PLAYING BOTH SIDES OF THE MARKET: SUCCESS AND RECIPROCITY ON CROWDFUNDING PLATFORMS

David Zvilichovsky [*] , Yael Inbar [*] , Ohad Barzilay [*]

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Abstract

Crowdfunding platforms enable the financing of projects by soliciting small investments from a large base of potential backers over the Internet. These platforms create a dynamic funding network. We use data collected from Kickstarter, the largest crowdfunding platform, to study some of the dynamics of such a network. We focus on project owners who choose to operate on both sides of the market, creating campaigns of their own as well as backing the projects of others. We find that an owner's backing-history has a significant effect on financing outcomes; campaigns initiated by entrepreneurs who have previously supported others have higher success rates, attract more backers and collect more funds. We extend network exchange theory to the domain of crowdfunding and find evidence for both direct and indirect reciprocity. We quantify the impact of such reciprocal forces on the performance of crowdfunding platforms and campaigns. We also show that owners who are backers form a sub-community that is active in backing projects, especially those initiated by its members. These findings suggest that backing the projects of others is a rewarding strategy.

Keywords: Crowdfunding, Reciprocity, Social Networks, IS-Economics, E-Finance

[*] *Recanati Business School , Tel Aviv University, Ramat Aviv, Tel Aviv, 69978, Israel*
Email addresses: *davidz@post.tau.ac.il (D. Zvilichovsky), yaelinba@tau.ac.il (Y. Inbar), ohadbr@tau.ac.il (O. Barzilay)*

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Introduction

Crowdfunding, the process of directly financing ventures over the Internet, is gaining momentum. Industry reports estimate that sums raised on crowdfunding platforms have more than doubled in 2013, totaling over US$5B[1]. Initially, crowdfunding was performed using social media such as mailing lists or online social networks. The maturity of Web 2.0 technologies and the success of crowdsourcing (Giudici et al. 2012; Kleemann et al. 2008) gave rise to dedicated crowdfunding *platforms*, which bring together project owners and potential backers, facilitating information flow and transactions.

More abstractly, project owners and backers constitute parties in a two-sided market, with the crowdfunding platform serving as an intermediary. In this study we explore how specific characteristics of an online crowdfunding platform might create theoretically and economically meaningful patterns of behavior among project owners and backers, patterns that are unlikely to be observed in offline fundraising settings. In particular, we utilize a comprehensive data-set harvested from Kickstarter,[2] the largest crowdfunding platform to date. We highlight four properties of this specific two-sided market that together not only foster but also provide opportunities to document and research such emergent online dynamics.

Information flow. From an information systems perspective, Kickstarter serves as a virtualization of offline funding and purchasing interactions (Overby et al. 2010). Bringing the fundraising process online has led to the exposure of information that is less accessible in offline settings. In particular, every Kickstarter campaign displays a complete, up-to-date list of backers that provides one-click access to a detailed profile page for each backer. The profile presents information that the backer has chosen to reveal (such as name, photo, short bio and address) as well as information pertaining to the user's previous activity on Kickstarter.

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[1] http://research.crowdsourcing.org/2013cf-crowdfunding-industry-report

[2] www.kickstarter.com

Research shows that users use such information in order to guide their actions (Kuppuswamy and Bayus 2013). Furthermore, this information may also generate online dynamics such as herding (Zhang and Liu 2012; Li and Wu 2014) and observational learning (Kim and Viswanathan 2013). In some settings, users have also been shown to react to weak signals that document the subtle actions of others (Umyarov et al. 2013).

Playing both sides: Another property of this platform is the potential dual role of each user. A Kickstarter user may serve as both a backer, backing others, and as an owner, creating her own campaigns. Similar duality may also be found on other online platforms such as YouTube (uploading and watching movies), Airbnb (hosting and renting) and eBay (buying and selling).

Visibility of two-sided activity: Kickstarter made an explicit design decision to make the platform history of each campaign owner visible. Figure 1 shows an example of a homepage of a campaign. This page provides easy access to the platform history of the campaign owner, including details on the number of previous projects the owner created as well as the number of previous projects he or she backed; furthermore, the details of these previous actions are easily accessible.

Clear success metrics: A Kickstarter campaign is designed with a clear measure of success. Upon initiation of a campaign, the owner announces her financing target and funding duration. These clear metrics enable the observer to easily evaluate campaign success as well as to calculate quantifiable outcomes.

We expect that, combined, these properties have a disruptive effect on fundraising process, and that they foster additional mechanisms, which are less apparent in an offline fundraising setting. Literature indicates that an entrepreneur's success is affected by her previous track record (Gompers et al. 2010; Hsu 2007; Packalen 2007). The Kickstarter platform enables us to investigate this idea from a broader perspective, in light of the fact that, in this environment, a project owner may also serve as a backer, and her track record (prior activity on the platform) is visible to all. More specifically, we study the impact of these visible two sided actions on the financing success of crowdfunding campaigns as well as the backing actions of campaign owners. We use the clear metrics provided by such a crowdfunding platform to quantify these effects.

We use a comprehensive data set that includes 78,061 projects, covering more than 90% of the projects created on Kickstarter.com prior to March 2013. The documented projects received 6,812,159 pledges from 3,273,893 users.

We find that backing other projects, prior to one's current campaign significantly increases the funding success of the project. The probability that a project achieves its targeted financing goal increases in the number of backing actions performed by its owner; Furthermore the total sum raised is significantly higher for those projects where the project owner is also a backer of other projects compared with projects owned by non-backers.

We also show that project owners who play both sides of the market and back other projects create a sub-community of backer-owners, which exhibits network dynamics that differ from those of the backer-only and owner-only populations.

This study extends the theory of network exchange in online communities (Faraj and Johnson 2011) by identifying the existence and importance of reciprocal forces in the context of crowdfunding. In our study, we are able to identify and quantify the significant effects of both direct and indirect reciprocity patterns on campaign success. Campaign owners who support others receive more backings from campaign owners whom they have supported (direct reciprocity) as well as from the community at large (indirect reciprocity). We interpret some of these effects as manifestations of social interaction, social capital and social solidarity (Coleman 1994; Molm et al. 2007).

In this paper, we decouple the effect of reciprocity *per-se* from the effects of other dynamics that are evident on the platform and that may serve as alternative explanations of the patterns we observe. One such force is *homophily* (Lazarsfeld and Merton 1954), i.e., two owners may support each other not because of reciprocal behavior between them, but rather because they share similar preferences, attributes or interests (McPherson et al. 2001). In our analysis, we control for the tendency of owners to back projects that are similar to their own project (in terms of category and size), and we show that the reciprocity effect dominates homophily.

Another potential explanation for our results is that, by participating in various actions on Kickstarter, future project owners learn the ins and outs of the platform, and this learning process enables them to create or position projects that are better candidates for funding success (Gompers et al. 2010). Indeed, several studies (e.g., Hsu 2007) have discussed such processes of learning by doing in similar settings. Yet our work suggests that learning by doing does not capture the full story: Our results show that having created multiple projects (possibly the most effective way of learning about project creation) does not in itself increase the likelihood of obtaining financing. Furthermore, when evaluating the combined effects of creation history together with backing actions, we find that the latter dominates.

Backing others (a social behavior) may be correlated with the innate characteristics of 'good' campaign owners; therefore, the success of such backer-owners may be driven not by reciprocity but rather by their quality or type. In order to address these unobserved characteristics, we focus on serial entrepreneurs and show that the reciprocity effect is still evident even when controlling for the success of previous projects initiated by these individuals as well their backing actions prior to their first project. Doing so, we are able to differentiate between different pseudo-archetypes of owners: social and not social (based on their backing history), successful and not successful (based on the success on their first campaign). We show that backing others increases the success likelihood of each type of owner, even in comparison to the owners of the same type. This estimation strategy is also useful in controlling for additional alternative explanations such as previous project experience and the channel from success to backing.

This paper makes the following contributions: We extend network exchange theory to the domain of crowdfunding platforms. Until recently, exchange theory was primarily identified in the lab (Cook and Rice 2006); our study adds to recent research efforts to apply network exchange theories to real-life settings. One such study considered social and network exchange theories in the context of technology-related discussion groups (Faraj and Johnson 2011) and identified the existence of both direct and indirect reciprocity. Crowdfunding platforms contextualize this theory by giving the network exchange patterns a monetary interpretation in a transactional setting, while enabling the monetary impact of such forces to be quantified. We identify, quantify and prove the existence of such reciprocal forces and measure their impact on campaign success.

This research also contributes to our understanding of the emerging phenomenon of crowdfunding and, in particular, the dynamics on crowdfunding platforms. We show that social mechanisms nurtured by the platform and its design play a significant role in campaign success. We consider social capital and its signaling from a broader perspective compared with that adopted in the literature thus far, by taking into account actions performed on both sides of the platform.

