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Crowdfunding digital platforms: Backer networks and their impact on project outcomes

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ABSTRACT

Crowdfunding platforms serve to connect project creators and backers. Previous research has explored several project and platform determinants that impact crowdfunding outcomes. However, there has been limited research on these determinants at an individual level. Our paper addresses how backers may influence the outcomes of projects in crowdfunding platforms. We explore several methods commonly used in the industry to identify influence and show that centrality measures through a backer affiliation network best exemplifies influence. Using data from Kickstarter, we construct a weighted backer network based on 52,678 common projects backed by 11,134 backers. Controlling for digital media mentions and project quality, we find evidence that backers in central positions within the network have a positive impact on multiple project outcomes such as the project success rates, amount of funds raised, speed of reaching the crowdfunding goal as well as the number of backers contributing to the project. These findings are replicated and reinforced by using data from a different crowdfunding platform using the entire backer network based on 1,095 projects backed by 87,896 backers. Several robustness tests are used to validate these results.

Keywords: Crowdfunding; Social Networks; Digital Strategy; Social Influence

On an online platform, Kickstarter, a project was posted asking help to fund the creation of the next generation virtual reality headset. On another platform, GoFundMe, a project asked for help for a local community to recover from earthquake and tsunami damage. On Campfire, a company is asking for the community to fund the creation of a TV series. These are a few examples of the projects that can be found on crowdfunding platforms online. However, not all projects succeed. The company may not get enough money for the development of that headset, or funds may not be sufficient to help the community through the natural disaster.

Crowdfunding platforms have gained widespread visibility and acceptance over the last decade. It has grown from a market of US$880 million in 2010 to US$34.4 billion in 2015 (Massolution, 2015). By 2025, it is slated to grow up to US$96 billion (The World Bank, 2013). With crowdfunding becoming a permanent fixture in the funding industry, there has been growing interest in crowdfunding and the factors that drive its success. With the success of crowdfunding itself, the prevailing question becomes less of whether project creators should launch a campaign but more of what they can do to ensure that their projects succeed.

Previous research has explored the key role that crowdfunding project characteristics play in project success, mainly by serving as signals that help potential investors with their funding decisions. However, these are not the only conspicuous signals available for backers to consider - a less obvious but equally important signal is other backers who have contributed to the project. Our paper contributes to the crowdfunding literature by exploring how the action of backing a project by certain influential backers can affect crowdfunding project outcomes. Specifically, we demonstrate that by using the backer network of the crowdfunding platform, we can use the centrality of backers as a proxy for their influence and their overall impact on crowdfunding outcomes such as the amount of money that the crowdfunding project can generate. This phenomenon has been understated in crowdfunding research as there has been little focus on the identification of influential backers and its effect on crowdfunding projects. To address this gap in extant research, our paper constructs a backer network from backers on a crowdfunding platform – Kickstarter. We compare the influential backers identified through the network with the industry convention of using backing activity (number of projects backed) as a signal of influence and see how both sets of backers impact project outcomes. We find that backers identified by their position within the backer network have greater influence over project outcomes compared to backers identified through conventional means. Additionally, we validate our findings by replicating our results using another crowdfunding platform, Demohour.

CROWDFUNDING

Crowdfunding refers to the practice of funding a project by drawing on small contributions from many individuals (Mollick, 2014). The crowdfunding platform provides a digital space for users to interact. Users generally fall into two main categories; project creators who are seeking funding for an idea, and backers who want to contribute to projects that interest them. In order to obtain funding, project creators will launch a campaign, providing backers the opportunity to contribute funds to their idea through the campaign page. From the campaign, project creators will receive funds, real-time feedback and community exposure while backers can receive a reward for backing the project. Notable examples of successes include the Pebble Watch and Oculus Rift. However, these successes are exceptions to the norm, with only 36.29% of projects seeking funding on Kickstarter, the largest crowdfunding platform, successfully obtaining sufficient funding (Kickstarter, 2018). Given the low success rates, it is in the interest of project creators and crowdfunding platforms to understand the determinants that can contribute to project success.

Past research has identified several determinants that can affect crowdfunding success. These include platform-specific determinants, project-specific determinants and individual-level determinants. Even with individual level determinants, research has focused on the attributes of the project creator such as geographical location (Agrawal et al., 2015) and crowdfunding experience (Zvilichovsky et al., 2015). With the focus placed on platform determinants, project characteristics and project creator attributes, researchers have generally not looked at backer characteristics as a possible determinant.

Like project creators, backers have an impact on determining project success as well. As backers interact on the crowdfunding platform, they tend to have a disproportionate amount of influence, with some influencing others in the community. The intuition behind this influence has been found in other contexts as well. Outside of the crowdfunding domain, Valente (1996) has shown that in the adoption of new innovations, network thresholds have been useful for identifying opinion leaders that can impact follower decisions as well as predict patterns of diffusion for innovations. Furthermore, other research has shown that when certain individuals have more influence over others, they exert an effect on others' decision-making processes. Bikhchandani, et al., (1998) posits that observational learning happens in information cascades when individuals observe others' actions within their community that will affect their future decisions. Similarly, Goldenberg et al. (2009) has argued that the value of a customer to the firm includes not only the purchases made by the customer but also the effect they have on others, showing that people with influence can affect decisions of others in the community. Piecing all the conclusions drawn from past research, we expect that influential backers within crowdfunding will be able to influence other backer's decision on whether to fund a crowdfunding campaign. One intuition for this is findings from crowdfunding research by Lin et al. (2014) on clustering different archetypes of crowdfunding users. Their research supports the idea that certain backers may seek out more influential backers for information on what projects they should back. With this, if we are able to show that there is a method to identify influential backers, we believe that the combined effect of the influencers and the influenced will not be trivial and will have a significant effect over how well a crowdfunding project performs.

