# PLAYING ON BOTH SIDES OF THE MARKET: EVIDENCE FROM A CROWDFUNDING PLATFORM

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This version: August 2017

## ABSTRACT

*Crowdfunding platforms constitute two-sided markets, bringing together entrepreneurs and potential backers. This peer-based schema facilitates new dynamics where entrepreneurs can easily play on both sides of the market, supporting the ventures of their peers. Using a database of over 6,500,000 pledges and 75,000 projects we find that this phenomenon is both prevalent and instrumental. We estimate the effects of such actions on crowdfunding outcomes and show that campaigns initiated by entrepreneurs who have previously supported others attract more backers and have higher success rates. Exploiting the existence of serial entrepreneurs we find support for a sequential process where playing on both sides of the market precedes and predicts increased crowdfunding success. Entrepreneurs that increase their backing-other activity increase their subsequent financing success.*

**Keywords:** Crowdfunding, Peer-Economy, Two-Sided-Markets, E-Finance

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We thank conference participants at the 8th bi-annual conference on the Economics of Intellectual property, software and the Internet, Toulouse, France ; the 7th conference on the economics of information and communication technology, Paris, France; the 12th ZEW conference on the economics of ICT, Mannheim, Germany and the 34th International Conference on Information Systems, Milan, Italy as well as seminar participants at the Harvard Business School, the University of Vienna, Tel-Aviv University and the University of Haifa for valuable feedback and insights. This paper is a substantially revised version of a conference paper which was circulated under the title: "Playing both sides of the market, success and reciprocity on crowdfunding platforms".

# 1. INTRODUCTION

Crowdfunding, the process of directly financing ventures over the Internet, has gained significant momentum. Industry reports estimate that crowdfunding has reached over 35 billion dollars in 2015, more than double the sum reported for 2014. Crowdfunding and many of the growing peer-economy markets are most often executed on dedicated platforms which facilitate information flow and transactions. In the classic incarnation of many of these markets, a clear dichotomy exists between the professional service provider and the individual consumer. On peer-economy platforms, such as Kickstarter, Airbnb, and Uber, this dichotomy is challenged, by design; today's backer is tomorrow's campaign owner, and today's guest is tomorrow's property owner; reputation and capital and knowledge may be accumulated on both sides of the market.[1] This setting raises the question whether agents who play on both sides of the market may increase their performance and gain a competitive edge over their peers. In this paper we study this phenomenon in the context of crowdfunding.

Classic offline funding is one example where entrepreneurs and investors most often constitute mutually exclusive groups. This is not the case on crowdfunding platforms, where investing in the campaign of others before and after one's own campaign is not only possible but also visible. In this study we focus on such 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 use a comprehensive data set harvested directly from Kickstarter (www.kickstarter.com), one of the largest rewards-based platforms. Our data set includes 6,561,975 campaign pledges from

[1] A recent poll published by Time Magazine and the Aspen Institute shows that as of November 2015, 44% of US adults reported participating in a peer-economy transaction. Many of those participating as offerors also reported participation as users. (http://time.com/4169532/sharing-economy-poll/)

3,263,259 users covering all backers which supported 75,039 projects. This unique data set allows us to investigate the following questions: How prevalent is "playing on both sides of the market"'? Does an owner who backs others receive more backings? Does backing the projects of others correlate with campaign success? Does backing the projects of others prior to one's own campaign impact financing outcomes?

We first document the existence of playing on both sides of the platform and show that more than 22% of project owners also engage in backing projects of others, prior to their own campaign. We find that projects initiated by owners who backed others prior to their own campaign have a significantly higher probability to succeed. Furthermore, the probability that a project achieves its targeted financing goal and the number of backers it secures increase in the number of backing actions performed by its owner. We also find that the propensity to receive a backing from a potential backer increases when the project owner is also a backer of other projects.

Further, we investigate whether the action of backing others predicts and increases the likelihood of future financing success. As with other observational studies, estimating a regression on a heterogeneous cross-sectional set is subject to endogeneity due to the confounding effects of omitted variables. Backing others may be correlated with innate characteristics of "good" campaign owners, thus we could, for example, be associating the additional success to backing actions while in reality they could be a manifestation of differences in some innate characteristic. To address these issues we exploit the existence of serial entrepreneurs in our data set. When these entrepreneurs start their *second campaign*, we already have important additional information regarding their first campaign. Specifically, we know whether (1) their first campaign was successful, and (2) we know whether the entrepreneur supported the campaigns of

others before starting her first campaign. Fortunately, a significant number of serial entrepreneurs change their backing patterns between their first and second project; thus, we can explore the impact of a change in the backing behavior of individual entrepreneurs. Doing so, we are able to study the impact of recent project backings while controlling for the past track record and behavior of the evaluated owners. We analyze the financing success of these "second projects" while controlling for the campaign outcomes and actions performed by each project owner in her first campaign as well as any changes in the backing others behavior of each owner. We control for project characteristics, category, geography and other covariates proposed in the literature (Agrawal et al. 2015; Burtch et al. 2013; Kuppuswamy and Bayus 2013; Mollick 2014). Our estimation shows a significant effect of backing others (between the first and the second campaign) on the success of the second campaign, which provides further support for the notion that entrepreneurs that increase their tendency to back the projects of others increase their subsequent success. Furthermore, project owners that change their "backing others" behavior following their first campaign and back the projects of others prior to their subsequent campaign, succeed at a rate that is significantly higher compared with project owners that remain *non-backers*. This estimation strategy is also useful in controlling for additional alternative explanations such as previous project experience and the reverse channel from success to backing.

Evaluating the explicit backing actions of platform participants we are also able to directly identify the increased propensity of potential backers to support projects initiated by owners who previously backed others. We do so by explicitly evaluating the projects that each platform participant selects to back out of his potential selection space, while controlling for individual

fixed effects. We find that potential backers are significantly more likely to back campaigns initiated by owners who previously backed others.

Using this method we are also able to identify the existence of reciprocal backings. We find that project owners back campaigns created by their backers with a propensity that is significantly higher than that which they grant others. We identify such mutual backings while controlling for other dynamics that are evident on the platform. One such force is *homophily* (Lazarsfeld and Merton 1954); that is, two owners may support each other 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 (in terms of category, size and geography), and show that mutual backings are not only a result of homophily.

