41)***	0.11 (25.32)***	0.10 (22.90)***	0.10 (23.07)***
PublicUpdate	0.17 (77.72)***	0.15 (69.29)***	0.14 (64.22)***	0.14 (64.27)***
ln(*LagBackers*)	0.26 (203.22)***	0.20 (155.12)***	0.13 (123.16)***	0.13 (123.99)***
Time-Invariant Control Variables				
ln(*Goal*)	0.16 (14.67)***	0.11 (12.49)***		
ln(*Goal*)^2	-0.01 (-12.67)***	-0.00 (-4.30)***		
Duration	-0.00 (-46.65)***	-0.00 (-61.04)***		
Video	0.05 (21.28)***	0.02 (10.69)***		
RewardCategories	0.01 (25.45)***	0.00 (15.24)***		
CreatorExperience	0.01 (2.87)**	0.01 (3.55)***		
TitleLength	-0.00 (-1.64)	-0.00 (-1.27)		
Colon	0.02 (7.80)***	0.01 (4.47)***		
Project Category	yes	yes		
Constant	-0.45 (-9.85)***	-0.21 (-5.84)***	0.27 (17.43)***	0.25 (15.86)***
Fixed Effects				
Day-of-Week	yes	yes	yes	yes
Month-Year	yes	yes	yes	yes
Project	no	no	yes	yes
N(observations)	1,011,701	1,0110,701	1,011,701	1,011,701
N(projects)	25,050	25,050	25,050	25,050
Adj R^2	0.26	0.30	0.35	0.35

*significant at 0.05 level; **significant at 0.01 level; ***significant at 0.001 level

Table 5
Panel Logit Robustness Results for Additional Project Backers
(cluster-robust standard errors; t-statistics in parentheses)

Variable	Model 1	Model 2	Model 3	Model 4
ln(*PastBackerSupport*)		0.31 (62.14)***	-0.34 (-28.07)***	-0.40 (-31.45)***
ln(*PaetBackerSupport*) x *FundingTime*		0.75 (73.23)***	0.58 (49.36)***	0.71 (54.77)***
ln(*PastBackerSupport*) x *PostFunded*				-1.09 (-5.94)***
ln(*PastBackerSupport*) x *FundingTime* x *PostFunded*				-0.09 (-0.63)
Time-Varying Control Variables				
FundingTime	-0.29 (-18.73)***	0.16 (-7.33)***	0.60 (19.08)***	0.86 (25.87)***
PostFunded	0.10 (8.36)***	-0.93 (-73.85)***	-1.17 (-79.09)***	-0.54 (-12.18)***
FundingTime x *PostFunded*				-0.74 (-13.01)***
FirstWeek	0.22 (26.70)***	0.47 (48.30)***	0.35 (30.14)***	0.33 (27.90)***
LastWeek	0.22 (27.42)***	0.39 (40.83)***	0.48 (45.82)***	0.52 (48.05)***
Popular	1.17 (47.91)***	0.88 (35.91)***	0.74 (26.82)***	0.71 (25.78)***
BlogPost	1.50 (8.29)***	1.31 (7.33)***	0.97 (5.60)***	0.95 (5.52)***
PrivateUpdate	0.83 (28.44)***	0.68 (24.09)***	0.65 (22.71)***	0.65 (22.81)***
PublicUpdate	1.03 (78.66)***	0.87 (68.38)***	0.87 (66.24)***	0.87 (65.82)***
ln(*LagBackers*)	1.44 (210.42)***	1.00 (170.05)***	0.68 (125.78)***	0.68 (125.12)***
Time-Invariant Control Variables				
ln(*Goal*)	0.95 (18.00)***	0.46 12.54)***		
ln(*Goal*)^2	-0.05 (-15.65)***	-0.00 (-0.19)		
Duration	-0.01 (-43.93)***	-0.02 (-65.47)***		
Video	0.29 (20.57)***	0.14 (12.61)***		
RewardCategories	0.04 (26.27)***	0.02 (16.60)***		
CreatorExperience	0.07 (3.40)**	0.07 (4.17)***		
TitleLength	-0.00 (-1.65)	-0.00 (-0.96)		
Colon	0.11 (8.32)***	0.05 (5.00)***		
Project Category	yes	yes		
Constant	-5.57 (-25.86)***	-3.40 (-22.25)***		
Fixed Effects				
Day-of-Week	yes	yes	yes	yes
Month-Year	yes	yes	yes	yes
Project	no	no	yes	yes
N(observations)	1,011,701	1,011,703	967,908	967,908
N(projects)	25,050	25,050	23,663	23,663
Chi-Square	87,373.98***	127,181.72***	453,112.83***	52,278.22***