SOCIAL NETWORKS AND INFLUENCE OF CENTRAL BACKERS ON PROJECT OUTCOMES

In seeking to understand the determinants of crowdfunding success, research has delved into determinants derived from project characteristics and from creator characteristics. However, little attention has been paid to the community that exists within the crowdfunding ecosystem. Backers do not exist within a vacuum, isolated from each other. Since they exist on the same platform, many of them will encounter and even interact with each other. In the crowdfunding space, actions such as backing a project or viewing projects that other backers have backed are all forms of interaction that these backers can have with each other within the platform. Research on other platforms, such as an auction platform, have shown that some actions influence others in the same ecosystem even though users of the platform do not communicate directly (Dass, Reddy and Iacobucci, 2014) We expect this to hold true for crowdfunding platforms as well, with backers being influenced by the actions of others in the platform even if they do not physically communicate with each other.

We believe that the influence generated by these backers are significant and may have an impact on project outcomes. Backer influence has generally been addressed as an unobserved factor in previous research and the disaggregate nature of backer influence across the entire backer community has not been considered or measured. The possibility that the actions of a singular backer may affect other backers and project outcomes has not been fully explored. As backers are idiosyncratic in nature and not all backers are similar, we propose that each backer has different levels of influence, with some backers having more influence over other backers.

The importance of an individual's backing action is compounded when we consider information spillover effects. Backers who observe other backers' backing actions before making their own funding decisions can, in turn, be used by others as a source of information when making decisions. This leads to an information cascade where actions by one individual can affect many others (Banerjee, 1992). This is especially so in a decision-making scenario such as crowdfunding where decisions are made sequentially where choices made earlier can be observed by others and affect future decisions. Since the backing history of backers is available for perusal, a potential backer can easily find out what another backer is backing currently, and projects they have backed in the past. Furthermore, early backers with expertise in the domain that the crowdfunding project is in can lead other backers into believing in these 'experts' and thus affecting their backing decision. To illustrate this, research into a crowdfunding platform created to fund the development of mobile applications have found that early backers that have a certain expertise in the mobile application development process and thus deemed as experts are found to be able to influence other backers on the platform as the crowd can identify these experts (Kim and Viswanathan, 2019). These experts will affect early adopters in the crowdfunding platforms and these early adopters will in turn impact larger and larger numbers of followers down the cascade. With the facilitation of this information cascade, backers who can reach more backers will be able to wield influence over other backers. Backer influence thus becomes an important determinant that we should consider.

The intuition that influential backers exist is not lost within the industry. Practitioners acknowledge the potential effects of these influencers, with third-party platforms such as BackerClub, Krowdster and Backercamp promising to connect project creators to backers that have influence. Kickstarter has also encouraged project creators to leverage on the "network effects of Kickstarter", encouraging creators to reach out to influential backers (Fenzi, 2013). However, industry players often use activity as an indicator of influence. For example, BackerClub identifies influential backers as backers who have backed an average of 106 crowdfunding projects (BackerClub, 2017). Krowdster targeting "Super backers" that have backed "at least 10, 20 or even 50" campaigns (Krowdster, 2017). These backers are considered influential due to their experience in backing multiple projects. As such, they will have influence over a typical backer that is engaging with the crowdfunding community and will be able to guide their backing decisions. However, is this the best method of identifying influence?

An alternative method of identifying influential backers is by their position in the backer network. It would be unreasonable to expect a backer to have influence on other backers if they are not connected in some way and we can explore this connection by studying the backer network on the crowdfunding platform. One of the main reasons for the absence of research on network structures in crowdfunding has been the difficulty in identifying a relevant network. Due to the complex nature of interactions between individuals across many projects, there is no pragmatic way of condensing actions into a network. Unlike other research on network influence that deals with explicit connections such as tracking user influence via referrals and friends, there is no distinct method of tracking backer influence. We propose a tangible way to track influence in the network - through the shared affiliation in project backing decisions made by backers.

Our research condenses backers' backing actions within various projects into a singular network. In our proposed network, we envision backers existing as nodes in the network, with links called edges connecting these backers. There are two main modes in the network, the backers and the projects. We use the action of backers backing decisions to form an affiliation network, where backers are linked to one another based on their shared membership of projects that they have backed (Borgatti and Everett, 1997). This means that for each pair of backers in the network, we examine their backing history and identify the number of similar projects they have backed. The number of shared projects between the two backers serves as weights to the edges that connect these two backers in our backer network.

The basis of our network construction can be observed in social network research where the relational position of a node determines how influential the node is. For instance, nodes that are densely surrounded by many other nodes can be said to hold influence over other nodes as information from that node is passed down directly into the large number of nodes that surround it. There are several methods of quantifying influence based on the position of a node within the network. These metrics are commonly known as centrality metrics (Freeman, 1978; Kiss and Bichler, 2008; Chen et al., 2011). We use three of these measures to capture the relational properties of a node and triangulate all three to identify influential nodes within the network. We discuss the three centrality measures – degree, closeness and betweenness, later in the paper.

The nature of network effects reinforces our earlier argument on the disaggregate nature of backer influence where a disproportionate amount of influence tends to exist within a small number of nodes (Malliaros et al., 2016). Using the backer network, we will identify this small group of influential backers, known as central backers, and examine their impact on project outcomes.