This paper contributes to the existing literature by being the first to evaluate the phenomenon of playing on both sides of the market in an online two-sided market. It conceptualizes and demonstrates that capital (whether, social or informational) that is useful on one side of the market may be accumulated by operating on the other side. Evaluating such forces in an online crowdfunding setting also facilitates the explicit quantification of the interaction between entrepreneurs who back the projects of others, financing success and backer support. It is also the first to explicitly identify mutual backing actions among same-side participants. We also show that backing others makes for increased financing success and direct financial returns. We shed new light on emerging peer-economy dynamics, where playing on both sides of the market is not only possible but potentially profitable. From a methodology perspective, this paper applies a novel identification technique by using serial entrepreneurs, to untangle selection bias and endogeneity while providing further control for unobserved characteristics.

## 2. RELATED LITERTURE

Our study relates to the growing literature on crowdfunding platforms. A recent survey by Belleflamme et al. (2015) focuses on the economic forces that impact the design of crowdfunding platforms and the manifestation of these forces in the execution of financing campaigns. The motivation of crowdfunders to back certain projects and the dynamics which impact campaign success have received significant attention. A number of papers emphasize the effect of reported cumulative backings on the propensity to grant a backing (Mollik 2014, Agrawal et al. 2015; Burtch et al. 2013; Kuppuswamy and Bayus 2013, Zhang and Liu 2012). This evidence provides support for the notion that potential backers search for information on the backing actions of others when deciding on their own action. However, all of the previous papers studying the effect of backing actions focused on the backing actions of project supporters while we focus on the phenomenon of backing actions executed by project owners.

The same stream of literature studies the impact of campaign parameters, such as the financing goal, campaign duration or having a video as part of the campaign description. We use these findings in our research and integrate such campaign parameters as controls. Agrawal et al. (2015) focus on the geographic proximity of backers and entrepreneurs on a crowdfunding platform which supports music artists (Sellaband), and find that such proximity increases the probability of receiving support in the early stages of a project campaign. Agrawal et al. (2015) attribute these results to offline connections (friends and family) between the entrepreneur and some of her potential backers. Lin and Viswanathan (2015) also find evidence for "home bias" on crowdfunding platforms. When we evaluate the dynamics of granting a backing we use the geographic location of the participants to control for such effects.

Marom and Sade (2013) study the impact of self-reference in a project's description on campaign success, while Marom et al. (2015) study the impact of the owner's gender on crowdfunding success. Both papers show how attributes which pertain to the project owner may impact campaign success even after controlling for project characteristics. Duarte et al. (2012) study pictures of loan seekers on Prosper, a peer-to-peer lending platform, and find that the lender's perceived trustworthiness, as independently assessed by his published profile picture, significantly correlates with the outcome of loan requests. While we do not claim that backing others necessarily impacts the trustworthiness of campaign owners this result has some qualitative similarities to the results that we report; neither the picture of the loan seeker nor the number of backings performed by a project owner should be expected to directly impact the outcome of the considered backing.

Mollick (2014) and others have found that previous success (or failure) by a crowdfunding entrepreneur impacts the success of her future campaigns. In our research we use the previous track record of serial entrepreneurs and control for its impact on both subsequent backing actions and campaign success.

Our research also relates to the classic literature on venture financing. Literature on offline financing indicates that an entrepreneur's previous track record affects her success. 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 (Packalen 2007). Serial entrepreneurs have been shown to be more likely to obtain venture finance, as well as to obtain better valuations (Hsu 2007). Compared with novice entrepreneurs, entrepreneurs with venture-backed experience tend to raise more early-stage venture capital. Research has also found that 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). Crowdfunding platforms allow us to investigate this idea from a novel perspective, studying not only the entrepreneur's history as an entrepreneur but also his history as a backer of others. Furthermore, we integrate the results which pertain to previous success and serial entrepreneurs into our models so as to increase the robustness of our results and control for these potential forces.

Shane and Cable (2002) study the ties between entrepreneurs and seed-stage investors and show how such ties impact the selection of ventures to fund. In the context of crowdfunding we study the impact of ties created when one entrepreneur receives a backing from another entrepreneur, a "relationship" which, we show, has a significant effect on future project backings.

Our study also relates to the emerging literature on peer-economy platforms. Einav et al. (2015) review the existing peer-economy literature and address the market design of such platforms, focusing on the search, matching, pricing and reputation systems which enable entry of new entities. However, to the best of our knowledge, the phenomenon of playing on both sides of a peer-market and outcomes associated with it have not yet received much research attention.

In this paper we investigate playing on both sides of the market in a crowdfunding context; backing the projects of others and creating one's own campaign. We exploit the crowdfunding setup where financing transactions, both current and past, are not only visible, but are also traceable. We show that this phenomenon is both prevalent and instrumental. Backing the projects of others is correlated with receiving more backings as well as increasing one's probability of success. We also provide evidence for an active channel from entrepreneur's activity on one side of the market to success on the other side. These findings suggest the important role of new dynamics enabled by the emergence of peer platforms.

## 3. DATA AND DESCRIPTIVE STATISTICS

We use data extracted from Kickstarter (www.kickstarter.com), the largest crowdfunding platform to date. Our data set consists of 75,039 projects which completed their campaign prior to March 21, 2013. These projects were created by 66,152 different owners that received a total of 6,561,975 pledges from 3,263,259 unique backers.

Data was scraped 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 backers to projects were performed until the number of newly discovered projects per iteration converged.

The crawler collected the following data:

- **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, subcategory.
- **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

Figure 1 shows a typical project page on Kickstarter as it was presented during the period covered by this research. The page provides details about the project as well as information pertaining to the project owner. It clearly shows the number of projects previously created or

backed by the project owner and facilitates easy access to all of these previous projects with a click of a button. The overlays to the left and right of the project page on Figure 1 display the type of data that can be viewed when clicking on the relevant links. This information was also visible to all potential project backers.