Current studies assume that the credibility of an entrepreneur results from her previous ventures (Aldrich and Zimmer 1986; Alexy et al. 2012; Dimov et al. 2007; Hoang and Antoncic 2003; Lawton and Marom 2010; Zhang 2011). We show that backing others is a strategy which provides for increased financing success and direct financial returns. We also highlight the impact of platform design on specific network dynamics and provide a theoretical reference which supports the highlighting of certain attributes such as owners' previous backing actions. We shed new light on the additional dynamics and implications of allowing users to participate on both sides of an online platform.

From a methodology perspective, this paper presents two novel identification techniques: (a) the use of serial entrepreneurs, to untangle selection bias and endogeneity while providing further control for unobserved characteristics; (b) the analysis of reciprocal actions while controlling for the attributes of the users and projects on both sides of the reciprocity links as well as the timing of said actions, thus further decoupling between homophily and reciprocity. Both of these techniques may be applied to a broad range of digital platforms that support recurring interactions and transactions.

Background

Using the "wisdom of the crowd" (Surowiecki 2005) for producing or supporting a product has become widespread, and crowdfunding is an emerging example of this phenomenon (Belleflamme et al. 2011). Researchers have begun to devote substantial attention to various facets of crowdfunding, including the business models of crowdfunding platforms (Hemer 2011), the relations between entrepreneurs and investors (Agrawal et al. 2011) and the information provided by the entrepreneur (Ahlers et al. 2012; Marom and Sade 2013). Other studies have dealt with motivations for participating in crowdfunding— from the perspectives of both the owner and the backer (Belleflamme et al. 2011; Schwienbacher and Larralde 2012); the decision-making process of potential funders who are considering whether to support a project (Agrawal et al. 2011; Burtch et al. 2013; Kuppuswamy and Bayus 2013); the key factors affecting successful financing of crowdfunding projects (Mollick 2014); and peer and herding effects (Ward and Ramachandran 2010; Zhang and Liu 2012).

A new stream of literature has begun to investigate community and peer effects on crowdfunding platforms. Ward and Ramachandran (2010) analyzed social data on the Sellaband crowdfunding platform and suggested that peer effects, and not network externalities, influence contribution and consumption even in a public goods setting. Burtch et al. (2013) investigated crowdfunding of journal articles and found that previous investments tend to crowd-out future investors. Kuppuswamy and Bayus (2013) observed a similar effect but showed that when the financing deadline draws closer, the effect of the deadline dominates and mitigates the crowding-out effect. Agrawal et al. (2011) found that previous investments tend to generate a herding effect, increasing the likelihood of future investments. In this paper, we evaluate the formation of an informal sub-community of backer-owners. We shall provide evidence that suggests that members of this sub-community not only have distinguishable attributes but also exhibit distinctive behavior patterns, which are different from those of users who are only backers or owners of projects.

From Fundraising to Crowdfunding Platforms

Crowdfunding can be seen as a virtualization of the fundraising process (Overby et al. 2010); therefore, we review some of the related literature which studied "traditional" entrepreneurship.

Vesterlund (2003) showed that an entrepreneur might benefit from exposing potential backers to information regarding previously received contributions ('announcement strategy'), as such information may be interpreted as revealing project quality. Other Studies have shown that an entrepreneur's reputation and social capital, both offline and online, may serve as a signal to other market participants (Krumme and Herrero 2009; Lin et al. 2013; Packalen 2007).

Serial entrepreneurs have been shown to be more likely to obtain venture finance, as well as to obtain better valuations (Hsu 2007). Firm-founding experience may increase an entrepreneur's skills and social connections (Zhang 2011), and such skills and social connections can provide some advantage in the process of raising venture capital. Compared with novice entrepreneurs, entrepreneurs with venture-backed experience tend to raise more early-stage venture capital. Entrepreneurs with a track record of success are more likely to succeed than first-time entrepreneurs and those who have previously failed (Gompers et al. 2010).

Social and Network Mechanisms

Crowdfunding platforms embrace features that are common on social media websites, such as maintaining a profile page for every user, and allowing users to publish posts and comments. In the few years in which these platforms have existed, they have attracted different types of users, characterized by different participation patterns. Thus, in shaping our research, we draw from the literature regarding participation patterns in social networks and online communities.

Online communities can be formed through dedicated social interaction mechanisms such as those promoted by Prosper.com (Freedman and Jin 2014), they can rely on off-platform affiliations such as those generated on external social websites or geography (Agrawal et al. 2011; Mollick 2014), or they can be inexplicitly created by information or actions shared on the platform itself (Hsu 2007; Shane and Cable 2002). In any case, the success of a community depends on the participation and contributions of its members (Butler 2001). Zooming in on such a community, one is able to identify different groups of users, who exhibit distinct behavioral patterns.

Kim (2000) differentiates among several participation roles in online communities: visitor, novice, regular, and leader. Oestreicher-Singer and Zalmanson (2013) suggested that users who are more socially involved in a community built around a website—i.e., achieve greater levels of participation—are more likely to pay. This increased willingness to pay corresponds to evidence that, as users increase their engagement with the site, they develop a deeper sense of commitment (Bateman et al. 2011) and perceived ownership (Preece and Shneiderman 2009). This also conforms to our setting, where project backing is a manifestation of a (paid) community activity. We classify Kickstarter users into three groups (based on their participation patterns): backers, owners and backer-owners. We find that backer-owners are more successful in financing their campaigns compared to owners who did not back; we also find that backer-owners are more active on the platform than other user types: they fund and create more projects than other backers and non-backers respectively.

In the marketing literature, it is widely accepted that propagation of trends in a network relies on the existence of few mavericks, mavens and social connectors (Gladwell 2000). Although these individuals are relatively few, they often serve as *likely adopters* and increase the chances of a product's success (Hill et al. 2006). In the context of our research, we explore whether backer-owners may be regarded as mavens, i.e., whether the projects they create draw more backers and have a higher likelihood of financing success. We further investigate whether they might also be considered as social connectors and opinion leaders (Iyengar et al. 2011), as their proportion in backing projects is significantly higher than their proportion in the overall population.

Freedman and Jin (2014) evaluated the use of dedicated social networks and affiliations on Prosper.com; these social tools were designed by the platform to drive business and increase the execution of credible loans. Their research shows that while certain types of social signaling may be used to screen for borrower quality the information derived from social group affiliation and peer endorsement does not always provide a good indication of loan quality. This is also due to the fact that such dedicated on-platform social mechanisms may be manipulated by the agents. Our research draws from the notion that Kickstarter's design decision to explicitly highlight the creation and backing history of each project owner may serve as a platform for such social signaling: For example, it may provide backer-owners with an opportunity to signal their affiliation with the (virtual) community of backer-owners.

Reciprocity

Reciprocity is defined as the practice of exchanging things with others for mutual benefit. [3] We interpret reciprocity in a broader sense such that it also includes reciprocal actions carried out as a result of community norms and interactions when no direct benefits are expected.

Reciprocity is evident in electronic networks of practice (McLure Wasko and Faraj 2000; Wellman and Gulia 1999), social network formation (Gaudeul and Giannetti 2013), content consumption and contribution (Sadlon et al. 2008) and interactions in social networks (Bapna et al. 2011; Chun et al. 2008). The possibility of future reciprocity has been found to be a major motivation driving participation in and contribution to online communities (Dellarocas et al. 2003; Wang and Fesenmaier 2003). Furthermore, it has a critical effect on social network maintenance, as it enhances commitment to the community (Chan and Li 2010; Gaudeul and Giannetti 2013) and trust among community members (Nquyen et al. 2010) .

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3 Oxford Dictionary

Direct reciprocity is captured in the principle: "You scratch my back, and I'll scratch yours" (Nowak and Sigmund 2005), while *indirect reciprocity* is represented by the principles "You scratch my back and I'll scratch someone else's" or "I'll scratch your back and someone else will scratch mine". Nowak and Sigmund (2005) further divide the indirect reciprocity perception into another level of differentiation: Upstream and downstream reciprocity. The former indicates a situation in which person A, who has received a donation from person B, is now motivated to donate in return—to another person C. Downstream reciprocity is based on reputation—an individual A who helped another individual B receives help from person C, due to A's original contribution.

Indirect reciprocity is an important dynamic social force that motivates individual contributions in social networks (Flynn 2005, Faraj and Johnson (2011)). Users increase their community contributions when they observe an increase in the contributions of others or when a norm of reciprocity is established (Gu et al. 2009). Participants who engage in such contributions do not necessarily expect to receive future help from the same individuals they helped ("direct reciprocity"), but ultimately may expect to receive support from others in the community (McLure Wasko and Faraj 2000; Ekeh 1974). Faraj and Johnson (2011) have found that participation in online communities follows the norms of both direct and indirect reciprocity, and that these two dynamics coexist in the network.

