

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

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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 these network dynamics. We focus on project owners who choose to operate on both sides of the market, backing the projects of others. We study the impact of such out-of-project actions on the successful financing of projects. We find that an owner's backing-history has a significant effect on financing outcomes. We also show that owners who are backers form a sub-community which is active in backing projects, especially those initiated by its members. We find evidence for both direct and indirect reciprocity. Backing the projects of other is a rewarding strategy. Projects created by active backers have higher success rates, attract more backers and collect more funds.

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

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Introduction

Crowdfunding, the process of directly financing projects and ventures over the internet, is gaining momentum. Industry reports estimate that sums raised on crowdfunding platforms have nearly doubled in 2012, totaling US\$2.7B. Initially, crowdfunding was performed using social media such as mailing lists or social networks. The maturity of Web 2.0 technologies enabled and inspired dedicated crowdfunding *platforms*. These platforms create a microenvironment where long term social interaction and accumulated information influence the success of crowdfunding projects.

Crowdfunding platforms serve as two sided markets which facilitate information flow and transactions between project owners and potential project backers. In some respects many of these platforms, such as Kickstarter and Indiegogo are similar to commercial two sided markets such as Ebay or the iPhone Appstore where the platform facilitates the purchase (or pre-purchase in the case of crowdfunding) of an assortment of goods and services. However, crowdfunding platforms differ in at least one fundamental aspect: Playing both sides of the market (i.e. creating projects and backing other projects) is not only possible on crowdfunding platforms but also very visible. The public profile of a project owner on many of the crowdfunding platforms includes both a summary and a detailed record of the user's creation and backing history. This dual role may support strategic interaction as well as community interactions. In this paper we study the effect of such on-platform actions and interactions on successfully funding a crowdfunding project.

We show that project owners who play both sides of the market and back other projects create a sub community of backers which exhibits network dynamics which are different from the general backing population. Our comprehensive data set includes a total of 78,061 projects, covering more than 90% of the projects created on Kickstarter.com (ending before March 2013). These projects received 6,812,159 pledges by 3,273,893 users. From an information systems perspective, the virtualization of the physical funding process (Overby et al. 2010) has allowed exposure of information which was less accessible in the "real world" of fund raising.

Our results indicate that backing other projects, prior to or during the creation of one's current project significantly increases the funding success of the project. The probability that a project achieves its targeted goal (above which the project materializes) increases in the number of active backing actions; Furthermore the total sum raised is significantly higher for those projects where the project owner is also a backer of others.

These results may be explained using a number of network dynamics. Several studies have discussed the role of learning by doing in a similar setting (e.g., Hsu 2007). In this sense the described results may be the outcome of a learning process by which the owners of future projects learn the ins and outs of the platform by participating in platform actions and are thereby able to create or position projects which are better candidates for funding success (Gompers et al. 2010). As we shall show, some of our results suggest that learning by doing does not capture the full story. One of the most effective ways to learn about project

creation is creating multiple projects. Our results show that having a history of projects *per-se* does not increase the likelihood of financing. Furthermore when evaluating creation history together with backing actions we find that the latter dominates.

Social capital and network effect are additional dynamic forces that could be in play (Aldrich and Zimmer 1986; Dimov et al. 2007; Hoang and Antoncic 2003). When project owners increase their social stock by performing network actions (Alexy et al. 2012; Zhang 2011), they increase their network visibility (Lawton and Marom 2010), network embeddedness (Wasko and Faraj 2005), and consequently, credibility, which could eventually lead to higher funding rates for projects initiated by such owners.

A third dynamic explanation lies in the realm of reciprocity (Kollock 1999; Wasko and Faraj 2005). Network participants often reciprocate the actions of others and such reciprocal actions have an impact on measurable outcomes. As we shall show in this paper, at least some of the financing success of new projects is generated by reciprocity dynamics and community recognition. We also show that the community of backers which are also owners is not only much more active in backing projects but also exhibits specific reciprocity dynamics.

We find that both *direct* and *indirect reciprocity* is apparent (Quan-Haase et al. 2002). The relative number of backers which reciprocate on one's backing actions is increasing in the number of backing actions. The proportion of project backers which have been backed by the owner out of the total project backers is increasing in the number of owner's backing actions. This is also true for the proportion of members of the backer-owner community out of the total project backers, a phenomenon we categorize as *indirect reciprocity*. These increasing proportions are documented in spite of the fact that the total number of project backers is also increasing in the number of backing actions performed by the owner.

Another attractive feature of our evaluation is the fact that we are able to decouple between the project information aspect and the platform actions undertaken by the owner. When evaluating in-project actions (such as post, videos or project updates), studies have shown (Chen et al. 2009; Mollick 2012) that these actions have a significant impact on the funding dynamics and funding success rate of crowdfunding projects. One may note that when such actions are evaluated it is difficult to distinguish between two channels: the first is the additional content or information added to the project data; and the second is the owner action itself. In our evaluation we analyze visible actions by the project owner, however such actions do not directly provide any additional direct information pertaining to the current project. Thus this method efficiently decouples between the project specific informational action and the platform action allowing a better understanding of the impact of the platform actions and network interaction *per-se*. From an information systems perspective, the decision of which information should be highlighted by platform designers affects the evolutionary dynamics of the platforms (Tiwana et al. 2010).

In economic terms we show that on average, owners who are also backers achieve a higher financing ratio and raise significantly larger amounts per project.

Background

Using the “The wisdom of the crowd” (Surowiecki 2005) for producing or supporting a product has become widespread; one such form is *Crowdfunding* (Belleflamme et al. 2010), the process of directly financing projects and ventures over the internet. A few studies have looked into the relationships between project owners and their crowd: Hemer (2011) explores the different business models of crowdfunding intermediaries, and discusses the economic relevance of crowdfunding and its applicability to start-up financing and funding. Agrawal *et al.* (2011) investigate the relations between artist-entrepreneurs and investors based on geographic and personal dimensions (“friends and family”).

Recent studies (Gerber et al. 2012; Ward and Ramachandran 2010) are looking into social and community aspects of crowdfunding platforms. Ward and Ramachandran analyzed social data of the Sellaband crowdfunding platform and suggest that peer effects, and not network externalities, influence consumption. Gerber et al. find that crowdfunding platforms are gradually adopting social networks attributes, and funders are looking for social interactions in those platforms. Zooming in on the “crowd” one is able to identify different groups of users which have their own behavioral patterns. These groups are formed via using the information exposed by the platform, and via the social interaction mechanism available on the platform and outside of it (Hsu 2007; Mollick 2012; Shane and Cable 2002).