*significant at 0.05 level; **significant at 0.01 level; ***significant at 0.001 level

Table 6
Panel OLS Estimation Results for Project Updates
(cluster-robust standard errors; t-statistics in parentheses)

Variable	Model 1 (Public Updates)	Model 2 (Private Updates)
FundingTime	-0.03 (-12.73)***	0.00 (1.81)
FundingTime x Funded	0.07 (32.06)***	0.01 (7.11)***
Time-Varying Control Variables		
PostFunded	-0.04 (-26.00)***	-0.00 (-1.50)
FirstWeek	0.01 (8.99)***	0.00 (5.27)***
LastWeek	0.02 (24.41)***	0.01 (21.47)***
Popular	0.03 (10.13)***	0.00 (3.93)***
BlogPost	0.06 (3.16)***	0.01 (1.21)
ln(*LagBackers*)	0.03 (51.13)***	0.01 (25.41)***
ln(*PastBackerSupport*)	0.00 (2.11)*	0.00 (4.49)***
Constant	0.04 (5.26)***	-0.00 (-0.70)
Fixed Effects		
Day-of-Week	yes	yes
Month-Year	yes	yes
Project	yes	yes
N(observations)	1,011,701	1,011,701
N(projects)	25,050	25,050
Adj R²	0.12	0.06

*significant at 0.05 level; **significant at 0.01 level; ***significant at 0.001 level

Table 7
Panel OLS Estimation Results by Project Type
(cluster-robust standard errors; t-statistics in parentheses)

Variable	Model 1 (Technology, Design, Games)	Model 2 (Not Technology, Design, Games)
ln(*PastBackerSupport*)	-0.05 (-6.61)***	-0.07 (-32.72)***
ln(*PastBackerSupport*) x *FundingTime*	0.03 (7.69)***	0.06 (41.80)***
ln(*PastBackerSupport*) x *PostFunded*	0.16 (7.86)***	-0.09 (-3.63)***
ln(*PastBackerSupport*) x *FundingTime* x *PostFunded*	-0.12 (-6.48)***	-0.01 (-0.48)
Time-Varying Control Variables		
FundingTime	0.00 (0.08)	0.13 (24.07)***
PostFunded	-0.05 (-2.69)**	-0.09 (-11.95)***
FundingTime x *PostFunded*	-0.01 (-0.42)	-0.12 (-12.84)***
FirstWeek	0.06 (9.47)***	0.06 (31.57)***
LastWeek	0.06 (10.67)***	0.08 (46.59)***
Popular	0.04 (4.97)***	0.05 (13.91)***
BlogPost	-0.02 (-0.39)	0.10 (5.14)***
PrivateUpdate	0.06 (4.59)***	0.11 (22.60)***
PublicUpdate	0.09 (27.62)***	0.14 (63.05)***
ln(*LagBackers*)	0.09 (27.62)***	0.13 (120.87)***
Constant	0.38 (8.49)***	0.23 (14.19)***
Fixed Effects		
Day-of-Week	yes	yes
Month-Year	yes	yes
Project	yes	yes
N(observations)	80,179	931,522
N(projects)	2,007	23,043
Adj R²	0.46	0.35