Studies of online networks have indicated that a determining factor for indirect reciprocity is the availability of information about the actions of others (Gu et al. 2009), while some have further suggested that in order to encourage generalized reciprocity, all previous interactions between community members should be traceable and visible (McLure Wasko and Faraj 2000). Wang and Fesenmaier (2003) have found that the likelihood to contribute to an online community increases with the extent to which past actions are traceable.

In our study we examine manifestations of both direct and indirect reciprocity on the Kickstarter platform. We evaluate whether owners tend to reciprocate the backings of their backers (direct reciprocity) or to support owners who have previously backed others (indirect reciprocity). We further investigate whether this tendency increases with the number of an owner's previous backing actions.

Hypotheses

Placing our analysis in a formal context, we form a number of hypotheses to be tested using data associated with 68,057 Kickstarter projects. For each project in the data set, we classify the owner on the basis of his or her actions prior to that project (the "current project") and evaluate the impact of those backing actions on the financing success of the current project. We categorize *success* as a project achieving its goal and raising at least the targeted amount within the allocated timeframe[4].

Our hypotheses first explore the correlation between owners' previous backing actions and campaign success. Next, we hypothesize that owners who engage in a greater number of backing activities also tend to attract a greater number of backers compared with owners who are not as "social". We further explore whether owners who are also backers support their fellow backer-owners, which would suggest that these individuals form a quasi-social network (Provost et al. 2009) whose members enjoy particular benefits. Further, we describe the identification strategy that we use to infer *causality* between previous backing and success, and the measures we have taken to increase our confidence in the theory and mechanism. Namely, we argue that previous backing may also be part of a network exchange process, which manifests itself in both direct- and indirect reciprocity.

We expect that the success rate of funding a project increases when the project owner had previously backed other projects:

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4 Kickstarter follows the "all or nothing" business model (Hemer 2011), where a minimum project-financing goal is set and a limited time period is given for achieving said goal. The sum is transferred to the project owner only if the targeted amount is pledged within the given period. Otherwise, the project is cancelled and the backers (funders) pay nothing.

H1(a): Projects initiated by owners who have backed other projects will have a higher likelihood of raising their stated goal, compared with projects initiated by non-backers.

Hypothesis *H1(a)* defines a class of project owners and proposes that being a member of this subgroup is an indication for a higher likelihood of financing success. The hypothesis does not speculate regarding the potential mechanism that drives success. We further hypothesize that backing actions may have a cumulative effect thus the likelihood of success may be positively linked to the number of backing actions, as formulated by *H1(b):*

H1(b): Projects initiated by owners who have backed more projects will have a higher likelihood of raising their stated target amounts. The rate of financing success is increasing in the number of backing actions.

While there may be a number of mechanisms that generate a correlation between an owner's backing history and the likelihood that the owner's current project will raise its stated goal, we draw on network exchange theory and focus on the issue of reciprocity; thus, we formulate the following hypotheses:

H2(a): Projects initiated by owners who have backed other projects will have a higher number of backers compared with projects initiated by non-backers.

H2(b): The number of project backers increases with the number of owner backing actions.

The number of project backers is highly correlated with the success odds of financing a project, which could be driven by a number of dynamic explanations, rather than solely by reciprocity, the focus of this paper. Thus, we attempt to isolate measures that might purely reflect reciprocity. We generate measures that evaluate the proportion of what we consider 'reciprocity-sensitive backers' among the total number of each project's backers. In doing so, we also further define the specific attributes of owners who are also backers.

For each project, we compute the following parameters:

B	Total number of project backers
BO	Project backers who had already initiated at least one project prior to backing this project
DR	Number of project backers who were backed by the owner of this project (Direct Reciprocity)
N	Number of previous backing actions by the project owner

From these backing parameters, we compute the following per-project *reciprocity ratios*:

$$\frac{DR}{B}\ ,\ \frac{BO}{B}\ ,\ \frac{BO-DR}{B}$$

We consider $\frac{DR}{B}$ as a measure of *direct reciprocity*, while $\frac{BO-DR}{B}$ measures *indirect reciprocity*.

We further conjecture that backers who are also owners may be more sensitive to the backings of other owners; if this is the case, they may have a higher propensity to back a certain project if the project owner is also a backer (Yang and Wei 2009). If this reaction becomes more pronounced with the number of backing actions that the project's owner has engaged in, this will further support the notion of a reciprocity or community reward mechanism. Thus, we formulate the following hypothesis:

H3: Projects initiated by owners who have backed more projects have higher reciprocity ratios. These ratios are increasing in the number of backing actions.

If indeed owners who have previously backed others are more likely than non-backers to finance their current project, and if a greater number of backing actions is associated with higher reciprocity ratios, then we may be able to infer that backing actions have a causal relationship to success; our identification strategy for this purpose is elaborated below.

Our final hypotheses seek to definitively identify the occurrence of reciprocity among Kickstarter users. To this end, we switch our perspective: instead of focusing on the likelihood of a given project to be financed (as in *H1-H3*), we focus on the propensity of a given owner to *back certain projects*. Thus, we formulate the following Hypotheses:

H4(a): Project owners have a significantly higher likelihood of backing a project started by one of their backers, compared with the likelihood of backing a project whose owner did not previously back them (Direct Reciprocity).

H4(b): Project owners have a significantly higher likelihood of backing a project started by a backer-owner, compared with the likelihood of backing a similar project started by an owner who is not a reported backer (Indirect Reciprocity).

Data Collection & Description

We use data extracted from Kickstarter (www.kickstarter.com), the largest crowdfunding platform. Since its launch in 2009, more than 65,000 projects have been successfully funded on this platform, raising an aggregate amount of over $1.2 billion USD. Kickstarter reports a campaign success rate of over 40%.

Data were collected utilizing a dedicated crawler using a recursive BFS algorithm (Pinkerton 1994), which traversed the project-user and user-project links. Kickstarter does not support a public API, nor does it provide access to an organized directory of past projects and users. Its web interface does not allow for exhaustive searches. Crawling was started using a publicly available seed consisting of 45,000 projects (Pi 2012). Recursive iterations from projects to backers and back to projects were performed until the number of newly discovered projects per iteration converged. Figure 1 shows a screen capture describing the landing page of a typical project. This project screen contains details and a link to all previous projects created or backed by the project owner.

The following data was collected by the crawler:

- **Project data**: project owner, financing goal, financing duration, project creator profile, profiles of all backers (funders), detailed reward levels and reward selections, the use of a video, amount of money pledged, comments, updates, location, category, sub-category.
- **User data**:
  - Personal data: name, location, date account was opened, number of Facebook friends
  - Owner-related data: Number of projects created by Owner, links to these projects
  - Backer related data: Number of projects backed by the user, links to these projects

Every Kickstarter user may be a project owner, backer, or both.

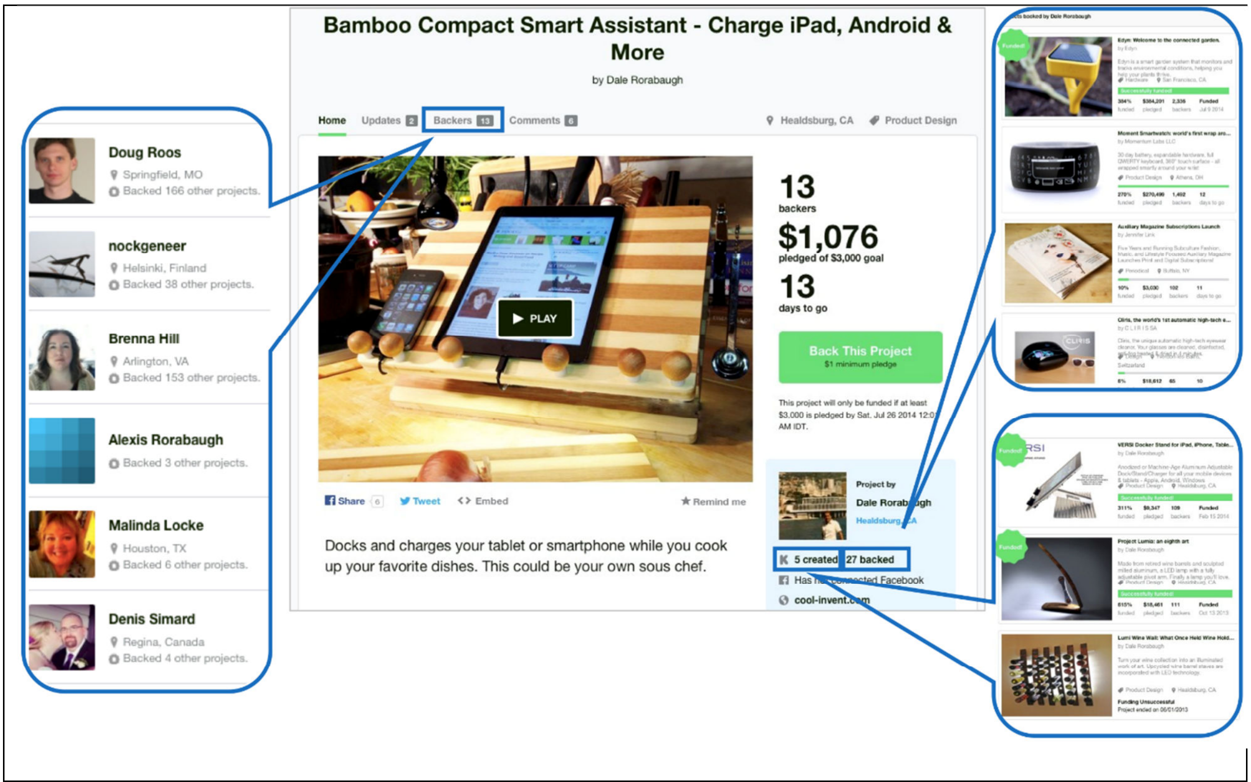

Figure 1. Screen Capture of a Kickstarter Project.