Our work draws on and adds to the literature examining social and community aspects of online Web 2.0 platforms.

From Fundraising to Crowdfunding Platforms

Literature regarding “physical” fundraising (not online) suggests that exposing potential backers to the information regarding already received contributions (‘announcement strategy’) may be optimal because it helps reveal the project’s quality (Vesterlund 2003). Also, positive entrepreneur reputation serves as a positive signal to potential investors that there is a higher chance of success (Packalen 2007). Researches in the area of peer-to-peer lending platforms, have found that the social capital of the borrower can serve as a trustworthiness signal to the potential lenders (Krumme and Herrero 2009; Lin et al. 2013).

Serial entrepreneurs are more likely to obtain venture finance, as well as obtain better valuations (Hsu 2007). Firm-founding experience increases entrepreneur’s skills and social connections (Zhang 2011). Such skills and social connections could give experienced founders 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 much more likely to succeed than first-time entrepreneurs and those who have previously failed (Gompers et al. 2010). These entrepreneurs exhibit persistence in selecting the right industry and time to start new ventures.

Crowdfunding can be seen as a virtualization of the fundraising process (Overby et al. 2010). It is considered a phenomenon that has passed the embryonic stage and is now rapidly moving towards the growth stage (Giudici et al. 2012). It owes its great popularity and success mainly to the maturity of Web 2.0 technologies, the global financial crisis (and the difficulties in raising funds for entrepreneurial projects), and the success of crowdsourcing (Giudici et al. 2012; Kleemann et al. 2008).

Crowdfunding can be divided into different types according to the method of raising money from the crowd: equity purchase; loan; donation; or pre-ordering / reward-based (Ahlers et al. 2012; Belleflamme et al. 2010). The latter method follows the "all or nothing" business model (Hemer 2011), where a minimum project financing goal is set and a limited 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. Pledging a payment entitles the project backer to receive a specific reward, typically this reward shall be one or more products, developed as part of the project, participation in an event or a special credit / thank-you gesture.

A new and developing research stream on crowdfunding is currently emerging. It involves multiple disciplines: finance, economics and management, sociology, and information systems (Giudici et al. 2012). The main research interests in this area include the motivation to participate in crowdfunding – both from the initiator and the funders sides (Belleflamme et al. 2010; Schwienbacher and Larralde 2012), the decision-making process of potential funders whether to support a project (Agrawal et al. 2011; Burtch et al. 2012; Kuppuswamy and Bayus 2013), the key success factors of a crowdfunding project (Mollick 2012), herding effect (Zhang and Liu 2012), and the social attributes of crowdfunding platforms (Ward and Ramachandran 2010).

Recent results by Marom and Sade (2013) investigate success factors of projects on Kickstarter. They show that experience from previous projects is only somewhat correlated with success in future projects, however having previous successes increases future success chances from 51% for novice entrepreneurs to 80% for entrepreneurs having more than 3 previous successful projects.

Social and Network Mechanisms

A recent study (Oestreicher-Singer and Zalmanson 2013) shows that there is a correlation between the user's willingness to pay and using social features on Web 2.0 websites. They suggest that users, who are more socially involved in the community built around the site, have a tendency to pay for premium content. As they increased their engagement with the site, they develop a deeper sense of commitment to the website (Bateman et al. 2011) and perceived ownership (Preece and Shneiderman 2009). This also conforms to our findings, where project backing is a manifestation of a (paid) community activity.

A successful community depends on the participation and contributions of its members (Butler 2001). Kim and Srivastava (2007) find that Web-based social communities drive the volume of traffic to retail sites and become a starting point for Web shoppers, Wasko and Faraj (2005) find that people tend to

contribute (their knowledge) when they are structurally embedded in the network. Surprisingly, contributions also occur when expectation of reciprocity as well as network commitment are low. Online participation may be rationalized via several mechanisms, including: increased recognition (Kollock 1999; Rheingold 1993), reciprocity (Wasko and Faraj 2005), Shin & Hall 2013), sense of community (Quan-Haase et al. 2002) and altruism (Lakhani and Von Hippel 2003).

In our study we indeed find evidence of community behavior. We find evidence for both direct and indirect reciprocity. Users who had previously created a project invest in projects created by their backers. We also find evidence of indirect reciprocity – Backer-Owners tend to back projects created by frequent Kickstarter backers. This tendency increases as the owner has backed more projects.

Kim (2000) differentiates among several participation roles in online communities: visitor, novice, regular and leader. In the context of our work this may be mapped to Kickstarter visitors without an account, users who have created an account but have not backed a project, backers, project owners and users who are both backers and owners. Li and Bernoff (2011) develop a ladder-type graph known as ‘social technographics profiling’, which uses findings from large-scale surveys to create profiles of online behavior. Preece and Schneiderman (2009) propose a ‘Reader to Leader’ framework with emphasis on different needs and values at different levels of participation. The different approaches were summarized by Oestreicher-Singer and Zalmanson (2013). Our research identifies three user groups based on their participation patterns: backers, owners & backer-owners. 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.

Bateman et al. (2011) show that users’ behavior on content sites is directly linked to their commitment levels, as defined by the organizational commitment theory (Meyer and Allen 1991). Community participation is derived from *affective commitment*, whereas community leadership was shown to be correlated with *normative commitment* (Bateman et al. 2011). Leaders of online communities have been shown to be the most active (Cassell et al. 2006; Yoo and Alavi 2004). These results also conform to our findings: many of Kickstarter backers, which can be considered as *community participants*, indeed back multiple projects (1.88 on average), demonstrating affective commitment. Backers who are also project owners, whom can be seen as *community leaders*, are very active in the community (about 2.5 times their proportion of the population, backing 4.87 projects on average).

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 they are relatively few, they often serve as *likely adopters* and increase the success chances of a product (Hill et al. 2006). In the context of our research we find that backer-owners may be regarded as mavens as the projects they create draw more backers and have a higher likelihood of financing success. They may also be considered as social connectors and opinion leaders (Iyengar et al. 2011) as their proportion in projects is higher than their proportion in the overall population.

Hypothesis and Methodology

Placing our analysis in a formal context, we form a number of hypotheses to be tested using the project backing and creation actions of owners of 68,057 Kickstarter projects.