We theorize that the act of backing a project by a central backer will increase the likelihood that other potential backers may be affected by the decisions of the central backer. As more central backers back a project, others within their network will use these actions as a signal which will result in more backers being aware of the project, positively impacting the crowdfunding project. We would thus expect that as the number of central backers backing a project increases, it will positively impact project outcomes by providing the project access to more potential backers and thus increasing its possibility of successfully reaching the funding goal. Moreover, as more backers are exposed to the project, the amount of funds being contributed to the project should increase while the time it takes for the project to meet its funding goal should decrease due to more backers contributing to the project. Therefore, we present our hypothesis:

H_1: The number of central backers backing a project will have *(a)* a significant positive impact on the likelihood of project success, *(b)* a significant positive impact on the percentage amount of funding received by the project, *(c)* a significant negative impact on the rate of reaching the funding goal and *(d)* a significant positive impact on the number of backers contributing to the project.

We present the model we are interested in empirically testing in Figure 1. [Insert Figure 1]

We are also aware of the industry's operationalization of influential as backers who back a large number of projects. Likewise, we will also use this alternative measure for identifying influential backers and test its impact on project outcomes. We present both results and compare the effectiveness of both operationalizations of influence in the crowdfunding context.

DATA

Our primary data source for much of the project related (project description, goal amount, amount funded etc.) and backer related information (number of backers, backer history etc.) is obtained from Kickstarter, the largest reward crowdfunding platform. Since 2009, Kickstarter has launched 412,687 projects that have raised over $3.83 billion (Kickstarter, 2018). Kickstarter categorizes its projects into 15 different categories. We chose the largest category on Kickstarter - Games, to collect data on active backers. As of 2016, there have been over 28,000 projects launched in the Games category, accumulating a total of over $570 million. This amount represents over 20% of the total funds collected by Kickstarter, making the Games category the largest category on Kickstarter.

SELECTION CRITERIA FOR NETWORK FORMATION

In order to test our hypothesis, we need to identify a list of central backers and a list of large backers. Before we can identify our list of central backers, we require a list of backers and projects to form our backer network. To do this we started off with 300 Games projects from three separate windows. We scraped all new projects listed on Kickstarter during ten day windows in the months of January, February and March of 2014. This allows us to track the projects from its launch to the end of the project duration and this provides us with an accumulation of a sizable number of projects will be used for our network formation. By following all the projects launched in these three windows, we were able to get information on all backers of these projects as well as other projects that they have backed.

Projects taken from this timeframe meet two conditions that are essential in our network formation; the backers chosen are recently active backers and there is a substantial window where we can draw past backing actions from. As the basis of our network is formed from past backing actions, a larger window will facilitate more accurate network estimations. The duration of our backing action window will thus be the entire backing history of these backers from Kickstarter's inception in April 2009 to April 2014. Tracing these backers and all the projects that they have backed on Kickstarter (51,678 projects) provided us with the means to form a joint affiliation network based on the common projects that they have backed.

Our data provides us with a two-mode network, where the backers serve as the primary node and the crowdfunding projects serve as the secondary node. This is similar to common two-mode networks that have been analysed in social network research such as the Davis' Southern Women network where attendance of a group of women to a series of events were the primary and secondary nodes respectively (Davis et al., 1941). As we are interested in how backers are influenced by others, we focus our initial network on repeat backers. These are backers who have backed more than one project.[1] In our Kickstarter dataset, this amounts to 11,134 backers.

We define X as a matrix of backers and projects representing 11,134 backers (rows) and 51,678 projects (columns) which captures the entire backing history of backers on all these projects:

$$X = \begin{bmatrix} X_{1,1} & \cdots & X_{1,51678} \\ \vdots & \vdots & \vdots \\ X_{11134,1} & \cdots & X_{11134,51678} \end{bmatrix}$$

The backing action of each backer *i* of project *j* is captured in X. For instance, if Backer *i* has backed Project *j*, the corresponding result for $X_{i,j}$ would be 1. If Backer *i* has not backed project *j*, $X_{i,j}$ would be 0.

[1] We will relax the assumption of repeat backers later in our Demohour study to show that even with non-repeat backers, the results still hold.

To transform the two-mode network to a one-mode network for analysis, we use projection, where we select our focal set of nodes, in this case the backer nodes, and link nodes from that set if they were connected to the same secondary node in our affiliation network. Backers do not necessarily have to communicate with each other to form the tie since we use to co-presence of any pair of backers across multiple projects to form the tie. We preserve the weights of the two-mode network by using the number of shared projects that the backers contributed to, a method that has been shown to be able to yield important insights (Padrón et al., 2011). [Insert Figure 2]

From X we construct a backer matrix B = XX' which captures the number of common projects that each backer had backed from their complete backing history in X.

$$B = XX' = \begin{bmatrix} B_{1,1} & \cdots & B_{1,11134} \\ \vdots & \vdots & \vdots \\ B_{11134,1} & \cdots & B_{11134,11134} \end{bmatrix}$$

The diagonal in the matrix provides the total number of projects that each backer has backed. The off-diagonal elements provides the number of common projects that each Backer *k* had with Backer *l*.

For instance, if Backer *k* and Backer *l* have previously backed 5 common projects, the corresponding result within the matrix for $B_{k,l}$ would be 5. As described, the weight of the edges of the network is derived from the number of shared projects these backers have in common.

We use this weighted adjacency backer matrix B to represent our backer affiliation network. This Backer to Backer matrix (B) has information on the links between each pair of backers as well as their weights - the number of common projects shared between backers. In our

Kickstarter data, a B matrix (11,134 x 11,134 with 61,977,411 cells) is created. 13% of these cells (7,986,299) were non-zero, indicating the number of potential joint incidences. Of these, there are 28,898,761 shared projects, since a set of paired backers could have backed multiple common projects, ranging from 1 to 21 in our data. These shared projects would form the basis for our weighted edges when formulating the network. This represents an average of 3.62 projects amongst these backers who share common projects. This data provides us with way to estimate the backer network and the influence each backer has on the network.