Both the funding history and the backing history of the project owner are visible and accessible

We extracted information regarding 78,061 identified projects that had been initiated prior to March 21, 2013. We removed from the data set all projects that were the campaign was not complete at the time of data collection, and projects with a target lower than $100. In addition, to prevent selection bias, we removed projects that received fewer than two backers; this was done because our method of project discovery, which relies on an iterative process of crawling from users to projects and back, has a higher probability of not discovering projects with 0 or 1 backers. We also removed very successful outliers with over 10,000 backers (fewer than 20 projects). Such projects often have very specific attributes that tend to overshadow other dynamic forces as well as create a skew when evaluating population results. For some of our regressions we were also forced to remove 1,500 failed projects whose owners had abandoned the platform, resulting in the loss of some of their profile data.

Our final data set consisted of 68,057 projects, created by 60,680 different owners. These projects received a total of 5,647,547 pledges from 3,001,417 backers. To the best of our knowledge, this is the largest and most comprehensive set of Kickstarter data that has been analyzed for research.

Among these projects, 36,869 were successfully funded (54.2%), and 31,188 (45.8%) were unsuccessful. Note that the success ratio in the evaluated data set is higher than the overall success rate reported by Kickstarter. This is due to the fact that we eliminated from our analysis all projects that failed to attract at least 2 backers.

Kickstarter divides all projects into 13 categories: Art, Comics, Dance, Design, Fashion, Film and Video, Food, Games, Music, Photography, Publishing, Technology and Theater. The most popular category (in terms of number of projects) in our data set is Film and Video (26.2% of projects), and the second most popular is Music (23.2%). The least popular category is Dance, with only 1056 (1.6%) projects. Surprisingly, this is the most successful category, with a success rate of 77.2%. Another successful category is Theater, with a 73.2% success rate. The most unsuccessful category is Fashion, with a success rate of only 37.7%.

In addition to the project attributes, Kickstarter provides its users with information about the project creator (owner). As can be seen in Figure 1, information about the creator's backing and project history is presented, along with additional personal information. The personal profile of the project owner includes details of all projects previously created or backed. For each project in our data set we collected the relevant information pertaining to the number and identity of all other projects that the owner of said project had backed. Kickstarter does not provide dates for backing actions; thus, we cross-referenced the dates of those project campaigns to identify the relative timing of such backing actions. [5]

Descriptive statistics of the project attributes used in our models are presented in Table 1.

[5] As some campaigns partially overlap in their funding period, we are faced with a challenge when identifying whether specific backing actions occurred prior to or following the start of the campaign being analyzed. We identified an owner's backing action as having an impact on the current campaign using a number of alternative specifications: (i) the campaign backed concluded before the launch of the focal project (ii) The campaign backed was launched before the focal campaign or (iii) the campaign concluded before the last date of the focal campaign. Qualitative results were similar for all of these alternative specifications.

Table 1. Descriptive Statistics – Project Attributes

Variable	Min-Max	Mean /Probability	s.dev
Goal (USD)	100-21.4M	14,587.75	193,799
Duration (days)	1-92	37.62	16.05
IsSuccessful (Goal Achieved)	0/1	.54	
Level of Funding Achieved (Raised/Goal)	0 - 1,340.9	.93	5.81
Num. of Backers	2 - 9,818	84.08	302.3
HasVideo	0/1	.83	
Num. of Reward Levels	0-138	8.71	4.86
Limits on Number of Backers in one or more reward category	0/1	.51	
Has FB Friends in profile	0/1	.52	
Time On Platform (Weeks)	0-196	22.29	28.8
Owner HadCreated Previous Projects	0/1	.1	
Num. Projects Previously Created by the Project's Owner	0-74	.19	1.45
Owner Had Succeeded	0/1	.0561	
Owner HadCreated Previous Projects but Never Succeeded	0/1	.0435	
Owner HadBacked Other Projects	0/1	.42	
Num. Projects Previously Backed by the Project's Owner [6]	0-433	1.52	5.28

Among all projects in our dataset, the owners of 6,780 projects (10% of all projects) had creation experience prior to initiating their current projects. Furthermore, 28,588 projects (42%) were created by owners who had previously backed other projects.

Table 2 includes a cross tabulation of *HadBacked* × *HadCreated.*

[6] Descriptive stats are presented using the specification where the backed campaigns were launched prior to the focal campaign.

Table 2 HadBacked × HadCreated Crosstab (at project launch)

		HadBacked		*Total*
		0	*1*	
HadCreated	*0*	*36,924*	*24,353*	*61,277*
	1	*2,545*	*4,235*	*6,780*
Total		*39,469*	*28,588*	*68,057*

The sub-population of backer-owners, i.e., owners who backed other projects prior to launching their own, comprises 34,275 individuals, 1.14% of the 3,001,417 backers in our data set. A closer examination of the backer-owner subpopulation reveals that the backing behavior of these individuals differs from that of non-owner backers. On average, non-owner backers back 1.88 projects, whereas backer-owners back 4.87 projects.

Backer-owners differ not only from the backer population but also from the general (non-backing) owner population on Kickstarter. Table 3 describes differences between projects based on the backing history of the owner. Projects initiated by owners who have also backed others attract more backers and achieve a higher rate of financing success. We will revisit these specific characteristics of the backer-owner community when we discuss the results.

Table 3. Comparing Projects Started by Owners Who Were Backers at Project Launch (Backer-Owers) to those Started by Non-Backers

Average Values		Projects of Owners with Backing History (BO) 28,588 projects	Projects of Owners without Backing History 39,469 projects	t-test P Value
Success Rate		61.8%	48.6%	0.00***
Number of Backers		124.33	54.92	0.00***
Goal		$16,968.4	$12,863.41	0.008**
Successful Projects Only	Goal	$7953.36	$5140.93	0.00***
	Money Raised	$13,551.98	$6927.93	0.00***

-Significant at the 0.01 level * - Significant at the 0.001 level

Table 4 focuses on serial entrepreneurs, detailing the financing success rates for 'second projects' classified according to the owners' backing behavior as well as the financing outcome of the first project. It can be seen that, for all four types of serial campaign owners, backing others (between the first and the second project) improves one's likelihood of achieving financing success. For example, non-backer owners whose first projects failed and who continued not to back others achieved a success rate of 45% on their second projects, while owners who changed their backing behavior between their first and second projects and backed the projects of others enjoyed a success rate of 59%.

Table 4. Success Rates of 'Second Projects'

	Backed Before First *(1779 Second Projects)*		
Success Rate *(# Projects)*	*Did Not Back Between 1st and 2nd*	*Backed Between 1st and 2nd*	*t-test P Value*
Succeeded in First *(977 Projects)*	71% *(194 successful, 80 failed)*	80% *(562 successful, 141 failed)*	*0.005****
Failed in First *(802 Projects)*	55% *(277 successful, 226 failed)*	65% *(194 successful, 105 failed)*	*0.006****

	Did Not Back Before First *(3031 Second Projects)*		
Success Rate *(# Projects)*	*Did Not Back Between 1st and 2nd*	*Backed Between 1st and 2nd*	*t-test P Value*
Succeeded in First *(1341 Projects)*	73% *(551 successful, 204 failed)*	79% *(463 successful, 123 failed)*	*0.021***
Failed in First *(1690 Projects)*	45% *(612 successful, 748 failed)*	59% *(195 successful, 135 failed)*	*0.000****

***- significant at the 0.05 level ; ***- significant at the 0.01 level*

Methodology

We start our analysis by estimating a binary logistic model for the successful financing of a new project. In our estimation, we control for project characteristics as well as project-specific design features, as suggested by existing crowdfunding literature (Burtch et al. 2013; Mollick 2014 and others). Further, we incorporate variables that characterize the out-of-project platform actions of the owner, specifically, those describing backing of other projects as well as the creation of previous projects.

As noted above, we define success as a project achieving its goal and raising at least the targeted goal. The predicted variable, *isSuccessful* has the value of 1 if a project achieves this target.