We classify all owners based on their actions prior to or during their currently offered project and evaluate the impact of their backing actions on the success of their current project. We categorize success as a project achieving its goal and raising at least the targeted goal amount. We expect that the success rate of funding new projects increases when the project owner had previously backed other projects:

H1(a): Projects initiated by owners who have backed other projects will have a higher likelihood of succeeding in raising the stated goal.

Hypothesis *H1(a)* has the property of defining a class of project owners, whereby being part of this subgroup is an indication for a higher rate of success. It does not yet speculate regarding the potential mechanism which drives the result. As we have reciprocity as well as possible community status in mind we wish to evaluate if the increased rate of success is linked to the number of backing actions, thus we hypothesize:

H1(b): Projects initiated by owners who have backed more projects will have a higher likelihood of succeeding in raising the stated goal. The rate of success will be increasing in the number of backing actions.

In order to support our claim that owner's backing actions have an impact on a project's funding success we expand our analysis to specific project subgroups. Backing actions may drive success, however past success may also drive backing actions. We evaluate the existence of causality from backing to success by evaluating a subgroup of projects which include only the first project of every owner together with backing actions performed prior to project initiation.

Recent studies have shown that increased success may be associated with certain owner attributes. One may suspect that some of these innate attributes also impact the propensity to back others. In order to improve our identification and address this endogeneity concern we further evaluate a subgroup of projects initiated by project owners who have already exhibited success. We attempt to identify if a change in the backing-others property (from a non-backer to a backer) increases the likelihood of subsequent successful financing.

When engaging in platform actions an owner potentially accumulates some information and knowledge. The success of projects may be linked to the experience gained by an owner's previous platform interactions. It would be reasonable that significant learning exists when one creates projects on platform. If learning is a primary force, we would expect that prior project creation experience would increase the chances of succeeding in the new project financing thus we formulate:

H2(a): Projects initiated by owners who have created one or more projects in the past will have a higher likelihood of succeeding in raising the stated goal.

If learning is a prominent mechanism for improving the success rate of one's project we should expect to see an increase in the success rate as an owner has created more projects thus we may expect to show that:

H2(b): Projects initiated by owners who have created more projects in the past will have a higher likelihood of successfully raising the stated goal of a subsequent project. The rate of success will be increasing in the number of previous projects created.

It could be the case that learning is not the primary factor generating a correlation between an owner's platform history and the success of the current project. In such a case previous actions, while not providing significantly relevant experience may nevertheless convey a signal regarding the quality of the owner. Thus it could be that owners would not increase their chances of success by creating projects *per se* but that their track record (i.e. have they succeeded or not based on having attempted a project) could impact the success of the current project:

H2(c): Projects initiated by owners who have a history of succeeding in previous projects will have a higher likelihood of successfully raising the stated goal of a subsequent project.

Obviously a negative signal may also be conveyed by an owners project history, thus we hypothesize that:

H2(d): Projects initiated by owners who have attempted to create projects but have not been able to succeed will have a lower likelihood of successfully raising the stated goal of a subsequent project.

While there may be a number of dynamic mechanisms which generate a correlation between an owner's backing history and the success of the owner's current project we wish to focus on the issue of reciprocity, whether it is individual reciprocity by those specific owners which repay a backing or some community reciprocity. Thus we formulate the following:

H3: Projects initiated by owners who have backed other projects will have a higher number of backers. The number of project backers will increase with the number of owner backing actions.

The number of project backers is highly correlated with the success of a project which could be driven by a number of dynamic explanations, thus we attempt an investigation into measures which are better tied into reciprocity. As detailed in the data descriptions section we generate reciprocity measures which evaluate the proportion of what we consider reciprocity sensitive backers to the total number of each project's backers, in doing so we also further define the specific attributes of owners which are also backers.

For each project we compute the following parameters:

B	Total number of Project Backers
$BOCurr$	Project Backers who had already initiated at least one project prior to backing this project
BO	Project Backers who had owned a project either before or after backing this project
M	Number of Project Backers who were backed by the owner of this Project
N	Number of previous backing actions by the project owner

From these backing parameters we compute the following per project ratios:

$$\frac{M}{B}, \frac{BO}{B}, \frac{BO-M}{B}, \frac{BOCurr}{B}, \frac{BOCurr-M}{B}$$

Note that backers in the $BOCurr$ category were owners of one or more projects at the time they backed the current project, while backers in the BO group are categorized as such even when their personal project was created following their current backing action. We call these ratios *reciprocity ratios*. We conjecture that backers who are also owners may be more sensitive to the backings of other owners, thus in such a case they may have a higher propensity to back a certain project when the project owner is also a backer. If this reaction increases with the number of backing actions, this will further support the notion of a reciprocity or community reward mechanism. Thus we formulate the following hypothesis:

H4: Projects initiated by owners who have backed more projects will have higher reciprocity ratios. These ratios will be increasing in the number of backing actions.

We consider $\frac{M}{B}$ as a measure of *direct reciprocity*, while $\frac{BO-M}{B}$ and $\frac{BOCurr-M}{B}$ are measures of *indirect reciprocity*. Indirect reciprocity results may also be explained by homophily, where members of the backer-owner's sub community have a higher propensity to invest in other backer-owners.

Estimation Methodology

We estimate a logistic model for the successful financing of a new project. In our estimation we control for project characteristics as well as project specific design feature and integrate the variables which 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.

We categorize success as a project achieving its goal and raising at least the targeted goal amount. The predicted variable, `isSuccessful` has the value of 1 if a project achieved this target.

Formally we estimate the following:

$$\begin{aligned}
V(isSuccessful) &= \alpha + \alpha_1 LogGoal + \alpha_2 Duration \\
&+ \sum_{j=1}^J \beta_j Project\ Category_j \\
&+ \sum_{j=1}^K \gamma_j ProjectAttributes_j + \alpha_3 HasFBFreinds \\
&+ \sum_{j=1}^P \delta_j Owners\ PastProject\ info_j + \eta OwnersProjBackinginfo + \epsilon
\end{aligned}$$

Where:

Project Category_j are binary dummy variables representing 12 out the 13 Kickstarter project categories (Games, Technology, Art ...).

ProjectAttributes_j are project specific attributes which include the project's reward structure as well as the use of a video in the product description (*NumRewardCategories*, *HasLimitedCategory*, *HasVideo*).

Owners PastProject info_j includes one or more of the variables which describe the previous project creation actions of the owner: *HadCreated* or *NumPrevCreated* or *HadCreatedAndSucceeded* alongside *HadCreatedAndNeverSucceeded*.

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

Variables are described in more detail in the data description section.

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 PastProject info_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.