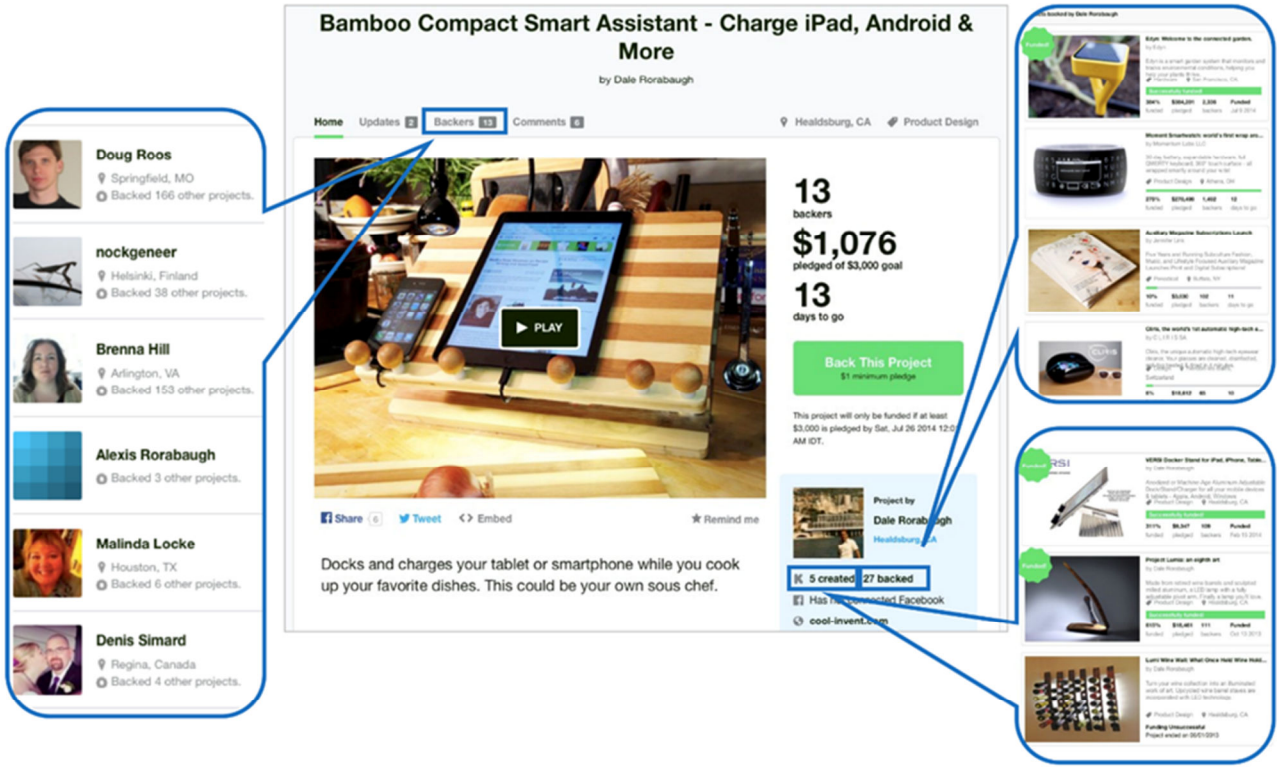


**Figure 1. Screen Capture of a Kickstarter Project.**
Both the funding history and the backing history of the project owner are visible and accessible.
(Note that the Kickstarter policy changed in 2015 and backer information is not public anymore.)

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 this project had backed. Kickstarter does not provide dates for backing actions; thus, we cross-referenced the dates of project campaigns to identify the relative timing of such backing actions.[2]

[2] We define a backing action as occurring prior to the launch of the focal campaign when such a timing sequence can be verified (i.e., when the backed campaign was concluded prior to the launch of the campaign being analyzed).

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Kickstarter employs an all-or-nothing contract; a campaign succeeds and the project owner receives the pledged funds only if the accumulated pledges secured exceed the targeted goal. This creates well-defined success criteria which we use in our empirical evaluations. 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 (26.6% of projects), and the second most popular is Music (22.8%). The least popular category is Dance, with only 1104 (1.5%) projects. Surprisingly, this category is the most successful one, with a success rate of 73.6%. The least successful category is Fashion, with a success rate of only 32.6%. Over all categories, 49% of financing campaigns were successful.

Descriptive statistics of the project attributes used in our models are presented in Table I. In our data set, the owners of 7521 projects (10% of all projects) had creation experience prior to initiating their current projects. Furthermore, 19,064 projects (25.4%) were created by owners who had previously backed other projects. Table II includes a cross-tabulation of *HadBacked* × *HadCreated.*

22% of first time project owners back others prior to initiating their own campaign, while the total population of backer-owners, that is, owners who backed other projects prior to launching any one of their campaign, comprises 16,683 individuals; about 25% of all owners. Interestingly, the backing behavior of backer-owners also differs from that of non-owners. On average, non-owner backers back 1.96 projects, whereas backers who are also owners back 4.94 projects, moreover backer-owners who start backing prior to their own financing campaign back on average 7.23 projects.

**Table I.**

**Descriptive Statistics – Project Attributes**

| Variable | Min-Max | Mean /Probability | s.dev |
|---|---|---|---|
| *Goal (USD)* | 0.01-21.4M | 15,251.18 | 204,528 |
| *Duration (days)* | 1-92 | 37.87 | 16.31 |
| *IsSuccessful (Goal Achieved)* | 0/1 | .49 | |
| *Level of Funding Achieved (Raised/Goal)* | 0 – 15,066 | 1.68 | 71.95 |
| *Num. of Backers* | 0-87,142 | 87.45 | 754.32 |
| *HasVideo* | 0/1 | .80 | |
| *Num. of Reward Levels* | 0-138 | 8.44 | 4.83 |
| *Limits on Number of Backers in one or more reward category* | 0/1 | .50 | |
| *Has FB Friends in profile* | 0/1 | .51 | |
| *Time On Platform (Weeks)* | 0-196 | 21.45 | 28.19 |
| *Owner HadCreated Previous Projects* | 0/1 | .10 | |
| *Num. Projects Previously Created by the Project's Owner* | 0-78 | .20 | 1.64 |
| *Owner Had Succeeded* | 0/1 | .053 | |
| *Owner HadCreated Previous Projects but Never Succeeded* | 0/1 | .047 | |
| *Owner HadBacked Other Projects* | 0/1 | .25 | |
| *Num. Projects Previously Backed by the Project's Owner* | 0-401 | .89 | 4.19 |

**Table II.**

***HadBacked* × *HadCreated* Crosstab (at Project Launch)**

| | | *HadBacked* | | *Total* |
|---|---|---|---|---|
| | | *0* | *1* | |
| *HadCreated* | *0* | *52,586* | *14,932* | *67,518* |
| | *1* | *3,389* | *4,132* | *7,521* |
| *Total* | | *55,975* | *19,064* | *75,039* |

Backer-owners differ not only from the backer population, but also from the general (non-backing) owner population on Kickstarter. Table III describes differences between projects based on the backing history of the owner at project launch. Projects initiated by owners who have previously backed others attract more backers and achieve a higher rate of financing success. The success rate of projects initiated by owners with a prior history of backing is 63.1% compared with a success rate of 44.5% for those owners who have not backed others prior to their campaign.