IDENTIFYING CENTRAL BACKERS

There are two main ways of measuring the power of a node – (1) looking at local network effects or (2) looking at global network effects. Local network effects account for the power that a node has over other neighboring nodes. In comparison, global network effects account for the entire structure of the network itself (Ebbes et al., 2016). Our study will make use of three different metrics to account for both these separate effects. We use degree to account for local network effects and measures such as closeness and betweenness to capture global network effects (Ebbes et al., 2016).

Degree measures the number of edges the node has with other nodes and the strength of these edges (Freeman, 1978). A backer that has many direct connections to others indicates that it has a high degree score within the network. Similarly, the weights of the connections can denote quality within a relationship as well, as a backer that has few connections but a lot of activity taking place between connections can also possess high degree scores (Barrat et al., 2004). To account for both the number of connections as well as the quality of connections, our network will be analysed by treating edge weights and the number of edges with equal importance and by calculating both the number of connections a backer has as well as how much information passes through each connection (Opsahl et al., 2010). We use:

$$\text{Deg}_i = (\sum_j^N x_{ij})^{(1-a)} \text{ x } (\sum_j^N w_{ij})^{(a)}$$

where *N* is the total number of nodes, *i* is the focal node, *j* represents all other nodes in the network, *x* represents the adjacency matrix, *w* represents the weighted adjacency matrix and *a* is the tuning parameter captures the importance ascribed to edge weights and number of edges.

Closeness is a measure of how quickly a node can access other nodes within a network (Freeman, 1978). A node that can easily reach the entirety of the network in a short time can be said to hold more power over the entire network as it is positioned at a location that can facilitate the spreading of information within the network. In the context of crowdfunding, closeness calculates the sum of distances of a backer to other backers in the network. A backer that can reach others within the network by passing through a smaller number of other backers has a high closeness score and thus will be more influential within the network. The ease of information passing through is determined by the weights of the edges, with a frequently used edge being more accessible than a less frequently used one. To account for both the number of connections needed to reach the ends of the network as well as the ease of information passing through the network, we used an established method to invert the edge weights and use them as costs to represent the cost of connecting two backers (Newman, 2001):

$$\text{Close}_i = [\sum_{j=1}^N min\,(\frac{1}{(w_{iz})^a} + \cdots + \frac{1}{(w_{zj})^a})]^{-1}$$

where the additional notations of *z* denotes all the other nodes in between nodes *i* and *j* and *min* indicates the minimum distance the weighted path takes in order to reach from node *i* to *j*.

The Betweenness metric measures informational bottlenecks. Betweenness quantifies a node's ability to make connections with other groups of nodes in a network, namely where the node bridges the shortest path between two other pairs of nodes (Freeman, 1978). Betweenness is a less common measure compared to degree or closeness, but it is of critical importance in social network research. This concept has been used to look at important issues such as brokerage, where a node can connect otherwise disconnected clusters together (Everett and Valente, 2016). If a backer is included in many paths linking other backers to each other, that backer is influential as they have the potential to control communication within the network. If a backer is the only bridge between two different sets of backers, they will have a high betweenness score and holds influence over these two nodes. We use Brandes' (2001) algorithm to calculate betweenness in weighted networks:

$$\mathrm{Betw}_{\mathrm{i}} = \frac{s_{mn}^{wa}(i)}{s_{mn}^{wa}}$$

where the additional notations of s_{mn}^{wa} denotes the weighted shortest path between two random nodes *m* and *n* and s_{mn}^{wa} (*i*) represents the number of paths that pass through node *i* when linking nodes *m* and *n* with the tuning parameter, *a*, adjusting the importance of the weights, *w*.

OUTCOME MEASURES

The principal variable that we are interested in is influential backers. We first identify central backers and observe their impact on project outcomes. After computing the three centrality scores for each backer, we classify backers according to whether they scored high in all three centrality scores. The first 10 backers in this classification will form our central backers. We intend to use a small pool of central backers due to the intuition that a small group of backers holds a disproportionately large amount of influence over the entire backing network. For each project, we indicate the number of central backers that have contributed to the project. As such, our number of central backer variable will be 0 if none of the 10 central backers contributed to the project and 10 if all 10 central backers contributed to the particular project.

To differentiate between influence from backing multiple projects and influence from the network, we further separate central backers into two mutually exclusive sets of backers – (1) Large Backers and (2) Exclusively Central Backers. This is required for us to isolate the impact of both forms of influence by excluding those that are both identified as central and large backers. To separate the effects of centrality and size of backing activity, we identified these backers by using the top 50 backers who have backed the most projects. Backers in this group that do not appear in the top 50 central backers are defined as Large Backers. Conversely, Exclusively Central Backers are backers who appear within the top 50 central backers but do not appear within the top 50 Large Backers. We re-estimated our model based on 10 Large Backers and 10 Exclusively Central Backers.

Our paper determines the impact of influential backers by examining their impact on four measures of project success – funding status, percent funded, goal rate and number of backers.

Funding Status is defined as a binary variable and captures whether the crowdfunding project was able to meet its funding goal (Zvilichovsky et al., 2015; Hu et al., 2015; Mollick, 2014; Kuppuswamy and Bayus, 2017). Projects that meet the goal amount by the end of the Kickstarter funding period are considered successful. Projects that fall short of the goal amount are defined as unsuccessful and the funds will not be collected from the backers.

Percent Funded measures how much funds the project was able to collect with respect to its funding goal (Kuppuswamy and Bayus, 2017). We define it as the percentage of the goal amount that was raised at the end of the funding period. This measure allows us to account for the magnitude of project success. We calculate this metric by using both the total funds raised and the funding goal amount.