In order to provide an indication as to the existence of causality from backing actions to financing success we repeated our estimations using a subset which includes only projects initiated by first time owners. In These estimations we also limited the backing actions to those performed prior to project initiation. This specification eliminates the channel from previous success to backing others, as the set only includes first-time owners.

In order to improve our identification and address the possible endogeneity attributed to owner attributes and capabilities we repeated the estimations using multi-project owners who have succeeded in securing financing for their first project without backing any other projects. We evaluated the backing actions of these owners and compared the success rate of their second project based on their backing actions between the first and the second project.

When testing $H3$ we use a linear regression model with the number of project backers (B) as the explained variable. The right hand side variables are the same as those described for the logistic estimation models except for the fact that only *NumPrevBacked* is used as the *OwnersProjBackingInfo* variable.

Data Collection

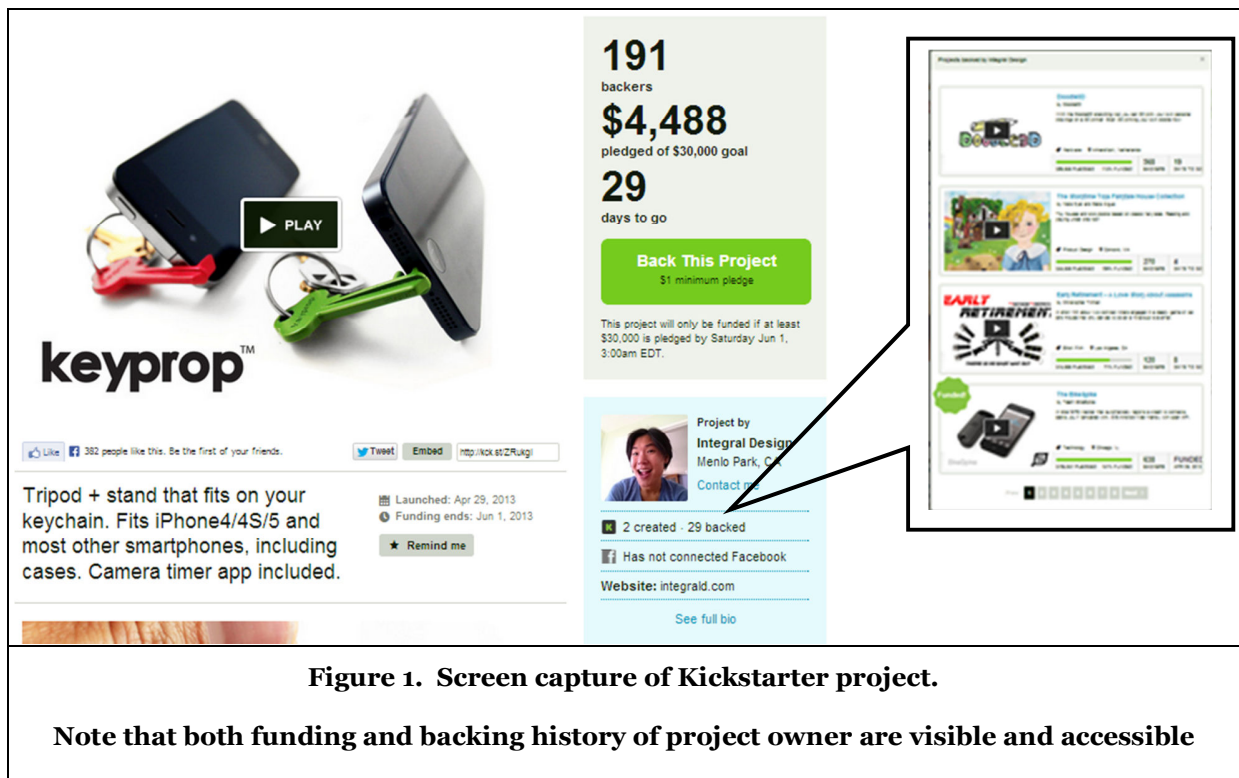
We use data extracted from Kickstarter (www.kickstarter.com) the largest crowdfunding platform. Since its launch in 2009 more than 42,000 projects were successfully funded on this platform, raising an aggregate amount of over 500 Million US\$. Kickstarter reports a success rate of over 40%.

Data was collected utilizing a dedicated crawler using a recursive BFS algorithm which traversed the project-user & 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 publically 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 typical screen capture describing the landing page of a project. This project screen contains details and a link to all previous projects created or backed by the project owner.

The following data presented by Kickstarter 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 FB friends
 - Owner related data: Number of and links to all projects created by Owner
 - Backer related data: Number of and links to all projects backed by the user

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



We crawled the Kickstarter site from January 21 until March 21 2013, and recorded the details of 78,061 projects. As we wish to evaluate the success rate of project funding as well as the funding results we focus on projects which have ended. We thus removed from the dataset all projects which were not finished when crawled. We further removed projects with a target lower than \$100 and projects which received less than two backers. The later projects were removed in order to prevent a selection bias. Our method of project discovery has the undesirable effect of having a higher probability of not discovering projects which had 0 or 1 backers as we use an iterative process from users to projects and back. Thus we selected to remove all such projects from the set. We also removed very successful outliers with over 10,000 backers. Such projects often have very specific attributes which tend to overshadow other dynamic forces as well as create a skew when evaluating population results.

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

Among these projects, 36,869 were successfully funded (54.2%), and 31,188 (45.8%) were unsuccessful.

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 dataset is Film and Video (26.2% of projects), and the second one is Music (23.2%). The most unpopular 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 only 37.7% success rates.

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 creating history is presented, along with additional personal information. The personal profile of the project owner includes details of all projects previously created or backed.