**Table III.**
**Comparing the Campaigns of Owners Who Were Backers at Project Launch to those Started by Non-Backers**

| Average Values | | Projects of Owners with Backing History (BO) 19,064 projects | Projects of Owners without Backing History 55,975 projects | t-test P Value |
|---|---|---|---|---|
| Success Rate | | 63.1% | 44.5% | 0.00*** |
| Number of Backers | | 147.93 | 66.85 | 0.00*** |
| Goal | | $16,375.73 | $14,868.18 | .379 |
| Successful Projects Only | Goal | $8235.28 | $6131.79 | 0.00*** |
| | Money Raised | $16,344.99 | $9399.05 | 0.00*** |

*** - Significant at the 0.001 level

Table IV 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 their first project. It can be seen that, for all four types of serial campaign owners, backing others between their first and 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 41% on their second projects, whereas 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 IV.**

**Success Rates of Serial Entrepreneurs in their "Second Project"**

| | **Backed before First** *(988 Second Projects)* | | |
|---|---|---|---|
| Success Rate *(# Projects)* | *Did Not Back between 1st and 2nd* | *Backed between 1st and 2nd* | *t-test P Value* |
| **Succeeded in First** *(554 Projects)* | 71% *(137 successful, 56 failed)* | 82% *(296 successful, 65 failed)* | *0.005*** |
| **Failed in First** *(434 Projects)* | 54% *(183 successful, 154 failed)* | 66% *(64 successful, 33 failed)* | *0.037*** |

| | **Did Not Back before First** *(4281 Second Projects)* | | |
|---|---|---|---|
| Success Rate *(# Projects)* | *Did Not Back Between 1st and 2nd* | *Backed Between 1st and 2nd* | *t-test P Value* |
| **Succeeded in First** *(1832 Projects)* | 71% (816 successful, 341 failed) | 79% (541 successful, 147 failed) | *0.000**** |
| **Failed in First** *(2449 Projects)* | 41% (893 successful, 1292 failed) | 59% (157 successful, 108 failed) | *0.000**** |

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

## 4. EMPIRICAL 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 the 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:

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

where:

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

**ProjectAttributes**$_{\text{j}}$ are project-specific attributes that include the project's reward structure as well as the use of a video in the product description and the reported geographical location (*NumRewardCategories, HasLimitedCategory, HasVideo*).

**OwnerAttributes**$_{\text{j}}$ are owner-specific attributes: Facebook friends and time since joining the platform (*HasFBfriends*,*TimeOnPlatform*).

**Owners PastProject info**$_{\text{j}}$ 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$_{\text{j}}$ and OwnersProjBackingInfo variable combinations.

In addition to full population regressions, we utilize different cut-off definitions for past backing actions and perform regressions on specific subgroups of projects or owners. For robustness, as well as confirmation that backing the projects of others is also correlated with attracting more

backers, we estimate a similar linear regression model where the explained variable is the number of project backers. The right-hand-side variables are the same as those described for the logistic estimation except for the use of *NumPrevBacked* as the only variable included in the OwnersProjBackinginfo variable.

### 4.1 Exploiting Serial Entrepreneurs

Our identification strategy to address concerns of endogeneity and unobserved characteristic exploits the existence of serial entrepreneurs. This methodology also provides for a further emphasis on the sequence of events, where the observed backing actions actually precede and predict increased success.

We focus this analysis on 5,269 project owners who initiated at least two projects. We evaluate the financing success of 5,269 "second projects", using the owners' history and the results from their first project as controls and/or selection criteria. Fortunately, some of the project owners changed their backing-others behavior between their first and second projects, providing us with the opportunity to further decouple the impact of backing actions from unobserved owner attributes.

This specification allows us to control for an owner's past history as well as any changes that occur in an owner's backing behavior between her first and second project. When evaluating the success of serial entrepreneurs on their second project campaign we incorporate variables that describe the change in their backing behavior, where the baseline is their individual backing behavior prior to their first campaign. Specifically, we add the following binary variables: *RemainedNonBacking*, *HasChangedFromNonBackingToBacking*, *RemainedBacking*, and *HasChangedFromBackingToNonBacking* and incorporate any three of these variables when evaluating the success of second campaigns.

This specification also allows us to perform additional analysis 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 that were initiated by owners who (a) did not back others prior to their first project and (b) failed to secure financing for their first project, 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 back others.

We run our estimation on the full set of "second projects" as well as on subsets of these "second projects" 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 financing his 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 the first-project campaign. When evaluating each subgroup, we evaluate the direct 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.

When evaluating the impact of a change in the backing-others behavior of serial entrepreneurs, we incorporate the behavioral change parameters defined above and compare the regression coefficients of such behavioral change while controlling for all other project attributes as well as

the success history of the entrepreneur. For example, we evaluate the impact of *HasChangedFromNonBackingToBacking* compared to the entrepreneurs who *RemainedNonBacking.* Evaluating the interplay between backing others and campaign outcomes for campaigns initiated by the same project owner, provides further support for the causation path. The event sequence is clear (as backing actions are counted before the start of each campaign) and individual parameters are fixed, as both campaigns have been initiated by the same person.

### 4.2 Evaluating Explicit Backing Actions

So far we have described our methodology as it pertains to the analysis of project success. We now describe how we perform the analysis of explicit backing actions. Tracking such explicit backing actions of individual platform participants allows us to further identify the impact of an owner's backing actions on the explicit backings she may receive. This specification is inherently sequential in nature, thus providing further support to the channel that originates with an owner's prior backing actions and concludes with an increased propensity to receive future backing from specific individuals. It also allows us to incorporate individual fixed effects in the analysis.

We perform a separate analysis of the potential backing actions of project owners, and non-owners. When analyzing the backing actions of non-owners we focus on a 6-month window that starts with the first backing action performed by the tracked individual. For project owners we track the actions of first-time owners during the six months that follow the start of their own campaign. In both cases we evaluate the propensity of an observed individual to back specific projects out of all of the projects that were available on the platform during the evaluated period.