Goal Rate is a success measure that defines how quickly the project was able to reach the goal. This metric has not been explored in prior crowdfunding research. To partition out the effects central backers have on meeting the goal, we only consider successful projects since projects that have failed are not able to meet the goal. We use the number of days the project took to hit its funding goal relative to the stipulated project duration to calculate the proportion of time the project took to meet its goal. This measure ranges from 0 to 1, where a score of .8 means that the project reached its goal amount using 80% of its funding duration. This metric is calculated using the project duration data from the Kickstarter project page and the longitudinal data on contributions from Kickspy, a third-party platform that captures daily information from Kickstarter. Using the data obtained, we can track the exact day that the project reaches its goal.

Number of Backers indicate the aggregate number of backers that contributed to the project (Mollick, 2014; Kuppuswamy and Bayus, 2017). We exclude backers identified as influential backers from this aggregate backer variable and only include all other non-influential backers in this measure.

In our model, we sought to control for other variables that may affect project outcomes by including variables that have been documented by past research to have an impact on project outcomes. These include characteristics that have been used to capture project heterogeneity, many of which are components found on the main project page. We acquire data on different project characteristics and present them here as covariates in our model.

Goal Amount captures the amount of funds the project is seeking. It has been shown to have a negative effect on project success, with projects that have larger goal amounts being less likely to succeed (Marom and Sade, 2013; Mollick, 2014; Zvilichovsky et al., 2015).

Duration specifies the length of time the project must reach its funding goal. This varies with projects, with the average duration length being 30 days. Duration has been shown to have a positive effect on project success, with projects that have a longer goal amount being more likely to succeed (Mollick, 2013; Mollick, 2014; Agrawal et al., 2015; Zvilichovsky et al., 2015; Kuppuswamy and Bayus, 2017).

Creator Experience indicates the number of previous projects started by the creator. We examine the history of the creator and the number of projects that they had before the current project. Previous research has found support that a creator's past projects will affect their current project's likelihood of success (Marom and Sade, 2013; Zvilichovsky et al., 2015).

Number of Projects Backed allows us to control for the number of other projects that the project creator has backed. Previous research has shown that if the creator has backed many other projects, other project creators may back the current project as a form of reciprocity which will increase the likelihood of project success as well (Zvilichovsky et al., 2015).

Tiers represent the number of reward tiers offered by the project. Reward tiers consist of an amount associated with the tier as well as a reward. Backers who meet that amount will be eligible for the reward. The reward is generally the product being funded. Previous research has shown that tiers will positively affect backer support (Kuppuswamy and Bayus, 2017).

Video is a binary variable that captures whether the project has a video on its project description page. This variable has been used by many crowdfunding researchers (Mollick, 2013;

Mollick, 2014; Agrawal et al., 2015, Kuppuswamy and Bayus, 2017). The presence of video is considered as an effective information source and is expected to have an impact on the evaluation of the project by backers and on the success of the project.

Updates is the number of updates posted by the project creator for the duration of the project. Previous research has shown that updates positively affect backer support and success rate (Kuppuswamy and Bayus, 2017).

Another possible variable that may affect not only project outcomes but also backers is digital buzz. Influential backers and Backers are exposed to online buzz through mediums such as social media or blog posts. This can influence them by increasing their awareness of the project, which can aid in increasing the number of influential backers and backers to the project thus generating positive project outcomes. To assess the impact of different sources of digital media buzz on backers, we collect data on the digital media buzz generated for the duration of the crowdfunding project campaign. We collect this data through scraping online mentions of the crowdfunding project from various media sources.

There are four avenues of digital media buzz that we focus on – Forums, Online Media, Blogs and Social Media. Forums are online threads or pages that moderators maintain while users can post responses or comment on various topics. Online Media are platforms that allow media such as pictures or videos to be shared. They include Podcasts, Tumblr, Instagram and Deviantart. Blogs are created by users and are often written in an informal or conversational style and have a certain length to each blog post. Social media includes posts on Twitter, Facebook or Google Plus. The data are gathered from the number of mentions in these respective avenues of digital media for the duration of the project.

It is likely that the quality of a proposed project can attract backers. In crowdfunding literature, proxies for quality have been used such as assessments of the project's innovativeness, feasibility as well as the presence of a video. A video is often seen as an indicator of project quality (Mollick, 2014). Similarly, innovativeness is defined by the novelty of a project from a technological and market standpoint. This variable has been used on new projects to denote product quality (Kleinschmidt and Cooper, 1991; Poetz and Schreier, 2012). Feasibility has also been used as a measure of the likelihood of the project being a success in the market in previous research on new products to show product quality (Poetz and Schreier, 2012). Hence, we consider these covariates so as to isolate the social network effects from the effects of quality.

To collect these two subjective measures of innovativeness and feasibility, we had three different raters rate the crowdfunding projects in our data on these two variables. They were asked to evaluate the project based on the descriptions used for innovativeness and feasibility used in previous new product research. Due to the nature of crowdfunding, we use the proportional reduction in loss measure by Rust and Cooil (1994) to measure ratings for new products to test for inter-rater reliability. Our proportional reduction in loss measure finds that our raters have a 75% inter-rater reliability. A summary of the data and data sources is presented in Table 1 with further discussion on each variable later in the paper. [Insert Table 1].