Formally, we estimate the following:

$$
\begin{aligned}
V(isSuccesful) &= \alpha + \alpha_1 Log(Goal) + \alpha_2 Duration \\
&+ \sum_{j=1}^{J} \beta_j \text{Project Category}_j \\
&+ \sum_{j=1}^{n} \gamma_j \text{ProjectAttributes}_j \\
&+ \sum_{j=1}^{K} \kappa_j \text{OwnerAttributes}_j \quad + \sum_{j=1}^{P} \delta_j \text{OwnersPastProjectInfo}_j \\
&+ \eta \text{ OwnersProjBackingInfo} \quad + \epsilon
\end{aligned}
$$

Where:

Project Category$_j$ are binary dummy variables representing 12 of the 13 Kickstarter project categories (Games, Technology, Art ….).

ProjectAttributes$_j$ are project-specific attributes that include the project's reward structure as well as the use of a video in the product description (*NumRewardCategories, HasLimitedCategory, HasVideo*).

OwnerAttributes$_j$ are Owner-specific attributes: Facebook friends and time since joining the platform (*HasFBfriends*,*TimeOnPlatform*).

Owners PastProject info$_j$ includes one or more of the variables that describe the previous project creation actions of the owner: *HadCreated* , *NumPrevCreated* , *HadCreatedAndSucceeded* , *HadCreatedAndNeverSucceeded.*

OwnersProjBackinginfo includes one of the variables that describe the project backing history of the project owner: *HadBacked or NumPrevBacked.*

The conditional probability that a project succeeds in raising its stated goal is thus: $\frac{e^V}{1+e^V}$.

We estimate a number of models based on the above described Owners PastProjectInfo$_j$ and OwnersProjBackingInfo variable combinations. In addition to full population regressions, we utilize different cut-off definitions for past backing actions as well as perform regressions on specific sub-groups of projects or owners.

When testing *H2(a) and H2(b)* we also estimate a linear regression model with the number of project backers as the explained variable. The right-hand-side variables are the same as those described for the logistic estimation except for the fact that *NumPrevBacked* is the only variable included in the OwnersProjBackinginfo variable.

In order to test *H4(a)* and *H4(b)* we use a different model specification and focus on owners' backing behavior rather than on the projects' financing outcome. We evaluate the actions of owners during and following their projects and evaluate the propensity of an observed owner to back specific projects. For this purpose, we consider the *backing decisions* of all 15,586 *first-time project owners*, within 6 months of initiating their own campaigns. For each such owner we identify all the backers who supported the owner's project as well as the space of all available projects within these 6 months. Note that the 6-month window is specific to every owner, thus eliminating any unobserved time effects, while the selection of first-time owners eliminates any unobserved residual impact from previous projects. For each project in a given space of available projects, we verify the identity of the owner and check whether the owner is also a backer; moreover, we identify those projects initiated by owners who backed the project of the owner under evaluation. Using this setup we attempt to confirm the existence of direct reciprocity and test for indirect reciprocity.

For each project presented on the platform within the 6 months following the focal owner's campaign, we compute the probability that the focal owner will back that project, conditioned on the attributes of the target project as well as the information regarding the backing actions performed by the owner of the target project. Note that the potential selection space for each owner is very large, averaging 15,350 potential project targets per owner.

For this analysis, we refer to the focal owner as a Potential Backer (also referred to as the Source Owner), and his project is called the Source Project. Each of the projects that this Potential Backer has an opportunity to invest in is referred to as a Target Project, and the owner of such a Target Project is referred to as the Target Owner. We construct a data set in which each record contains all the attributes of the Potential Backer, the attributes of the Source Project, the attributes of the Target Project and the attributes of the Target Owner.

Next, we perform a large-scale binary logistic regression where the explained variable is the occurrence of a backing action by a Source Project Owner in the specific Target Project with a specific Target Owner.

For each of these records we incorporate the previously described project- and owner attributes for both source- and target projects with the addition of the following variables:

- **TargetHadBacked**: Has the value of 1 if the Target Owner was one of the backers of the Source Project.
- **SourceSucceeded** : Has the value of 1 if the Source Project was successful in raising financing
- **IsTargetSameCatAsSource**: Has the value of 1 if the category of Target Project is the same as that of the Source Project.
- **IsTargetSameSizeAsSource**: Has the value of 1 if the size of the Target Project is the same as that of the Source Project. We categorized projects as: Small (Under $1000), Medium ($1000-$10000) or Large (over $10,000)

Note that this specification creates a very large data set with a record for every potential pair of <*Potential Backer, Target Project*>. The total number of such records exceeds 230 million.

We run a binary logistic regression where the explained variable: ***BackedTarget***, has a value of 1 if the Potential Backer has backed the Target Project and 0 otherwise. We estimate this model using random subsamples of 1000 Source Owners (i.e., Potential Backers) along with their respective selection spaces. This specification generates as many as 18,000,000 records for every 1,000 Source Owners evaluated.

Identification & Robustness Strategy

When evaluating the interplay between the backing behavior of a project owner and the financing success of his project, we wish to address three levels of analysis: correlation, causality and mechanism. When performing this task we employ various identification techniques aimed at increasing the robustness of our results, addressing issues such as unobserved characteristics, endogeneity, learning and the direction of causality. As discussed above, we also use two different objects of analysis: the outcome (financing success) of a given campaign, and the explicit backing actions of a given project owner. The latter provides us with a way to explicitly prove the existence of a reciprocity mechanism, while providing us with a methodology to control for inter-owner and inter-project homophily. We further elaborate on the identification challenges and the measures taken to address them:

The Impact of Learning and History: We use controls that correlate with learning, and analyze specific subsets of our database selected so as to decrease or normalize the effect of previous learning. For example, in some of our regressions we analyze a subsample that includes only campaigns initiated by first-time owners. This specification normalizes project history while at the same time eliminating the channel from success to backing, thus enabling us to examine the direction of causality. We also take advantage of the fact that some project owners on Kickstarter are serial entrepreneurs. Specifically, we use an entrepreneur's behavior and performance on her first project as a control for analyzing the performance of her second project. This specification enables us to perform analysis on datasets in which history and experience are more homogeneous.

In each of our regressions, the control variables include the number of projects created by the owner prior to initiation of the current project, as well as the time elapsed since the owner joined the platform.

Unobserved Characteristics: To address the concern of unobserved characteristics, we analyze the financing success of 'second projects' while controlling for the campaign outcomes and actions performed by the each project owner in her first campaign. This specification focuses on specific subgroups of owners while partially revealing some of their relevant but unobserved characteristics. For example, when evaluating the successful financing of all second projects which were initiated by owners who (a) did not back others prior to their first project and (b) failed in their first projects we are evaluating a specific subset of owners who have a lower innate tendency to back others. Second, this subgroup enables us to evaluate subsequent backing actions without the endogenous impact of success, which may affect the propensity to reciprocate. Some of the owners in this subgroup did back others between their first and second projects. This allows us to evaluate the impact of backing actions when the performance of such actions is decoupled from the initial propensity of the owner to perform such actions. We repeat this analysis for all possible backing/outcome combinations, as further detailed below.

Robustness and Stability: We perform regressions using multiple subgroup specifications as noted above, and verify that the coefficients of primary concern are stable in both their magnitude and significance. We also repeat our analysis using various cutoff dates for the definition of pre-project backing actions as well as various inclusion and exclusion criteria and verify that our results are not sensitive to these specific selections.

Mechanism Identification: to further support our assumption that network-exchange-driven-reciprocity plays a role in people's actions on Kickstarter, we evaluate the explicit backing actions of owners following the completion of their projects. We control for the attributes of the evaluated owner, his project, the Target Projects and the Target Owners. This allows us to evaluate how the backing actions of the Source Owner are affected by the backings he received as well as the backing actions of the owners of potential Target Projects that he might back. This specification allows us to control for homophily among projects and owners and isolate the impact of reciprocity *per-se*.

Further, we provide additional details regarding each of the strategies employed and their design:

Using Serial Entrepreneurs for Owner Classification: We focus this analysis on 4,810 project owners who initiated at least two projects. We evaluate the financing success of 4,810 'second projects' while using the owners' history and the results from their first project as controls and/or selection criteria. Fortunately, some of the project owners change their backing-others behavior between their first and second project, providing us with the opportunity to further decouple the impact of backing actions from unobserved owner attributes.

We run our estimation on subsets of these 'second projects' according to subgroups based on the owners' previous success and backing patterns. This specification generates four 'second project' groups such that each one of the projects is classified according to the following criteria: (i) owner succeeded in his financing first project without backing others; (ii) owner failed in financing his first project without backing others; (iii) owner succeeded in financing his first project while backing others; or (iv) owner failed in financing his first project, although he backed others prior to or during his first project. We evaluate the impact of the backing actions performed between the first and second campaigns on the financing results of the second campaign.