More specifically, for each first-time project owner evaluated (let us call each such owner a *source-owner*) we identify all the backers who supported this owner's project as well as the space of all available projects that the source-owner could back within the six months that followed the initiation of her campaign. Each of the projects that this owner has an opportunity to invest in is referred to as a *target-project*, and the owner of each target-project is referred to as the *target-owner*. We construct a data set in which each record contains all the attributes of the source-owner, the attributes of the source-project, the attributes of the target-project and the attributes of the target-owner. Note that this specification creates a very large data set with a record for every potential pair of <*source-owner, target-project*>. The total number of such records exceeds 230 million.

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

- **HasTargetOwnerPrevBackedSource:** 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 goal set by the target-project is similar to that of the source-project. We categorized projects as: Small (Under $1,000), Medium ($1,000-$10,000) or Large (over $10,000)
- **IsTargetSameGeographyAsSource**: Has the value of 1 if the target-project is in the same state / country as the source-project.

These added variables allow us to address the issue of homophily. For example, if owners of a project in a certain category tend to back projects within the same category at a higher rate, one

could observe an increase in co-backing actions that are not necessarily a result of one's previous backing actions; thus, we control for such homophony by incorporating the attributes of both source and project owners and their respective projects.

Note that the six-month window is specific to every evaluated individual, thus eliminating any unobserved time effects. To limit any countervailing effects we also exclude from this backer-owner analysis any source-project owners that initiated another project within the 6-month window as well as source-project owners who did not back any other project within these six months. Evaluating first-time owners also eliminates any unobserved residual impact from previous projects.

Using this specification we perform a binary logistic regression in which the explained variable is the occurrence of a backing action by a source owner in a specific target project created by a specific target owner. Many owners back more than one other campaign, which allows us to incorporate individual fixed effects into the regression.

When evaluating the propensity of non-owner backers to back, we use a similar technique, evaluating the potential selection space available to a potential non-owner backer during the six months following his or her first backing action. We incorporate individual fixed effects in this specification as well and use the attributes of the first project that such a non-owner has backed as a reference point for the interest domain of such a backer.

Because of the large data set generated by this specification, we estimate these backing occurrence models using random sets of 1,000 individuals (source-owners or non-owner backers, as the case may be) along with their respective selection spaces. This specification generates as many as 20,000,000 records for every 1,000 individuals evaluated.

# 5. RESULTS & ANALYSIS

We evaluate the interplay between the backing behavior of a project initiator and project financing using two different units of analysis: (i) the success of the said project campaign and (ii) the explicit propensity to grant (or receive) a backing action from a given constituency.

First, we show that a correlation exists between being a backer of other projects and financing success. We then provide evidence that supports the notion that entrepreneurs which increase their backing other activity increase their subsequent financing success.

Furthermore, we show that the propensity of a potential backer to select a specific project increases when the owner of the target project has backed the projects of others. We also show that this propensity to back increases with the number of target-owner backings. When evaluating the backing actions of project owners we also document the existence of mutual backings among project owners and show that this phenomenon exists even after controlling for homophily.

## 5.1 Backing Others and Campaign Success

Table V 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 owner's prior backing actions, with an odds ratio for *HadBacked* in the range of 1.885 to 1.912. The estimation results of Models 2 and 6 also show that the odds ratio of successfully financing a project increases by 1.055 to 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. 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 previous backing actions attributed to each campaign owner include only those performed prior to the start date of the current campaign. 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 V.**

**Predicting the Successful Funding of a Crowdfunding Project on Kickstarter**

**Binary Logistic Regression Models**

| | 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* | 0.217*** (0.019) | 0.220*** (0.019) | 0.219*** (0.019) | 0.216*** (0.019) | 0.204*** (0.02) | 0.205*** (0.02) |
| *Duration* | 0.99*** (0.001) | 0.989*** (0.001) | 0.99*** (0.001) | 0.99*** (0.001) | 0.991*** (0.001) | 0.99*** (0.001) |
| *HasVideo* | 2.163*** (0.023) | 2.207*** (0.023) | 2.174*** (0.023) | 2.170*** (0.023) | 2.232*** (0.024) | 2.264*** (0.024) |
| *NumRewardCategories* | 1.118*** (0.002) | 1.122*** (0.002) | 1.118*** (0.002) | 1.117*** (0.002) | 1.119*** (0.002) | 1.122*** (0.002) |
| *HasLimitedCategory* | 0.879*** (0.018) | 0.889*** (0.018) | 0.88*** (0.018) | 0.881*** (0.018) | 0.882*** (0.019) | 0.888*** (0.019) |
| *WeeksOnPlatform* | 1.004*** (0.00) | 1.005*** (0.00) | 1.003*** (0.00) | 1.003*** (0.00) | 1.003*** (0.00) | 1.006*** (0.00) |
| *HasFBFriends* | 0.991 (0.017) | 1.013 (0.017) | 0.988 (0.017) | 1.001 (0.017) | 1.007 (0.018) | 1.03 (0.018) |
| *HadCreated* | 0.820*** (0.031) | | | | | |
| *HadCreated AndSucceeded* | | | | 1.404*** (0.044) | | |
| *HadCreatedAnd NeverSucceeded* | | | | 0.502*** (0.041) | | |
| *NumPrevCreated* | | 0.973*** (0.005) | 0.975*** (0.005) | | | |
| *HadBacked* | 1.885*** (0.022) | | 1.878*** (0.022) | 1.855*** (0.022) | 1.912*** (0.024) | |
| *NumPrevBacked* | | 1.055*** (0.004) | | | | 1.071*** (0.006) |
| *Category & Geography Controls* | Yes | Yes | Yes | Yes | Yes | Yes |
| *Constant* | 53.566*** (0.096) | 51.548*** (0.096) | 51.114*** (0.096) | 54.535*** (0.097) | 57.793*** (0.103) | 58.130*** (0.103) |
| | | | | | | |
| Observations | 75,039 | 75,039 | 75,039 | 75,039 | 67,518 | 67,518 |
| Log likelihood: | 85995.72 | 86596.36 | 86014.82 | 85646.47 | 77058.64 | 77587.94 |
| Cox & Snell R-Square: | 0.213 | 0.207 | 0.213 | 0.217 | 0.216 | 0.210 |
| Nagelkerke R-Square: | 0.285 | 0.276 | 0.284 | 0.289 | 0.288 | 0.280 |

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

### 5.1.1 From Backing to Success?

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 affect 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, analyzing the "second projects" of serial entrepreneurs. One such analysis evaluates all "second projects" initiated by owners who (i) did not back others prior to their first campaign and (ii) failed to secure financing for their first project. By evaluating the success of these second-project campaigns while focusing on the backing actions of such owners between their first and second campaign, 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 VI show that the results of this specification are qualitatively similar to those of the full set, with statistically significant odds ratios of 1.913 for *HadBackedBetweenFirstAndSecond* and 1.109 for *NumBackedBetweenFirstAndSecond.*

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 successful financing. Table VI also 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 the owners having backed others. Models 13 and 14, reported in Table VI, 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, even

though they backed others. Some of these owners continued to back prior to their second project, whereas others stopped doing so. Estimation results report statistically significant odds ratios of 1.638 for *HadBackedBetweenFirstAndSecond* and 1.212 for *NumBackedBetweenFirstAndSecond.* Quantitatively similar results were achieved for all other second-project estimations.