With the inclusion of these variables, we construct an a priori theory driven model linking the variables that have been found to affect project outcomes such as project characteristic variables and digital buzz variables. We plan to validate our findings by also running an alternative model to deal with endogeneity concerns. We will estimate this model to ensure that our results hold up as a robustness check in the later sections. Table 2 provides descriptive statistics of the data gathered. [Insert Table 2]

MODEL FORMULATION & ESTIMATION

We model the impact of our predictor variables on crowdfunding project success for project k as follows:

(1) $\mathrm{NCB_k} = \alpha_0 + \beta_1\mathrm{Goal_k} + \beta_2\mathrm{BZSoc_k} + \beta_3\mathrm{BZForums_k} + \beta_4\mathrm{BZBlogs_k} + \beta_5\mathrm{BZMedia_k} + \beta_6\mathrm{Video_k} + \beta_7\mathrm{Feas_k} + \beta_8\mathrm{Innov_k} + \mu_{\mathrm{NCB_k}}$

(2) $\mathrm{Projout_k} = \beta_0 + \beta_1\mathrm{NCB_k} + \beta_2\mathrm{Goal_k} + \beta_3\mathrm{Dur_k} + \beta_4\mathrm{NPast_k} + \beta_5\mathrm{NBacked_k} + \beta_6\mathrm{NTiers_k} + \beta_7\mathrm{Video_k} + \beta_8\mathrm{NUp_k} + \beta_9\mathrm{BZSoc_k} + \beta_{10}\mathrm{BZBlogs_k} + \beta_{11}\mathrm{BZForums_k} + \beta_{12}\mathrm{BZMedia_k} + \mu_{\mathrm{Projout_k}}$

for projects k = {1,2,…}, where

$\mathrm{Projout_k}$ = Outcome of project k, (success status of the project k, percentage of the goal funded for project k, the rate that the project k takes to reach its goal or the number of backers backing project k). Status of the project will be analyzed using a probit model as it is binary for failure and success,

$\mathrm{NCB_k}$ = Number of central backers that contributed to project k,

$\mathrm{Goal_k}$ = the goal amount that project k sought to raise,

$\mathrm{Dur_k}$ = the funding window duration allocated for project k,

$\mathrm{NPast_k}$ = the number of past projects the creator of project k had on Kickstarter,

$\mathrm{NBacked_k}$ = the number of past projects backed by the creator of project k,

$\mathrm{NTiers_k}$ = the number of reward tiers project k had,

$\mathrm{Video_k}$ = a binary variable denoting if project k had a video or not,

$\mathrm{NUp_k}$ = the number of updates project k had,

$\mathrm{BZSocial_k}$ = the number of mentions project k had on social media pages,

$\mathrm{BZForums_k}$ = the number of mentions project k had on forums,

$\mathrm{BZBlogs_k}$ = the number of mentions project k had on blogs,

$\mathrm{BZMedia_k}$ = the number of mentions project k had on online media pages,

$\mathrm{Innov_k}$ = the innovativeness rating of project k,

Feas_k = the feasibility ratings of project k.

We estimate both equations simultaneously with a maximum likelihood estimation.

NETWORK ANALYSIS RESULTS

To estimate our network, we used 300 projects to generate our backer list. As mentioned earlier, these projects have 11,134 unique active backers who have backed more than one project in their entire backing history. With this, we can create the backer network by compiling the complete backing history of these 11,134 backers from April 2009 to April 2014, resulting in a total of 51,678 projects. Based on the information provided by their entire backing history, we build the backer incidence matrix, B.

From matrix B, we derive the backer network. The three centrality measures - degree, closeness and betweenness, were estimated for each backer. We find that most backers have low centrality scores with only a small proportion with high scores, this is in line with what other research have suggested, with only a small number of nodes having disproportionately larger influence over others. To test our hypothesis that a small number of backers will be able to drive influence within the network, we identify the top 10 backers who scored high in all three centrality measures. We determine these central backers by evaluating all backers' scores on degree, closeness and betweenness. The top 10 backers that scored high on all three centrality measures will be used as our central backers. With our central backers identified, we proceed with our model estimation.

EMPIRICAL MODEL RESULTS

We first present the effects of the presence of central backers on crowdfunding projects using descriptive data in Figure 3. We removed canceled projects from our dataset as projects can be canceled for many reasons and these projects tend to not run through their entire project duration, which leaves us with 240 projects. Projects were split depending on whether they had any central backers backing the project. On average, we find that projects backed by central backers garnered more positive project outcomes compared to projects that were not backed by central backers, with 85.56% being successful compared to 26.57% ($t=11.44$, $p<.01$); achieving an average funding of 482.96% compared to 66.72% ($t=2.86$, $p<.01$) and with an average of 690.96 backers compared to 76.15 ($t=7.19$, $p<.01$). [Insert Figure 3]

The results of our empirical model are presented in Table 3. We estimate both equations in our model simultaneously, while estimating all four response variables separately, with each estimation comprising of a different project outcome. The status outcome variable was estimated using a probit model. Our intermediary response variable in our model, the Number of Central Backers variable is specified to have a negative binomial distribution when estimating our model due to its nature of being a count variable. We impose no other assumptions on our model and estimate the full model seen in Figure 1. [Insert Table 3]

Consistent with our expectations, the number of central backers backing a project has a significant positive impact on several crowdfunding project outcomes. We find that an increase in the number of central backers can (1) increase the likelihood of project success ($\beta=.65$, $p<.01$), (2) increase the percentage amount of the project ($\beta=158.72$, $p<.01$), (3) decrease the rate at which the project meets its funding goal ($\beta=-.04$, $p<.01$) and (4) increase the number of backers backing the project ($\beta=181.25$, $p<.01$). [Insert Table 3]

Our analysis on control variables in our model yielded results that are consistent with prior research as well. Previous research has shown that goal amount affects the likelihood of project success, with projects that have a larger goal amount taking a longer time to achieve success (Marom and Sade, 2013, Mollick, 2013, Mollick, 2014, Zvilichovsky et al., 2015, Kuppuswamy and Bayus, 2017). We find that the project's goal amount negatively affects the project success status (β=-.63, *p<.01*) and percent funded (β=-116.22, *p<.01*) but positively affects the time taken to reach the goal (β=.11, *p<.01*).