Formally, we re-estimate the above-described binary logistic model on each of these subsets with one modification to our main specification: The variable **OwnersProjBackinginfo** only accounts for backing actions performed by each project owner following the completion of his first project campaign.

Mechanism Identification and Controlling for Homophily

We focus this analysis on the explicit backing actions of first-time project owners during and after the completion of their crowdfunding campaign, and evaluate the propensity of each of these owners to back other projects. In this evaluation, we also incorporate all the properties and attributes of both the evaluated project and owner and every potential backing target, thus controlling for other mechanisms such as sub-group affiliations, which could provide an alternative explanation for increased backing probabilities. One possible driver for increased backing by one's peers is within-category homophily. If owners of a project in a certain category, e.g., design, tend to back projects within this category at a higher rate, one would observe an increase in co-backing actions without an active reciprocity mechanism.

To evaluate direct reciprocity and limit the countervailing effects, we evaluate a subgroup of projects, which have the following properties:

- Created by a first-time owner
- Project owner did not create any other projects within the 6 months following the selected project
- Project owner backed at least one other project within the 6 months following the selected project.

For each of the 15,586 projects that match the above criteria, we compute the probabilities for the corresponding owner to back specific projects within a 6-month window following the start of his campaign. Specifically, we look at the owner's likelihood of backing Target Projects in the following sub-groups:

- All available projects
- All projects within the same category as the owner's project
- All projects within the same category and size as the owner's project
- All projects in which the owner was a backer of the backer-owner being evaluated

- All projects within the same category, and in which the owners were backers of the backer-owner being evaluated
- All projects within the same category and size, and whose owners backed the backer-owner being evaluated

Using the same data-view of potential and actual backing actions we evaluate a logistic regression in which the explained variable is the backing action itself, while controlling for the attributes of both source and target projects as well as source and target owners as detailed in the previous section. This model allows us to explicitly identify and quantify the existence of direct and indirect reciprocity.

Results & Analysis

When evaluating the interplay between the backing behavior of a project initiator and the financing success of his project, we address three levels of analysis. Initially, we show that a correlation exists between being a backer of other projects and financing success. We then attempt to provide evidence that at least some of this correlation is generated due to a causal relationship from backing to success. Finally, we show that there is strong evidence that supports the hypothesis that a reciprocity mechanism exists on the observed platform. We then use the theoretical framework of network exchange to situate our findings in a broad context.

Table 5 reports the logistic regression estimation using the full data set as well as a subset that includes only those projects created by first-time owners. All models demonstrate that the successful funding of a project is significantly associated with the owners' backing actions, with an odds ratio for *HadBacked* in the range of 1.822 to 1.851. The estimation results of models 3, 4 and 5 also show that the odds ratio of successfully financing a project increases by more than 1.07 for each additional backing action performed by the owner.

Models 5 and 6 evaluate the subset of projects created by first-time owners, as described in the Identification and Robustness Strategy section above. The definition of backing actions in the evaluation of these models is limited to actions performed by the project owner prior to project launch. This specification eliminates the possibility of causality going from success to backing, as these owners do not have any prior project creation history, and the backing actions counted for this model only include those performed before these owners received any backing for their current project. The odds ratios for *HadBacked* and *NumBacked* in these two models are qualitatively similar to the estimates obtained when evaluating models 1 through 4.

Table 5.

Binary Logistic Regression Models

Predicting the Successful Funding of a Crowdfunding Project on Kickstarter

	Model 1	Model 2	Model 3	Model 4	Model 5 1st projects only	Model 6 1st projects only
	Exp(B) (S.E.)	Exp(B) (S.E.)	Exp(B) (S.E.)	Exp(B) (S.E.)	Exp(B) (S.E.)	Exp(B) (S.E.)
LoggedGoal	0.201*** (0.02)	0.200*** (0.02)	0.207*** (0.02)	0.207*** (0.02)	0.189*** (0.022)	0.193*** (0.022)
Duration	0.99*** (0.001)	0.99*** (0.001)	0.99*** (0.001)	0.99*** (0.001)	0.991*** (0.001)	0.991*** (0.001)
HasVideo	1.869*** (0.024)	1.876*** (0.024)	1.919*** (0.024)	1.926*** (0.024)	1.919*** (0.026)	1.969*** (0.026)
NumRewardCategories	1.099*** (0.002)	1.098*** (0.002)	1.101*** (0.002)	1.101*** (0.002)	1.099*** (0.003)	1.102*** (0.003)
HasLimitedCategory	0.844*** (0.019)	0.847*** (0.019)	0.856*** (0.018)	0.857*** (0.018)	0.850*** (0.019)	0.861*** (0.019)
WeeksOnPlatform	1.004*** (0.00)	1.004*** (0.00)	1.005*** (0.00)	1.005*** (0.00)	1.004*** (0.00)	1.005*** (0.00)
HasFBFriends	0.885*** (0.018)	0.893*** (0.018)	0.921*** (0.018)	0.919*** (0.018)	0.894*** (0.019)	0.928*** (0.019)
HadCreated	0.882*** (0.033)		0.846*** (0.033)			
HadCreated AndSucceeded		1.41*** (0.043)				
HadCreatedAnd NeverSucceeded		0.552*** (0.043)				
NumPrevCreated				0.979*** (0.007)		
HadBacked	1.834*** (0.019)	1.822*** (0.019)			1.851*** (0.021)	
NumPrevBacked			1.059*** (0.003)	1.058*** (0.003)		1.070*** (0.004)
Category Controls	Yes	Yes	Yes	Yes	Yes	Yes
Constant	85.578*** (0.084)	88.289*** (0.084)	89.264*** (0.084)	85.666*** (0.083)	94.763*** (0.091)	98.052*** (0.091)
Observations	67,040	67,040	67,040	67,040	60341	60341
Log likelihood:	77915.78	77658.36	78523.33	78540.18	70040.768	70620.869
Cox & Snell R-Square:	0.194	0.197	0.186	0.186	0.198	0.190
Nagelkerke R-Square:	0.259	0.263	0.249	0.249	0.264	0.254

- significant at the 0.05 level ; *- significant at the 0.01 level

As discussed, observed platform actions may correlate with some innate owner characteristics that are not observed but affect the ability of the project owner to create successful projects. In turn, these same characteristics could also impact the propensity to back others, thus inducing an identification problem that could influence the interpretation of the presented results. To address this concern, we re-estimated the model using only the second projects of owners who failed in their first project without backing others. Some of these owners backed other projects between their first and second projects, whereas others did not back others at all. By evaluating the subsequent projects of failed owners who did not back others prior to their first project, and comparing the success of their subsequent project based on their backing actions following their first project, we are able to further isolate the impact of backing actions *per-se* and decouple the impact of backing actions from the effect of innate unobserved owner attributes. Models 18 and 19 reported in Table 6 show that the results of this specification are qualitatively similar to those of the full set, with statistically significant odds ratios of 1.955 for *HadBackedBetweenFirstAndSecond* and 1.113 for *NumBackedBetweenFirstAndSecond.* These results support both *H1(a)* and *H1(b).*

In order to provide additional evidence for a causality channel from backing actions to financing success, we repeated the above procedure on additional samples of second projects, investigating how previous project success or failure coupled with a change in backing behavior between first and second projects, influenced the second project's likelihood of financing success. Table 6 reports the estimation results for the second projects of owners whose first projects succeeded, either with or without backing actions; it also shows the results for owners whose first projects failed, despite their having backed others. For each group we estimated the model to quantify the impact of a change in backing behavior from the first project to the next. For example, models 13 and 14, reported in Table 6, describe how backing behavior between first and second projects influences the likelihood of second-project success among owners who failed to secure financing for their first projects, although they backed others. Some of these owners continued to back prior to their second project, while others stopped backing others. Estimation results report statistically significant odds ratios of 1.608 for *HadBackedBetweenFirstAndSecond* and 1.093 for *NumBackedBetweenFirstAndSecond.* Quantitatively similar results were achieved for all other second project estimations, as reported in Table 6.

Table 6.

Binary Logistic Regression Models.