**Table VI.**

**Binary Logistic Regression Models**

**Predicting the Successful Funding of a Second Project Incorporating Owners' Previous Success Record, Previous Backing Behavior and Pre-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* | 0.309*** (0.241) | 0.317*** (0.240) | 0.243*** (0.233) | 0.232*** (0.238) | 0.445*** (0.117) | 0.444*** (0.118) | 0.243*** (0.099) | 0.243*** (0.098) |
| *Duration* | 0.984 (0.009) | 0.984 (0.009) | 0.974*** (0.009) | 0.975*** (0.009) | 0.985*** (0.004) | 0.984*** (0.004) | 0.982*** (0.003) | 0.982*** (0.003) |
| *HasVideo* | 2.058** (0.322) | 2.008** (0.318) | 1.174 (0.309) | 1.245 (0.312) | 2.175*** (0.140) | 2.162*** (0.140) | 1.678*** (0.113) | 1.702*** (0.113) |
| *NumRewardCategories* | 1.032 (0.021) | 1.034 (0.021) | 1.129*** (0.030) | 1.128*** (0.030) | 1.053*** (0.014) | 1.054*** (0.014) | 1.145*** (0.014) | 1.145*** (0.014) |
| *HasLimitedCategory* | 1.586 (0.249) | 1.594 (0.248) | 1.113 (0.246) | 1.148 (0.244) | 0.895 (0.124) | 0.891 (0.124) | 0.781** (0.099) | 0.792** (0.098) |
| *WeeksOnPlatform* | 1.00 (0.004) | 1.001 (0.004) | 0.999 (0.004) | 0.998 (0.004) | 1.004** (0.002) | 1.004** (0.002) | 1.002 (0.002) | 1.003** (0.002) |
| *HasFBFriends* | 0.836 (0.241) | 0.835 (0.240) | 1.237 (0.242) | 1.251*** (0.242) | 0.705*** (0.115) | 0.705*** (0.115) | 1.392*** (0.095) | 1.396*** (0.095) |
| *HadBackedBetweenFirst AndSecond* | 2.078*** (0.252) | | 1.638 (0.285) | | 1.523*** (.127) | | 1.913*** (.157) | |
| *NumBackedBetweenFirst AndSecond* | | 1.056 (0.029) | | 1.212** (0.089) | | 1.101*** (0.031) | | 1.109** (0.044) |
| *Category Controls* | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| *Constant* | 148.27*** (0.988) | 166.9*** (0.990) | 124.28** * (0.913) | 137.29** * (0.922) | 50.57*** (0.528) | 51.32*** (0.528) | 24.03*** (0.373) | 23.42*** (0.372) |
| | | | | | | | | |
| *Observations* | 554 | 554 | 434 | 434 | 1832 | 1832 | 2449 | 2449 |
| *Log-Likelihood:* | 508.315 | 512.057 | 491.216 | 488.129 | 1945.281 | 1941.904 | 2813.636 | 2824.408 |
| *Cox & Snell R-Square:* | 0.124 | 0.118 | 0.210 | 0.215 | 0.085 | 0.086 | 0.195 | 0.192 |
| *Nagelkerke R-Square:* | 0.191 | 0.181 | 0.281 | 0.289 | 0.124 | 0.126 | 0.262 | 0.257 |

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

### 5.1.2 Serial Entrepreneurs and a Change in Backing Behavior

To provide additional evidence for the fact that an increase in the tendency of an entrepreneur to back others manifests in increased subsequent financing success; we evaluate a binary logistic regression utilizing the full set of all "second projects" executed by serial entrepreneurs while incorporating variables which measure a change in their backing others classification. In this regression, we incorporate binary state variables for each potential behavioral change. For example, the variable *HasChangedFromNonBackingToBacking* has a value of 1 if the entrepreneur of the evaluated second project backed others prior to his second project but did not do so prior to his first-project campaign (and a value of 0 otherwise).

Table VII reports the results of these regressions. The odds ratio for the success of a serial entrepreneur who *RemainedNonBacking* on his second campaign is significantly lower than 1 (0.746), whereas the odds ratio for a successful second campaign jumps to a significant 1.336 if this entrepreneur *HasChangedFromNonBackingToBacking*. The omitted variable reference baseline in the reported regression refers to entrepreneurs who backed prior to their first campaign but did not back between their first and second campaign.

Entrepreneurs that back the projects of others increase the likelihood of a subsequent successful financing; moreover, changing one's backing behavior and becoming a backer of others increases the odds of succeeding in one's subsequent campaign.