Table 1. Descriptive Statistics – Project Attributes

Variable	Min-Max	Mean /Probability	s.dev
<i>Goal (USD)</i>	100-21.4M	14,587.75	193799.22
<i>Duration (days)</i>	1-92	37.62	16.05
<i>IsSuccessful (Goal Achieved)</i>	0/1	0.54	
<i>Level of Funding Achieved (Raised/Goal)</i>	0 - 1,340.9	0.93	5.81
<i>Num. of Backers</i>	2 - 9,818	84.08	302.3
<i>HasVideo</i>	0/1	0.83	
<i>Num. of Reward Levels</i>	0-138	8.71	4.86
<i>Limits on Number of Backers in one or more reward category</i>	0/1	0.51	
<i>Has FB Friends in profile</i>	0/1	0.52	
<i>Owner HadCreated Previous Projects</i>	0/1	0.1	
<i>Num. Projects Previously Created by the Project's Owner</i>	0-74	0.19	1.45
<i>Owner Had Succeeded</i>	0/1	.0561	
<i>Owned HadCreated Previous Projects but Never Succeeded</i>	0/1	.0435	
<i>Owner HadBacked Other Projects</i>	0/1	0.42	
<i>Num. Projects Previously Backed by the Project's Owner</i>	0-433	1.52	5.28

For each project in our dataset we calculated the relevant information which pertains to the number of other projects the owner of this project had backed prior to project launch. Kickstarter does not provide dates for backing actions, thus we used the current project backing list from each owner's profile and cross checked it with the dates which pertain to the backed projects. For each project evaluated we included a project in the list of projects backed by the owner if the backed project has *started before* the

said project has started.^b For every project we also calculated the number of projects which satisfy this condition. We also identified and recorded the success history of the project owner at the time of project start. Descriptive statistics of the projects attributes used in our models are presented in Table 1.

Among all projects in our dataset, the owners of 6,780 projects (10% of all projects) had creation experience prior to initiating their current project. Backing history of an owner has much higher rates - 28,588 projects (42%) were created by owners who backed other projects before creating their subsequent project. Table 2 includes a crosstabulation of *HadBacked* x *HadCreated*

Table 2 HadBacked x HadCreated Crosstab

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

Focusing on the sub-population of owners who had backed other projects (before, during or after creating their own project) yields a new type of user – "Backer-Owner" (BO). Among 3,001,417 unique backers in our dataset, the BO sub-population comprised of 34,275 backer-owners (1.14%). Comparing the total backings of all backers and of backer-owners suggests that backer-owners have different patterns of backing. While the average number of backing by a non owner is 1.88, the average number of backing actions by a backer-owner is much higher – 4.87 backings.

Table 3 describes differences between owners who have not backed other projects, and backer-owners. BOs create more projects than non-backer owners and their projects are significantly more successful in achieving the targeted financing goal.

Table 3. Comparing Backer Owners and Non-Backer Owners

Mean Values	<i>BO (56.46%)</i>	<i>Non-BO (43.56%)</i>	<i>t-test P Value</i>
<i>Number of Projects Created</i>	1.15	1.08	0.00***
<i>Success Rate (Reaching the finance goal)</i>	63.6%	41.4%	0.00***
<i>Level of Funding Achieved over All Projects (% of goal)</i>	106%	65%	0.00***

*** - Significant at the 0.001 level

^b In order to evaluate the robustness of our exclusion criteria as well as the cutoff dates for calculating the backing variables we tested a number of alternatives. We also evaluated our models and tested our results using a modified definition for producing the owner's pre project backing history, considering only those projects which *finished before* the said project has started. This approach guarantees that the owner backing indeed occurred before project launch. Qualitative results were similar for these alternative specifications.

Table 4 describes differences between projects based on the backing history of the owner at the time of the project.

Table 4. Comparing Projects Started by Owners which were Backers at Project Launch to those Started by Non-Backers

Mean Values	<i>BO (42%)</i>	<i>Non-BO (58%)</i>	<i>t-test P Value</i>
<i>Number of Backers</i>	124.33	54.92	0.00***
<i>Success Rate (Reaching the finance goal)</i>	61.8%	48.6%	0.00***
<i>Level of Funding Achieved over All Projects (% of goal)</i>	118%	76%	0.00***

*** - Significant at the 0.001 level

It is evident that these two subpopulations on the Kickstarter platform behave differently and achieve their goals with very different probabilities. We will revisit these specific characteristics of the BO community when we discuss the results.

Results & Discussion

Table 5 reports the logistic regression estimation results on the full data set as well as a subset of first projects. All models demonstrate that the successful funding of a project is significantly associated with the owners backing actions. Backing other projects significantly increases likelihood of success with an odds ratio for *HadBacked* in the range of 1.94 to 2.004. The estimation results of models 3,4 & 5 show that the odds ratio of successfully financing the project increases by more than 1.07 for each additional backing action performed by the owner.

Models 5 & 6 evaluate a subset of projects which have been created by first time owners. The definition of backing actions in the evaluation if these models is limited to actions performed by the project owner prior to project initialization. This specification eliminates the possibility of causality going from success to backing actions as these owners do not have any prior project creation history and the backing actions evaluated only include actions performed before these owners have received any backing for the current project. The odds ratios for *HadBacked* and *NumBacked* in these two models are qualitatively similar to the estimates obtained when evaluating all projects in models 1 to 4. . This provides support for the existence of a significant causality from backing to success.

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	Model 6
	Exp(B) (S.E.)	Exp(B) (S.E.)	Exp(B) (S.E.)	Exp(B) (S.E.)	Exp(B) (S.E.)	Exp(B) (S.E.)
<i>LoggedGoal</i>	0.202*** (0.02)	0.201*** (0.02)	0.207*** (0.02)	0.207*** (0.02)	0.197*** (0.021)	0.194*** (0.021)
<i>Duration</i>	0.99*** (0.001)	0.99*** (0.001)	0.99*** (0.001)	0.99*** (0.001)	0.990*** (0.001)	0.991*** (0.001)
<i>HasVideo</i>	1.877*** (0.024)	1.883*** (0.024)	1.938*** (0.024)	1.938*** (0.024)	1.999*** (0.026)	1.962*** (0.026)
<i>NumRewardCategories</i>	1.099*** (0.002)	1.098*** (0.002)	1.102*** (0.002)	1.102*** (0.002)	1.105*** (0.003)	1.102*** (0.003)
<i>HasLimitedCategory</i>	0.848*** (0.019)	0.85*** (0.019)	0.863*** (0.018)	0.863*** (0.018)	0.874*** (0.019)	0.866*** (0.019)
<i>HasFBFriends</i>	0.929*** (0.018)	0.936*** (0.018)	0.982 (0.017)	0.982 (0.017)	1.00 (0.018)	0.965 (0.019)
<i>HadCreated</i>	1.014 (0.03)		1.005 (0.03)			
<i>HadCreated AndSucceeded</i>		1.638*** (0.043)				
<i>HadCreatedAnd NeverSucceeded</i>		0.601*** (0.043)				
<i>NumPrevCreated</i>				0.994 (0.007)		
<i>HadBacked</i>	2.004*** (0.019)	1.966*** (0.019)				1.946*** (0.022)
<i>NumPrevBacked</i>			1.07*** (0.003)	1.07*** (0.003)	1.097*** (0.005)	
<i>Category Controls</i>	Yes	Yes	Yes	Yes	Yes	Yes
<i>Constant</i>	85.238*** (0.083)	88.002*** (0.084)	89.303*** (0.083)	89.947*** (0.082)	98.170*** (0.090)	96.308*** (0.090)
Observations	68,057	68,057	68,057	68,057	61,277	61,277
Log likelihood:	79223.514	78921.75	80055.487	80054.925	72107.602	71577.638
Cox & Snell R-Square:	0.194	0.197	0.184	0.184	0.186	0.193
Nagelkerke R-Square:	0.259	0.264	0.246	0.246	0.248	0.257