Predicting the successful funding of a Second Project incorporating owners' previous success record, previous backing behavior and second project backing behavior

	Backed Before 1st Project				Not Backed Before 1st Project			
	Succeeded in 1st		Failed in 1st		Succeeded in 1st		Failed in 1st	
	Model 11	Model 12	Model 13	Model 14	Model 15	Model 16	Model 18	Model 19
	Exp(B) (S.E.)	Exp(B) (S.E.)	Exp(B) (S.E.)	Exp(B) (S.E.)	Exp(B) (S.E.)	Exp(B) (S.E.)	Exp(B) (S.E.)	Exp(B) (S.E.)
LoggedGoal	0.373*** (0.176)	0.367*** (0.177)	0.23*** (0.175)	0.232*** (0.173)	0.367*** (0.149)	0.365*** (0.15)	0.20*** (0.128)	0.202*** (0.128)
Duration	0.987** (0.006)	0.988** (0.006)	0.969*** (0.006)	0.969*** (0.006)	0.984*** (0.004)	0.984*** (0.004)	0.984*** (0.004)	0.984*** (0.004)
HasVideo	1.567** (0.229)	1.516 (0.228)	1.276 (0.222)	1.329 (0.224)	2.276*** (0.173)	2.263*** (0.173)	1.329** (0.139)	1.383** (0.139)
NumRewardCategories	1.029 (0.016)	1.029 (0.017)	1.115*** (0.021)	1.113*** (0.021)	1.059*** (0.017)	1.06*** (0.017)	1.130*** (0.016)	1.128*** (0.016)
HasLimitedCategory	1.233 (0.18)	1.247 (0.181)	0.825 (0.178)	0.839 (0.177)	0.793 (0.15)	0.8 (0.15)	0.77** (0.12)	0.787** (0.119)
WeeksOnPlatform	1.002 (0.002)	1.0 (0.002)	1.001 (0.003)	1.001 (0.003)	1.004 (0.002)	1.004 (0.002)	1.0 (0.002)	1.001 (0.002)
HasFBFriends	0.737 (0.173)	0.714 (0.173)	1.56** (0.176)	1.591*** (0.176)	0.702** (0.14)	0.701** (0.14)	1.17 (0.115)	1.199 (0.114)
HadBackedBetweenFirst AndSecond	1.812*** (0.182)		1.608*** (0.179)		1.504*** (0.148)		1.955*** (0.15)	
NumBackedBetweenFirst AndSecond		1.086*** (0.023)		1.093** (0.038)		1.087** (0.033)		1.113** (0.044)
Category Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	79.32*** (0.697)	107.02*** (0.704)	139.286*** (0.663)	136.18*** (0.659)	178.09*** (0.77)	181.91*** (0.769)	66.04*** (0.473)	64.422*** (0.471)
Observations	977	977	798	798	1329	1329	1652	1652
Log likelihood:	963.789	954.13	910.584	910.751	1338.544	1338.422	1929.682	1942.011
Cox & Snell R-Square:	0.075	0.084	0.194	0.194	0.095	0.095	0.196	0.190
Nagelkerke R-Square:	0.114	0.128	0.262	0.261	0.142	0.143	0.261	0.253

The results presented above provide further evidence for a causal relationship from backing to successful project financing, supporting both hypotheses *H1(a)* and *H1(b)* . Backing the projects of others increases the likelihood of a subsequent successful financing; moreover, every additional backing action further increases the odds that one's own project will subsequently be financed successfully.

As discussed, mechanisms that associate previous backing actions with the probability of financing success can have roots in the dynamics of learning, reciprocity, visibility or network status. In what follows we shall attempt to provide further support for the existence of reciprocity *per-se*. We shall first provide evidence as to the correlation between the number of backing actions an owner engages in and the number of project backers he attracts, as detailed in *H2(b).* Further evidence suggesting the possible existence of reciprocity will be demonstrated using the reciprocity ratios defined in the "Hypotheses and Methodology" section. We shall then use a different model specification to provide direct evidence for the existence of an explicit reciprocity mechanism.

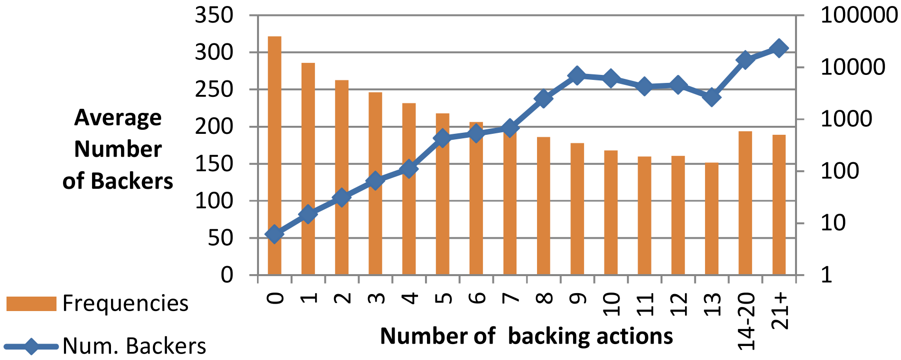

Figure 2. Number of Project Backers as a Function of the Number of Owner Backing Actions.

Figure 2 shows the average number of backers per project as a function of the number of prior backing actions undertaken by the owners of those projects. This figure suggests that an owner's backing actions not only influence her project's financing success but also the number of backers the project attracts. We executed a linear regression with the dependent variable *NumBackers,* incorporating all the variables listed in Model 4 of Table 5. The coefficient of the predictor *NumPrevBacked* was significant (3.913*** (.214)), which supports both *H2(a) and H2(b).* That is, the number of backers which a project attracts is significantly and positively related to the number of prior backing actions performed by the project owner.

We now turn to compute the *reciprocity ratios*. Note that we use the term reciprocity to identify both *direct and indirect reciprocity.* Direct reciprocity as embodied by the ratio $\frac{DR}{B}$ is easily interpreted in this setting. as *DR* enumerates pairs of owners who have backed each other's projects. Indirect reciprocity is best interpreted as some form of community response to the actions of the project owner or to the strength of the owner's group affiliation (in this case the group of owners who are also backers). Recall that for this measure we evaluate the ratio

$\frac{BO-DR}{B}$, which reflects the proportion of backers who are backer-owners but have not received direct backing from the current project owner.

Note that we have shown that the number of backers (B) that a project attracts increases with the number of backing actions performed by the project owner. In the absence of reciprocity dynamics, one might expect that this phenomenon, which causes an increase in the denominator of the reciprocity ratios, should decrease the reciprocity ratios. Figure 3 details the reciprocity ratios for projects as a function of the number of backing actions undertaken by the project owners. All reciprocity ratios show a tendency to increase with the number of backing actions performed by the project owner.

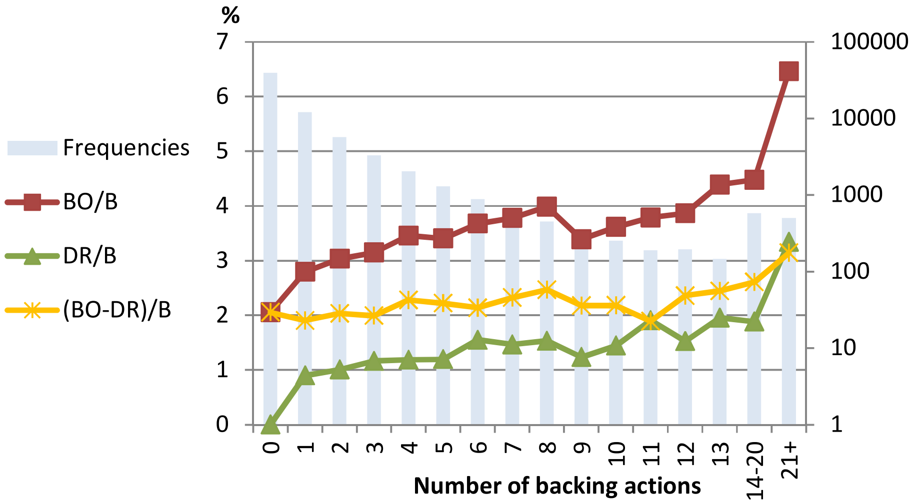

Figure 3. Reciprocity Ratios as a Function of the Number of Owner Backing Actions.

Table 7 provides summary statistics as well a comparison between average reciprocity ratios documented for projects initiated by backer-owners compared to projects initiated by owners who did not previously back other projects. Average indirect reciprocity ratios for projects initiated by owners who have a history of backing others are significantly higher than those recorded for projects initiated by owners who did not back others. These results provide support for *H3*.

Table 7. Comparing Reciprocity Ratios of Backer-Owners' and Owners' Projects

Mean Values (%)	All Projects (%)	Projects initiated by Owner with a history of backing (%)	Projects initiated by Owner who did not back others (%)	t-test P Value
BO/B	2.52	3.16	2.05	0.00***
DR/B	-	1.12	-	
(BO - DR)/B	-	2.05	-	

*** - significant at the 0.01 level

In order to prove the existence of an explicit reciprocity mechanism we evaluate a new data view which allows us to examine the explicit backing actions of project owners. We focus this analysis on the backing actions of first-time project owners during and after the completion of their crowdfunding campaign, and evaluate the propensity of each of these owners to back other projects, while taking into account the backing actions performed by the owners of such potential target projects.

On average, each owner evaluated had the opportunity to select from 15,350 projects. The average number of backing actions performed by an owner within the observed 6-month period following project initiation was 2.5 (SD 3.715). Thus, each owner's unconditional likelihood of backing a given project was approximately 0.016%. Obviously, a project's backers do not select their targets at random; it is plausible to assume that owners have a higher tendency to back projects within the same category as their own. This type of homophily could potentially produce a higher rate of mutual backings compared with a random selection, even if explicit reciprocity does not exist. To address this, our analysis controls for such potential project homophily.