**Table VII.**

**Binary Logistic Regression Models.**

**Predicting the Successful Funding of Second-Project Campaigns**

**Incorporating Owners' Change in Backing-Others Behavior**

| | **Model 21** | **Model 22** | **Model 23** |
|---|---|---|---|
| | Exp(B)<br>(S.E.) | Exp(B)<br>(S.E.) | Exp(B)<br>(S.E.) |
| *LoggedGoal* | 0.302***<br>(0.067) | 0.299***<br>(0.068) | 0.301***<br>(0.067) |
| *Duration* | 0.983***<br>(0.002) | 0.983***<br>(0.002) | 0.983***<br>(0.002) |
| *HasVideo* | 1.835***<br>(0.081) | 1.838***<br>(0.081) | 1.860***<br>(0.081) |
| *NumRewardCategories* | 1.098***<br>(0.009) | 1.098***<br>(0.009) | 1.099***<br>(0.009) |
| *HasLimitedCategory* | 0.888<br>(0.069) | 0.883<br>(0.070) | 0.893<br>(0.069) |
| *WeeksOnPlatform* | 1.002<br>(0.001) | 1.001<br>(0.001) | 1.003**<br>(0.001) |
| *HasFBFriends* | 1.051<br>(0.066) | 1.052<br>(0.066) | 1.064<br>(0.066) |
| *HadSucceeded* | 2.859***<br>(0.071) | 2.850***<br>(0.071) | 3.023***<br>(0.070) |
| *HasChangedFromNonBackingToBacking* | 1.336**<br>(0.130) | 1.359**<br>(0.152) | |
| *HasChangedFromBackingToNonBacking* | | | |
| *RemainedNonBacking* | 0.746***<br>(0.108) | 0.846<br>(0.125) | |
| *RemainedBacking* | 1.606***<br>(0.162) | 1.341<br>(0.173) | |
| *NumBackedBeforeFirst* | | 1.064**<br>(0.030) | 1.085***<br>(0.026) |
| *NumBackedBetweenFirstAndSecond* | | 1.046***<br>(0.017) | 1.091***<br>(0.018) |
| Constant | 31.957***<br>(0.281) | 24.941***<br>(0.263) | 23.854***<br>(0.262) |
| Observations | 5269 | 5269 | 5269 |
| Log likelihood: | 5874.874 | 5859.356 | 5881.578 |
| Cox & Snell R-Square: | 0.215 | 0.217 | 0.214 |
| Nagelkerke R-Square: | 0.290 | 0.2930 | 0.288 |

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

### 5.2 Backing Others and Receiving Backings

So far our reported results focused on campaign success, as manifested in securing the targeted financing goal. In this section we address the impact of prior backings on receipt of backing per-se. Note that while project success is indeed correlated with receiving backings, these are two separate results as success can also be attained by better tuning project parameters without securing more backers. For example, setting a more informed financing goal could result in an increase in success probabilities without manifesting in or being caused by securing additional backer. We first address the number of backers which a project receives and then proceed to the evaluation of explicit backing actions. We provide evidence as to the correlation between the number of backing actions an owner engages in and the number of backers he attracts. Next, we use a different model specification to provide direct evidence for the fact that the propensity of a platform member to back a given target project increases with the prior backing actions of the target owner.

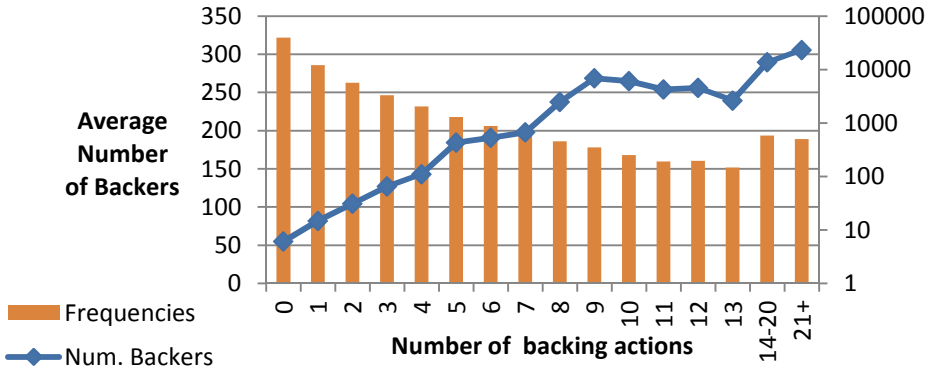


**Figure 2. Number of Project Backers as a Function of the Number of Owner-Backing Actions**

(Plot incorporates all projects that had up to 10,000 backers.)

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 2 of Table V. The coefficient of the predictor *NumPrevBacked* was significant (4.661*** (.689)). That is, the number of backers that a project attracts is significantly and positively related to the number of prior backing actions performed by the project owner.

### 5.2.1 The Propensity to Grant a Backing

We now turn to the analysis of backing actions. Table VIII reports the results of a logistic regression in which the explained variable is the execution of a backing action by a specific individual in a specific target-project within an observed 6-month window. This specification allows us to gain insights into the impact that an owner's prior backing actions may have on the probability that an observed individual actually grants said owner a backing.

On average, each platform member evaluated had the opportunity to select from ~19,000 projects available on the platform within the evaluated 6-month period. As described in the methodology section, we evaluate the potential backing actions of backer-owners and non-owner-backers separately, where the six-month period for each individual starts with either the initiation of one's own project or the first backing action performed on the platform. Evaluating the backing actions of owners also allows us to identify the existence of mutual backings, even after controlling for homophily.

We performed estimations on sets of 1,000 platform participants selected randomly as described in the methodology section. Individual fixed effects were incorporated into all models. Each set includes a potential backing space of about 19,000,000 projects.

**Table VIII.**

**Binary Logistic Regression Models: Predicting the Occurrence of a Backing Action**

(Incorporating individual fixed effects)

Models 31-33 predict the backing by the Source-Project Owner within six months following the launch of the Source Project; Models 34-35 predict the backing by a non-owner within six months following her first backing on the platform