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

Observed platform actions may correlate with some innate characteristics which are not observed but have a positive impact on 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 which could impact the interpretation of the presented results. To address this concern we re-estimated the model using only the second projects of owners who were successful in their first project without backing others. Some of these owners backed other projects between their first and second project while others did not back others at all. By evaluating the subsequent projects of successful owners who did not

back others prior to their first success 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 further decouple the impact of backing actions from the effect of innate owner attributes. This specification produced results qualitatively similar to the full set with statistically significant odds ratios of 1.626 for *HadBacked* and 1.104 for *NumBacked* supporting both *H1(a)* and *H1(b)*.

As discussed, mechanisms which associate previous backing actions with an increased probability for success can have roots in the dynamics of learning, reciprocity, visibility or network status. In what follows we shall attempt to show that at least some of these results are driven by reciprocity related forces.

The coefficients estimated for *HadCreated* as well as *NumPrevCreated* do not produce significant results. Hypothesis *H2(a)* and *H2(b)*, which were based on the assumption that owners on-platform experience, as embodied in project creation, increases the chances for subsequent success, cannot be supported by the data.

The odds ratio for *HadCreatedAndSucceeded* is significantly above 1 (1.638) which supports *H2(c)*. Demonstrating previous success significantly increases the probability to achieve the goal set for subsequent projects. This result could be explained if potential backers use this information as a signal for the quality of the owner. It could also be explained by the fact that success is a separating mechanism which identifies better entrepreneurs which have a greater chance of succeeding, regardless of the signaling mechanism.

The odds ratio for *HadCreatedAndNeverSucceeded* is significantly below 1 (0.601) which supports *H2(d)*. Demonstrating that having only failures to show-for significantly decreases the probability to achieve the goal set for subsequent projects. This result could be explained by the same signaling or separating mechanism detailed for its positive counterpart.

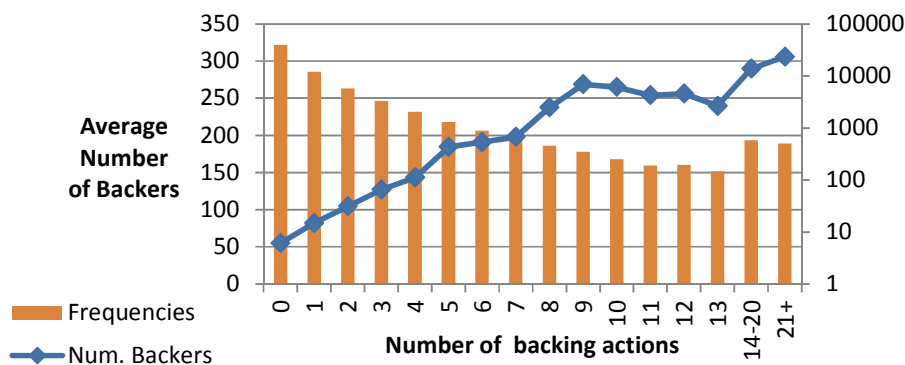


Figure 2. Number of project backers as a function of the number of owner backing actions.

We executed a linear regression with the dependent variable *NumBackers*, incorporating all of the variables listed in Model 4 of Table 5. The coefficient of the predictor *NumPrevBacked* was 3.913*** (.214) which supports H3. Backing actions of a project’s owner significantly increase the number of project backers. Figure 2 shows the average number of backers per project based on the number of owner backing actions.

Backing actions not only increase the chances of success but also the number of backers. These combined results have a measurable economic impact on the financing outcome of projects initiated by Owners which are also active Backers.

Table 6. Comparing the financial average achieved by Backer Owners

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 6 describes the success ratios and financial parameters comparing projects initiated by owners which were backers prior to or during their project, to projects initiated by non backing owners. The differences are significant. Projects initiated by BOs target a higher goal, achieve a higher financing rate and collect a much higher \$ amount of pledges in their successful projects. Successful projects initiated by BOs raise, on average, almost twice as much money. It is worth noting that the success rate of BO initiated project is higher despite of the fact that on average they also set significantly higher goals which should have had a negative impact on the rate of success.

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

for this measure we evaluate the ratios $\frac{BO-M}{B}$ and $\frac{BOcurr-M}{B}$ which serve as an indication for the rate of backing by other BOs who have not received direct backing from the current project owner.

Note that we have shown that the number of project backers increases with number of owner’s backing actions. In the absence of reciprocity dynamics, one might expect that an increase in the denominator should decrease these ratios as the number of backing actions increases. However, figure 3 details the reciprocity ratios for projects based on the number of owner backing actions. All reciprocity ratios show a tendency to increase with the number of backing actions performed by the project owner.