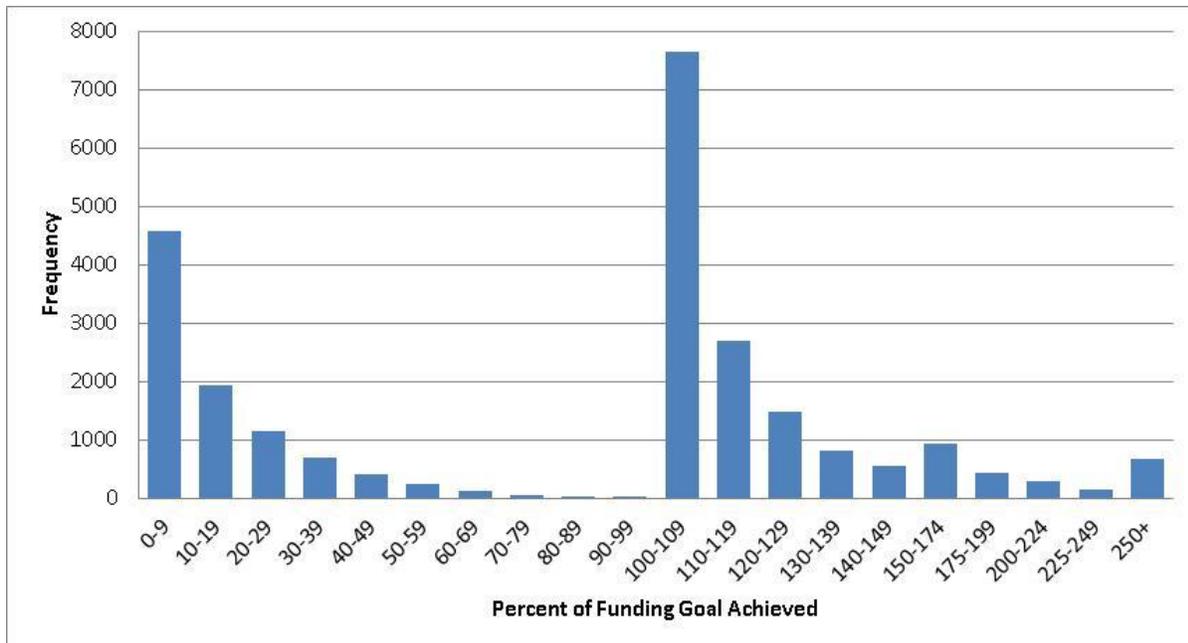*significant at 0.05 level; **significant at 0.01 level; ***significant at 0.001 level

Figure 1
The Dynamics of Backer Support for Cody Webb's New CD
(http://www.kickstarter.com/projects/codywebb/cody-webbs-new-cd)
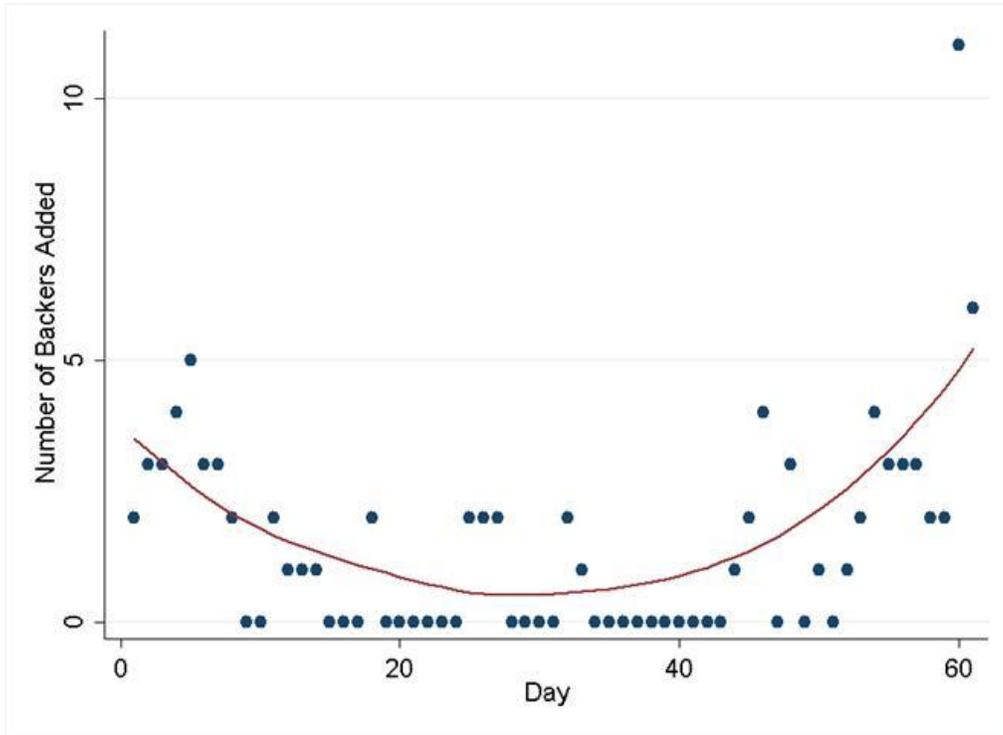
Figure 2
Distribution of Project Funding Outcomes
(N=25,058)

Figure 3
Average Number of Backers Added to a Project in Any Day
(N=25,058)