Table 8 reports the propensities for an owner to back a given project within the detailed 6-month window. It is apparent that an owner's propensity to back a project of another owner who is a direct backer of one’s project is much higher than the propensity to back a project created by a non-backer.

Table 8. Propensity of a Project Owner to Back another Project Within a 6-Month Window

	Project inclusion criteria	**Propensity to Back**
Considering all projects	***All projects***	0.016 %
	Project of backing owner and target project share the same category	0.050 %
	Project of backing owner and target project belong to the same category & size	0.058 %
Considering only those projects created by the backers of the owner being evaluated	***All projects initiated by the owner's backers***	21.19 %
	All projects initiated by the owner's backers which share the same category as the owner's project	25.08 %
	All projects initiated by the owner's backers which share the same category and size as the owner's project	28.69 %
	All projects initiated by the owner's backers which have a different category than the owner's project	17.73 %
		N= 15,586

The propensity of an owner to back another project within the same category and size classification is 0.058%, three times higher than the propensity to back a randomly selected project; however the propensity to back a project owned by a user who previously backed the focal owner is 28.69%, a ratio of almost 500:1. Owners reciprocate by backing approximately one out of every 5 projects initiated by their backers. This ratio is even higher when the backer initiates a project within the same category. These results support hypothesis *H4(a)* and provide proof that direct reciprocity exists on this platform.

In our hypotheses we also postulated the existence of indirect reciprocity: owners would show an increased tendency to back another project if the other projects' owner was also a backer, not necessarily a backer of their own project. To do so, we identify those potential project targets in which the Target Owner was a backer but did not back the focal owner we are evaluating. In order to perform this evaluation, we created a data-view that included all the potential backing actions available to 15,586 owners across the 6-month windows following the launches of their respective campaigns. Note that the number of potential backing pairs in this setup is over 230 million. Due to this large data set we performed the regressions on subsets of 1000 owner and compared the results across sets for consistency. Each such regression had on average over 15 million records.

Table 9.

Binary Logistic Regression Models

Predicting the Occurrence of a Backing Action by the Source Project Owner Within 6 Months Following the Launch of the Source Project

	Model 21	Model 22	Model 23
	Exp(B) (S.E.)	Exp(B) (S.E.)	Exp(B) (S.E.)
SourceDuration	1.005*** (.002)	1.005*** (.002)	1.006*** (.002)
SourceLoggedGoal	.776*** (.049)	.763*** (.052)	.891** (.053)
SourceHadBacked	1.709*** (.050)	1.656*** (.050)	1.815*** (.054)
SourceSucceeded	.981 (.053)	1.019 (.054)	1.082 (.056)
TargetHasVideo	1.450*** (.076)	1.454*** (.076)	1.451*** (.081)
TargetDuration	.991*** (.002)	.991*** (.002)	.992*** (.002)
TargetNumRewardCategories	1.036*** (.002)	1.036*** (.002)	1.036*** (.002)
TargetHasLimitedCategory	1.034 (.046)	1.033 (.047)	1.054 (.050)
TargetHasFBFriends	.862*** (.045)	.862*** (.045)	.855*** (.048)
TargetLoggedGoal	1.731*** (.040)	1.729*** (.040)	1.858*** (.042)
TargetHadCreated	1.126 (.064)	1.123 (.065)	1.276*** (.068)
TargetHadBacked	1.812*** (.049)	1.814*** (.049)	1.725*** (.049)
IsTargetSameCatAsSource	5.079*** (.047)	5.389*** (.047)	7.031*** (.051)
IsTargetSameSizeAsSource	1.247*** (.044)	1.247*** (.044)	1.239*** (.048)
HasTargetOwnerPrevBackedSource	1014.78*** (.068)	938.16*** (.069)	No
Constant	.000*** (.262)	.000*** (.284)	.000*** (.284)
Source Project Attribute	Yes	Yes	Yes
Source Project Category Controls	No	Yes	No
Target Project Category Controls	Yes	Yes	Yes
Observations	18,856,060	18,856,060	18,853,807

- significant at the 0.05 level ; *- significant at the 0.01 level

Table 9 reports model estimations where the explained variable is the backing action itself (1-backed, 0-did not back). This set includes a potential backing space of 18,856,060 projects and 2380 backing actions performed by 1,000 owners during the 6-month period observed. Models 21 and 22 report the results for the full set, while model 23 reports the estimation of the model after removing all of the direct reciprocity pairs. These results reconfirm the existence of both direct and indirect reciprocity, supporting both *H4(a)* and *H4(b).* The odds-ratio for direct reciprocity (*HasTargetOwnerPrevBackedSource)* is between 938 and 1014, which is consistent with the propensities to back a backer reported in Table 8. The odds ratio for *TargetHadBacked* are 1.725 to 1.812 (significant at 0.01 level), reconfirming that even after controlling for project attributes, an owner's inclination to back a project created by a backer-owner is significantly higher.

Limitations

Like other empirical studies, this research faced data limitations and identification challenges. In this study we examined the campaigns after they had ended; hence, we did not have information regarding some of the dynamics that occurred during the financing period. This makes it impossible for us to incorporate herding dynamics into our analysis. A second data point that is missing in our data set is the pledge amount of each user. This information is not revealed by the platform, but the owner being funded does have access to this information, which may affect his propensity to reciprocate. Furthermore, it is impossible to completely decouple individual decisions and observed actions from unobserved backer characteristics. Also, it is possible that some of the dynamics observed are the result of community interactions that exist outside Kickstarter, either online or offline, which we have not incorporated into our analysis.

In this research we utilized the rich characteristics of our large data set which enabled the use of identification techniques designed to increase one’s confidence in the reported results as further discussed in the estimation and identification and sections.

Discussion & Conclusion

Our results provide evidence for network exchange patterns on crowdfunding platforms as manifested by both direct and indirect reciprocity. While literature has shown that such dynamics occur on other digital platforms such as forums and Q&A sites, our research suggests that this phenomenon goes beyond knowledge creation platforms and may also generate monetary rewards.

This work joins a recent stream of research that examines crowdfunding platforms from a social network perspective. Migrating the funding process online creates additional channels in which funding decisions are made, disrupting some of the known offline dynamics. One such channel is the social capital of the entrepreneur. There is a consensus that the social network of an entrepreneur affects her financing success. However, in offline settings there is a clear dichotomy between entrepreneurs and the network of potential investors. On Kickstarter, this dichotomy is challenged, by design; today's backer is tomorrow's campaign owner, and social capital is accumulated on both sides of the market. We expect that this notion may be extended to other two-sided markets in which the user may serve in a dual role.

Our results also show that the sub-community of backer-owners has distinct characteristics that set it apart from other owners as well as other backers. This sub-community is highly engaged in platform actions and provides additional community support to its members. This community-reaction seems to further increase with the backing actions of a member of this community. This sub-community forms naturally in our setting without formal links or structures to set it apart. We can assume that such a community reinforces and justifies its existence due to potential long-term as well as short-term strategic benefits to its members. The emergence of such a sub-community may also be driven by feelings of affiliation among individuals who share similar participation habits. Our results show that being a contributing member of such a community or signaling that one is a member pays off.

The literature has noted the pivotal role of sub-communities and power users in the overall performance of online platforms. Power users are often characterized by their level of activity, which in our context may be interpreted as users who are serial backers or serial entrepreneurs. In this research we propose another inclusion criterion for being considered as dominant, namely, participating in the community of users who play on both sides of the market. This research is but a first step in evaluating these dynamics in such the context of online funding.

Our results have shown that projects initiated by backer-owners have different outcomes compared with projects whose owners do not back others. Campaigns initiated by backer-owners have higher success rates, raise more money and secure pledges from a larger number of backers.

Such projects also receive a higher level of backing from other backer-owners. The rate of both success and support is increasing in the number of backing actions undertaken by the project owner.

By tracking specific backing actions of owners and evaluating the extent to which reciprocal actions were executed, we were able to provide direct proof for the existence of a mechanism of reciprocity, both direct and indirect. Using the fact that some owners create more than one project on the platform, we were able to track the impact of a change in backing behavior on the success of subsequent projects. This specification provides further evidence supporting a causal relationship from backing to financing success, while controlling for unobserved characteristics and endogeneity.

When evaluating the interplay between the backing behavior of a project initiator and the financing success of her project, we addressed three levels of analysis. Initially we showed that a correlation exists between being a backer of other projects and the likelihood of successfully obtaining financing for one's own project. We then provided evidence that at least some of this correlation is due to a causal relationship from backing to success. Finally, we provided evidence supporting the existence of a reciprocity mechanism on the observed platform.

From a platform perspective this study explores dynamics nurtured by explicit design decisions on two side markets. Our results suggest that allowing users to operate on both sides of the market, while making this activity visible to all, opens new channels which have not yet been fully investigated.

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