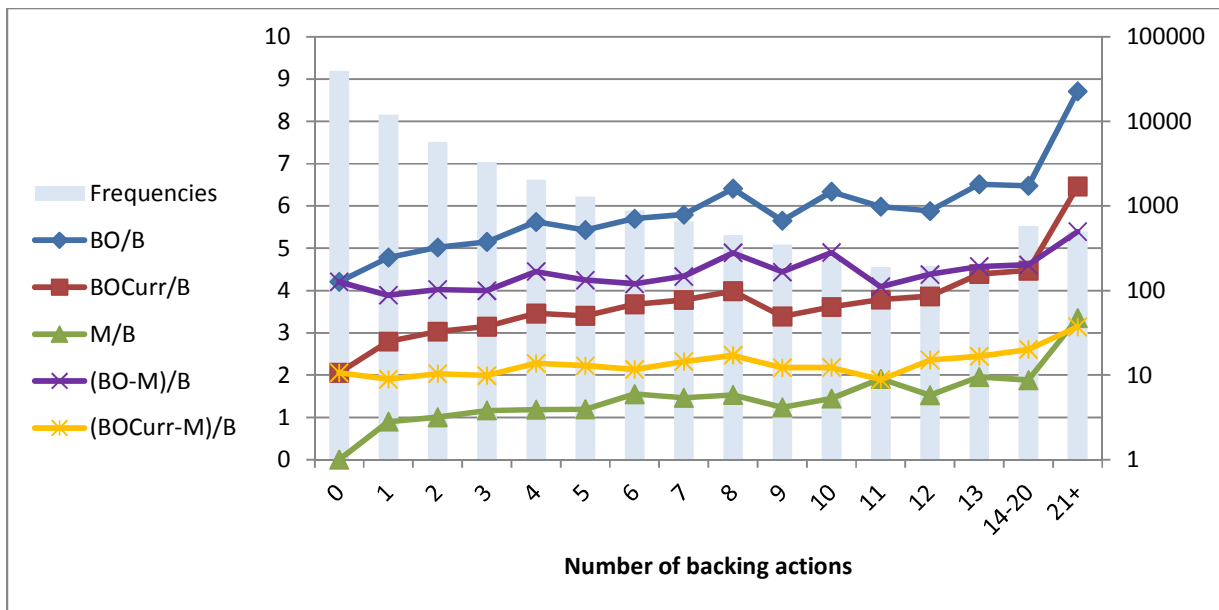


Figure 3. Reciprocity Ratios as a function of the number of owner backing actions.

Table 7 provides summary statistics as well a comparison between average reciprocity ratios documented for projects initiated by BOs compared to projects initiated by owners who have never backed other projects. These results provide further support for H_4 .

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

Mean Values (%)	All Projects (%)	Projects with Backing History (%)	Projects without Backing History (%)	t-test P Value
<i>BO/B</i>	4.62	5.19	4.2	0.00***
<i>BOcurr/B</i>	2.52	3.16	2.05	0.00***
<i>M/B</i>	-	1.12	-	
<i>(BO-M)/B</i>	-	4.08	-	
<i>(BOcurr-M)/B</i>	-	2.05	-	

*** - significant at the 0.01 level

Conclusion

Our results have shown that projects initiated by owners who have backed other owners (BOs) have different outcomes when compared to those initiated by owners who have not backed others. Projects initiated by BOs have a higher success rate, raise more money and secure pledges from a larger number of backers. Moreover the number of backing actions by an owner has a significant impact on the likelihood of successfully financing the project. Such projects also receive a higher level of backing from other BOs. This increased rate of support which we called *indirect reciprocity* is increasing in the number of backing actions.

The increased success of BOs may be explained by a number of nonexclusive mechanisms: learning, reciprocity, community recognition or increased visibility. It may also be an observation which relates to some unobserved characteristics of the owner which are correlated with both the observed actions and his or her ability to succeed. By utilizing various model specifications and project subgroups we have provided evidence that suggests that a significant part of the increased funding success is caused by the backing actions *per-se*. We have also provided support that at least some of these results are driven by communality interactions and reciprocity-like behavior. This explanation is also supported by the fact that the reciprocity ratios described are correlated with the backing actions of the owner.

We have also demonstrated that the sub-community of backer-owners has distinct characteristics which set it apart from other owners as well as other backers. This sub-community is much more 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. Such a sub-community may also exist as members have a stronger feeling of affiliation with other members who share their participation habits. This research is but a first step in evaluating these dynamics in such a context of online funding.

While sub-communities and reinforcing interactions are common in online social networks, crowdfunding platforms create a setting where such interaction may also generate monetary rewards. Our results show that being a contributing member of such a community or signaling that you are such a member pays-off. Our results indicate that the return to this investment is significant. Future research is required to investigate the strategic nature of such actions.

References

- Agrawal, A. K., Catalini, C., and Goldfarb, A. 2011. "The Geography of Crowdfunding," Working Paper 16820, National Bureau of Economic Research. <http://www.nber.org/papers/w16820>.
- Ahlers, G., Cumming, D., Guenther, C., and Schweizer, D. 2012. "Signaling in Equity Crowdfunding," *Available at SSRN 2161587*.
- Aldrich, H., and Zimmer, C. 1986. "Entrepreneurship through social networks," *University of Illinois at Urbana-Champaign's Academy for Entrepreneurial Leadership Historical Research Reference in Entrepreneurship*.
- Alexy, O. T., Block, J. H., Sandner, P., and Ter Wal, A. L. 2012. "Social capital of venture capitalists and start-up funding," *Small Business Economics* (39:4), pp. 835-851.
- Bateman, P. J., Gray, P. H., and Butler, B. S. 2011. "Research Note—The Impact of Community Commitment on Participation in Online Communities," *Information Systems Research* (22:4), pp. 841-854.
- Belleflamme, P., Lambert, T., and Schwienbacher, A. 2010. "Crowdfunding: tapping the right crowd," in *International Conference of the French Finance Association*, pp. 11-13.
- Burtch, G., Ghose, A., and Wattal, S. 2012. "An Empirical Examination of the Antecedents and Consequences of Contribution Patterns in Crowd-Funded Markets," *Available at SSRN 1928168*.
- Butler, B. S. 2001. "Membership size, communication activity, and sustainability: A resource-based model of online social structures," *Information systems research* (12:4), pp. 346-362.
- Cassell, J., Huffaker, D., Tversky, D., and Ferriman, K. 2006. "The language of online leadership: Gender and youth engagement on the Internet," *Developmental Psychology* (42:3), pp. 436-449.
- Chen, X.-P., Yao, X., and Kotha, S. 2009. "Entrepreneur passion and preparedness in business plan presentations: a persuasion analysis of venture capitalists' funding decisions," *Academy of Management Journal* (52:1), pp. 199-214.
- Dimov, D., Shepherd, D. A., and Sutcliffe, K. M. 2007. "Requisite expertise, firm reputation, and status in venture capital investment allocation decisions," *Journal of Business Venturing* (22:4), pp. 481-502.
- Eisenmann, T., Parker, G., and Van Alstyne, M. W. 2006. "Strategies for two-sided markets," *Harvard business review* (84:10), pp. 92.
- Gerber, E. M., Hui, J. S., and Kuo, P. 2012. "Crowdfunding: Why people are motivated to post and fund projects on crowdfunding platforms," In *Proceedings of the International Workshop on Design, Influence, and Social Technologies: Techniques, Impacts and Ethics*.
- Giudici, G., Nava, R., Rossi Lamastra, C., and Verecondo, C. 2012. "Crowdfunding: The New Frontier for Financing Entrepreneurship?," *Available at SSRN 2157429*.
- Gladwell, M. 2000. *The tipping point: How little things can make a big difference*, Little, Brown and Co.
- Gompers, P., Kovner, A., Lerner, J., and Scharfstein, D. 2010. "Performance persistence in entrepreneurship," *Journal of Financial Economics* (96:1), pp. 18-32.
- Hemer, J. 2011. "A snapshot on crowdfunding," *Working Papers*.
- Hill, S., Provost, F., and Volinsky, C. 2006. "Network-based marketing: Identifying likely adopters via consumer networks," *Statistical Science*, pp. 256-276.
- Hoang, H., and Antoncic, B. 2003. "Network-based research in entrepreneurship: A critical review," *Journal of business venturing* (18:2), pp. 165-187.
- Hsu, D. H. 2007. "Experienced entrepreneurial founders, organizational capital, and venture capital funding," *Research Policy* (36:5), pp. 722-741.
- Iyengar, R., Van den Bulte, C., and Valente, T. W. 2011. "Opinion leadership and social contagion in new product diffusion," *Marketing Science* (30:2), pp. 195-212.
- Kim, A. J. 2000. *Community building on the web: Secret strategies for successful online communities*, Addison-Wesley Longman Publishing.
- Kim, Y. A., and Srivastava, J. 2007. "Impact of social influence in e-commerce decision making," in *Proceedings of the Ninth International Conference on Electronic commerce, ACM*, New York, NY, USA, pp. 293-302.
- Kleemann, F., Voß, G. G. and Rieder, K. 2008. "Un (der) paid Innovators: The Commercial Utilization of Consumer Work through Crowdsourcing," *Science, Technology & Innovation Studies* (4:1), pp. 5-26.