| | Model 31 (Owners) | Model 32 (Owners) | Model 33 (Owners) | Model 34 (Backers) | Model 35 (Backers) |
|---|---|---|---|---|---|
| | Exp(B) (S.E.) | Exp(B) (S.E.) | Exp(B) (S.E.) | Exp(B) (S.E.) | Exp(B) (S.E.) |
| *TargetHasVideo* | 1.428*** (0.075) | 1.499*** (0.075) | 1.549*** (0.074) | 1.974*** (0.086) | 2.078*** (0.076) |
| *TargetDuration* | .991*** (0.002) | .991*** (0.002) | .992*** (0.002) | 0.984*** (0.002) | 0.985*** (0.002) |
| *TargetNumRewardCategories* | 1.037*** (0.002) | 1.037*** (0.002) | 1.036*** (0.002) | 1.040*** (0.001) | 1.040*** (0.001) |
| *TargetHasLimitedCategory* | 1.059 (0.046) | 1.083 (0.046) | 1.090 (0.045) | 0.941 (0.046) | 0.976 (0.046) |
| *TargetHasFBFriends* | .951*** (0.045) | .977 (0.044) | .929 (0.044) | 0.681*** (0.040) | 0.703*** (0.040) |
| *TargetLoggedGoal* | 1.771*** (0.039) | 1.777*** (0.039) | 1.771*** (0.039)) | 3.588*** (0.031) | 3.582*** (0.031) |
| *TargetHadCreated* | 1.082 (0.064) | 1.202** (0.064) | 1.087*** (0.063) | 1.378*** (0.062) | 1.554*** (0.061) |
| *TargetHadBacked* | 1.545*** (0.046) | | 2.110*** (0.043) | 1.715*** (0.041) | |
| *TargetNumBacked* | | 1.006*** (0.002) | | | 1.014*** (0.002) |
| *IsTargetSameCatAsSource* | 5.156*** (0.047) | 5.177*** (0.047) | 7.458*** (0.045) | 5.389*** (0.045) | 5.392*** (0.045) |
| *IsTargetSameSizeAsSource* | 1.244*** (0.045) | 1.263*** (0.045) | 1.352*** (0.045 | 1.219*** (0.045) | 1.217*** (0.045) |
| *IsTargetSameGeographyAsSource* | 7.650*** (0.052) | 7.695*** (0.052) | 10.741*** (0.051) | 2.102*** (0.052) | 2.136*** (0.052) |
| *HasTargetOwnerPrevBackedSource* | 403.861*** (0.070) | 462.135*** (0.069) | No | NA | NA |
| *Source Project Attributes* | Yes | Yes | Yes | Yes | Yes |
| *Source Project Category Controls* | No | No | No | No | No |
| *Target Project Category Controls* | Yes | Yes | Yes | Yes | Yes |
| Observations | 18,856,322 | 18,856,322 | 18,854,070 | 19,441,170 | 19,441,170 |

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

(note that for non-owner-backers, the source variables refer to the first project they backed)

Models 31 and 32 report estimates for backing actions executed by the observed project owners within the observed period. Model 33 estimates the propensity to back a given project, while considering only backing actions that do not involve pairs of owner who have backed each other.

The odds ratio for *HasTargetOwnerPrevBackedSource* is significant and very high (403-462), providing strong evidence for the existence of reciprocated backings among project owners even after controlling for homophily parameters. The aggregate statistics associated with this coefficient correspond with these results, the random propensity to receive a backing from an observed owner is 0.016%, this propensity goes up to 0.06% when the target project belongs to the same category as the source owner's project and jumps to 21.2% when the target-owner has backed the source-owner.

The described estimation incorporates homophily/interest measures which pertain to project category, size and geographic location. For project owners, the reference project for determining the source attributes relates to the project they have initiated, whereas the same parameters for non-owner-backers relate to the attributes of the first project they backed on the platform.

In a manner similar to that described above, Models 34 and 35 report the analysis of explicit backing actions by non-owner backers in the six-month window which follows their first documented backing on the platform. The odds ratios for *TargetHadBacked* (1.54 to 2.11) and *TargetNumBacked* are positive and significant for all models. The propensity for a platform participant to back a given project is significantly higher when the target owner has backed other projects; furthermore, the propensity to back increases with each backing action performed by the target-project owner. Note that the models confirm and control for the increased propensity to back a project within the same category as your own project (for project owners) or the same category you previously backed (for non-owner-backers).

In summary, our results provide evidence that backing the projects of others is not only correlated with success but that backing projects of others is indeed rewarding. Owners who

back others prior to their current campaign attract more backers and achieve higher success rates. Capital can be built by playing both sides of the market.

### 5.3 Limitations

In this study we analyze campaigns after they have ended; hence, we do not have access to 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 element that is missing in our data set is the pledge amount of each backing action. This information is not revealed by the platform and is also not available to potential backers, except for the owner of each project. It is possible that the propensity of a project owner to back one of his backers is affected by the size of the pledge received; however, we cannot investigate this due to this data limitation. 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.

This paper does not address the identification of the explicit mechanisms by which entrepreneurs that increase their backing actions cause subsequent success. The literature has identified a number of possible channels that can be used to explain this phenomenon, namely, learning, visibility, reciprocity and reputation. We do show the existence of direct reciprocity among project owners, but obviously this identification cannot explain the full magnitude of our results. We further show a clear sequence whereby increased activity on one side of the market supports subsequent success on the other side. However, the identification and quantification of the explicit type of capital that this activity generates, whether, social or informational, is beyond the scope of this paper.

This paper has identified new and important dynamics and outcomes generated by playing both sides of the market on a peer-economy platform; however, it is only a first step in fully understanding the phenomenon.

## 6. CONCLUSION

In offline settings there is often a 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. We show that this peer-economy phenomenon is not only prevalent in the context of crowdfunding platforms, but that it also has a significant effect on outcomes; that is, entrepreneurs that increase their backing-others activity also increase their propensity to succeed and the number of backers they attract. In this context capital may be indirectly accumulated on both sides of the market.

In this study we focus on project owners who operate on both sides of the market, creating campaigns of their own as well as backing the projects of others. We find that campaigns initiated by entrepreneurs who have previously supported others have higher success rates and attract more backers. We estimate the effect of such entrepreneur activity, as recorded by their backing actions, on the performance of crowdfunding campaigns and show that playing on both sides of the market is rewarding. Furthermore, we find that this effect is cumulative: more backings prior to one's campaign predict an increase in (i) the probability of financing success, (ii) the number of backings received and (iii) the number of backings reciprocated.

Using serial entrepreneurs who create more than one project on the platform, we show that project owners who change their backing behavior and begin backing the projects of others increase their subsequent funding success. Our results provide support for the notion that

entrepreneurs that increase their activity on one side of the market by backing others increase their financing success on the other side. Using serial entrepreneurs also allows us to better control for unobserved characteristics and endogeneity.

We further evaluate the impact of playing on both sides of the market by performing a multilevel analysis, focusing on the propensity to grant (or receive) backing actions. Projects initiated by backer-owners receive a higher level of backing even after controlling for homophily; interestingly, when possible, project owners reciprocate one out of every five backings they receive. Moreover, a project owner's propensity to back one of her backers is more than 400 times higher than her propensity to back a similar project, even after controlling for project attributes such as category, size or geography.

Overall, our results provide significant evidence that supports the notion that "playing on both sides of the market" is prevalent and rewarding. From a platform perspective, this study explores dynamics nurtured by facilitating a dual role for platform participants. Our results suggest that allowing users to operate on both sides of the market opens new peer-economy channels that may significantly impact outcomes; channels that invite further investigation. In the context of crowdfunding, playing on both side of the market provides an edge. This research is a first step in evaluating such dynamics in the context of peer-economy platforms.

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