- Kollock, P. 1999. "The Economies of Online Cooperation: Gifts, and Public Goods in Cyberspace," in *Communities in cyberspace*, M.A. Smith and P. Kollock (eds.), Routledge, New York, pp. 220-239.
- Krumme, K. A., and Herrero, S. 2009. "Lending behavior and community structure in an online peer-to-peer economic network," in *International Conference on Computational Science and Engineering*, pp. 613-618.
- Kuppuswamy, V., and Bayus, B. L. 2013. "Crowdfunding Creative Ideas: The Dynamics of Project Backers In Kickstarter," SSRN Working Paper.
- Lakhani, K. R., and Von Hippel, E. 2003. "How open source software works: "free" user-to-user assistance," *Research policy* (32:6), pp. 923-943.
- Lawton, K., and Marom, D. 2010. *The Crowdfunding Revolution: Social Networking Meets Venture Financing*, CreateSpace Independent Publishing Platform.
- Li, C., and Bernoff, J. 2011. *Groundswell: Winning in a world transformed by social technologies*, Harvard Business School Press.
- Lin, M., Prabhala, N. R., and Viswanathan, S. 2013. "Judging borrowers by the company they keep: friendship networks and information asymmetry in online peer-to-peer lending," *Management Science* (59:1), pp. 17-35.
- Marom, D., and Sade, O. 2013. "Are the Life and Death of a Young Start-Up Indeed in the Power of the Tongue? Lessons from Online Crowdfunding Pitches," *Available at SSRN 2255707*.
- Meyer, J. P., and Allen, N. J. 1991. "A three-component conceptualization of organizational commitment," *Human resource management review* (1:1), pp. 61-89.
- Mollick, E. 2012. "The dynamics of crowdfunding: Determinants of success and failure," *Available at SSRN 2088298*.
- Oestreicher-Singer, G., and Zalmanson, L. 2013. "Content or Community? A Digital Business Strategy for Content Providers in the Social Age," *MIS Quarterly* (37:2), pp. 591-616.
- Overby, E., Slaughter, S. A., and Konsynski, B. 2010. "Research Commentary—The Design, Use, and Consequences of Virtual Processes," *Information Systems Research* (21:4), pp. 700-710.
- Packalen, K. A. 2007. "Complementing capital: The role of status, demographic features, and social capital in founding teams' abilities to obtain resources," *Entrepreneurship Theory and Practice* (31:6), pp. 873-891.
- Pi, J. 2012. "AppsBlogger." <http://www.appsblogger.com/kickstarter-infographic> Visited: May 1, 2013
- Preece, J., and Shneiderman, B. 2009. "The reader-to-leader framework: Motivating technology-mediated social participation," *AIS Transactions on Human-Computer Interaction* (1:1), pp. 13-32.
- Quan-Haase, A., Wellman, B., Witte, J. C., and Hampton, K. N. 2002. "Capitalizing on the net: Social contact, civic engagement, and sense of community," *The Internet in everyday life*, pp. 291-324.
- Rheingold, H. 1993. *The virtual community: Homesteading on the electronic frontier*, Addison Wesley Publishing Company.
- Schwienbacher, A., and Larralde, B. 2012. "Crowdfunding of small entrepreneurial ventures," in *The Oxford Handbook of Entrepreneurial Finance*, D. Cumming (ed.), Oxford University Press, pp. 369-391
- Shane, S., and Cable, D. 2002. "Network ties, reputation, and the financing of new ventures," *Management Science* (48:3), pp. 364-381.
- Surowiecki, J. 2005. *The Wisdom of Crowds*. Random House Digital, Inc.
- Tiwana, A., Konsynski, B., and Bush, A. A. 2010. "Research Commentary—Platform Evolution: Coevolution of Platform Architecture, Governance, and Environmental Dynamics," *Information Systems Research* (21:4), pp. 675-687.
- Vesterlund, L. 2003. "The informational value of sequential fundraising," *Journal of Public Economics* (87:3), pp. 627-657.
- Ward, C., and Ramachandran, V. 2010. "Crowdfunding the next hit: Microfunding online experience goods," in *Workshop on Computational Social Science and the Wisdom of Crowds*.
- Wasko, M. M., and Faraj, S. 2005. "Why should I share? Examining social capital and knowledge contribution in electronic networks of practice," *MIS Quarterly* (29:1), pp. 35-57.
- Yoo, Y., and Alavi, M. 2004. "Emergent leadership in virtual teams: what do emergent leaders do?," *Information and Organization* (14:1), pp. 27-58.
- Zhang, J. 2011. "The advantage of experienced start-up founders in venture capital acquisition: Evidence from serial entrepreneurs," *Small Business Economics* (36:2), pp. 187-208.

Zhang, J., and Liu, P. 2012. "Rational herding in microloan markets," *Management science* (58:5), pp. 892-912.