Our estimates also show that the number of updates affects both funding status (β=.06, *p<.01*) and percent funded (β=13.73, *p<.05*). This corresponds to what Mollick (2014) and Kuppuswamy and Bayus (2017) found in their research. Our results also indicate that the number of reward tiers available in the project will affect project success (β=.06, *p<.1*). This is in line with research by Kuppuswamy and Bayus (2017) that have shown that the number of tiers will affect the success of a crowdfunding project.

Moving on to project creator characteristics, we find results comparable to the findings on backing reciprocity by Zvilichovsky et al., (2015), where the number of previously backed projects by a creator will increase in the likelihood of project success (β=.01, *p<.01*). Surprisingly, we find that the more projects a creator has previously created, the lower the number of backers (β=-9.17, *p<.05*) and the likelihood of success (β=-.06, *p<.1*).

We find that there is disparity between the different digital media buzz in affecting our two groups of backers. Mentions in forums (β=29.45, *p<.01*), online media (β=144.15, *p<.01*) and social media (β=.26, *p<.01*) have positive significant effects on backers while mentions in forums (β=.25, *p<.01*) and blogs (β=.13, *p<.01*) have a positive significant impact on central backers. We also note that central backers are negatively impacted by social media (β=-.001, *p<.01*) which affects their impact on project status, funding and number of backers and are negatively impacted by online media (β=-.23, $p<.01$) which affects their impact on the rate of reaching the funding goal.

COMPARISON BETWEEN CENTRAL BACKERS & LARGE BACKERS

In order to ascertain the validity of our hypothesis, we re-estimate the model only using Large Backers (those who back many projects) and Exclusively Central Backers after excluding backers that fall into both categories.

To visualize the difference between the presence of Large Backers and Exclusively Central Backers, we compare projects backed by these two groups in Figure 4. We find that Large Backers are distinctly dissimilar from Exclusively Central Backers. Projects backed by Exclusively Central Backers outperform projects not backed by them. However, we observe that projects backed by Large Backers perform worse than projects not backed by them, generating (1) a lower success rate (35.96% compared to 58.94%), (2) lower average funding (148.81% compared to 285.72%) and (3) taking longer to reach the funding goal (0.42 compared to 0.38). Although the average number of backers in projects with Large Backers is higher than the number of backers in projects without Large Backers, the magnitude of this difference is smaller than what is observed from Exclusively Central Backers (413.70 against 273.13 compared to 807.76 against 122.09). The disparity in impact on outcomes of Large Backers and Exclusively Central Backers suggests that there is a fundamental difference between them. [Insert Figure 4]

To empirically test the difference between Large Backers and Exclusively Central Backers, we repeat our estimation by replacing the number of central backers with either the number of Large Backers or the number of Exclusively Central Backers. Our results show that unlike central backers, large backers do not significantly affect percent funded, the goal rate and the number of backers in the crowdfunding project. It, however, has a significant negative impact on funding status, which indicates that a project with Large Backers is less successful (β=-.82, *p<.01*). Comparatively, evidence based off Exclusively Central Backers replicate our previous results, showing that they have an (1) increased likelihood of success (β=.66, *p<.01*), (2) increased percent funding (β=155.16, *p<.01*), (3) decreased goal rate (β=-.05, *p<.01*) and (4) increased number of backers (β=182.42, *p<.01*). This implies that backers with high centrality and large backers are fundamentally different, with centrality having an impact on project outcomes while backing size having little impact on most project outcomes. [Insert Table 4]

ROBUSTNESS CHECKS & ENDOGENEITY

We ran a few robustness checks to ensure that the effect is driven by central backers and not by other types of backers. We re-estimated the model using two other categories of backers – non-central backers and repeat backers. For non-central backers, we randomly picked 10 sets of 10 non-central backers. Our analysis in Model 3 returned negative results, indicating that non-central backers had no impact on project outcomes.

Another consideration that we address is our model itself. Currently, our model is formulated based on theories based on previous research and hypothesized determinants between variables, central backers and project outcomes. We check if our results still hold when all variables are linked to central backers and project outcomes. Similarly, we also seek to address for endogeneity in this alternative model by using a different endogeneity correction method. We use the instrumental variable approach with competitive intensity as an instrumental variable. Backers deciding to contribute to a project do not make this decision in isolation, the decision to contribute is often couched in the current ecosystem of the platform itself as they will inevitably be exposed to other projects. This means that the quality of other projects on the platform will be judged relative to the quality of the current project and as such the current competitive intensity at the time of the project's duration can become an instrumental variable of project quality. Our competitive intensity variable is modified from previous research (Sridhar et al., 2016) and is formed by using the average number of central backers in the same subcategory and month of launch as the project after excluding the current project. To compute competitive intensity for a project, we take the total number of central backers for other projects in that period and average it across the number of projects in that period. This resulting variable will correlate with the number of central backers but will not directly correlate with unobserved determinants of project outcomes for the project. Performing an additional estimation with our potentially endogenous variable, number of central backers as the dependent variable and our competitive intensity will provide us with residuals that we can use to provide a control function correction to our endogenous variable in our main estimation. We use a two-stage least squares estimation on our model:

(3) $\mathrm{NCB_k} = \alpha_{20} + \alpha_{21}\mathrm{Dur_k} + \alpha_{22}\mathrm{NPast_k} + \alpha_{23}\mathrm{NBacked_k} + \alpha_{24}\mathrm{NTiers_k} + \alpha_{25}\mathrm{NUp_k} + \alpha_{26}\mathrm{Goal_k} + \alpha_{27}\mathrm{Video_k} + \alpha_{28}\mathrm{BZForums_k} + \alpha_{29}\mathrm{BZMedia_k} + \alpha_{30}\mathrm{BZBlogs_k} + \alpha_{31}\mathrm{BZSoc_k} + \alpha_{32}\mathbf{ComInt}_\mathrm{k} + \mu_{\mathrm{Ncb_k}}$

(4) $\mathrm{Projout_k} = \beta_{20} + \beta_{21}\widehat{\mathrm{NCB}}_\mathrm{k} + \beta_{22}\mathrm{Dur_k} + \beta_{23}\mathrm{NPast_k} + \beta_{24}\mathrm{NBacked_k} + \beta_{25}\mathrm{NTiers_k} + \beta_{26}\mathrm{NUp_k} + \beta_{27}\mathrm{Goal_k} + \beta_{28}\mathrm{Video_k} + \beta_{29}\mathrm{BZForums_k} + \beta_{30}\mathrm{BZMedia_k} + \beta_{31}\mathrm{BZBlogs_k} + \beta_{32}\mathrm{BZSoc_k} + \mu_{\mathrm{Projout_k}}$

with two new additions, where $\mathrm{ComInt_k}$ represents the instrumental variable, competitive intensity faced by project *k*, and $\widehat{\mathrm{NCB}}_\mathrm{k}$denotes the values of central backers after correcting for endogeneity. The results are shown in Table 5. [Insert Table 5]

Our results still hold, with central backers (1) increasing the likelihood of success (β=.94, *p<.01*), (2) increasing percent funding (β=243.45, *p=.05*), (3) decreasing the goal rate (β=-.11, *p=.05*) and (4) increasing the number of backers backing the project (β=144.61, *p<.01*).

We also find that goal amount has a negative impact, with a larger goal amount significantly reducing the likelihood of project success (β=-.55, *p<.01*), decreasing the funding of the project (β=-124.83, *p<.01*) and increasing the time taken for the project to meet its funding goal (β=.14, *p<.01*). There is a significant impact on number of tiers and creator experience on success rates, with projects that have more rewards tiers having a higher chance of success (β=.06, *p<.05*) and creators that have more past projects having a lower chance of success (β=-.07, *p<.01*). We also observe projects with videos can reach their goal faster (β=.19, *p<.1*).

Unlike the other three project outcomes, the Number of Backers is also driven by the digital buzz that they are exposed to, with a significant impact of forum mentions (β=35.84, *p<.05*), online media mentions (β=137.78, *p<.01*) and social media mentions (β=.23, *p<.01*).

Our alternative model also indicates that central backers are driven by multiple project characteristics as well as several sources of digital buzz. From our model, we find that a project creator with more experience will be able to attract more central backers to their project (β=.07, *p<.01*). Similarly, if the project has more updates (β=.05, *p<.05*), a larger goal amount (β=.14, *p<.05*) and a video in the project description (β=.57, *p<.01*), it will attract more central backers. Projects that have more mentions on forums (β=.10, *p<.05*) and blogs (β=.17, *p<.01*) will also gain attention from central backers. However, we note that projects that have fewer tiers will be able to attract more central backers (β=-.04, *p<.05*). The digital buzz results mirror what we find in our main model – that central backers are affected by blogs and forums rather than online and social media. We also note that the previously observed negative significance of social media and online media on central backers in different project outcomes do not appear in our alternative model. We also find that central backers pay attention to project and creator characteristics, unlike mainstream backers. Since our model provides insights on the project and creator characteristics that influence central backers, we can use these different elements to reach this influential segment of the community and from there improve crowdfunding success.

Additionally, we conducted a sensitivity check to ascertain our use of all three different centrality measures as proxies for influence. In our previous analyses, we used the 10 backers that scored high in degree, closeness and betweenness. However, what if we used backers that scored high on one instead of three individual centrality measures? How different would the two groups be? To provide an idea on how similar these groups are, we look at the overlap of backers between the identified central backers and backers scoring high on degree, closeness and betweenness measures. We find that there is a sizable overlap between the central backers identified and this overlap decreases as we increase the number of backers. This suggests that we can safely use any centrality measure to identify a small group of influential backers. However, this gets progressively harder as we increase the number of influential backers. With this, platforms can do well to only focus on a small number of influential backers and use them to predict crowdfunding outcomes. [Insert Table 6]

ADDRESSING LIMITATIONS WITH A SECOND STUDY

Data from Kickstarter, although extensive has some limitations. One key limitation is the lack of temporal backing data. This has limited us from identifying the order in which backers contribute to a project. We addressed this issue by imposing an assumption of symmetry between the nodes (Bramoulle and Fortin, 2010). This assumption assumes that the links are bi-directional, forming a more conservative representation of a network. However, this is not optimal as it is impossible to confirm that central backers are early supporters of projects and can, therefore, influence other potential backers who offer later support. Secondly, our model uses a subset of projects on Kickstarter and not all projects on the entire platform.

To address both these issues, we conducted a second study where we gathered data from an alternate platform, a crowdfunding platform known as Demohour. Demohour is a reward crowdfunding platform based in China. It is similar to Kickstarter, with project creators creating a project with a fixed funding goal and duration. It has been active since 2011 and has raised over USD$7.2 million across 1,095 projects with an average success rate of 53.4%. Unlike Kickstarter, Demohour provides information on the specific time when backers contribute.

Another major difference in Demohour data and Kickstarter data is the use of the entire population of Demohour's projects and backers in our analysis. This adds up to 1,095 projects and 87,896 backers from 2011 to 2016. With the availability of backing information on when backers backed a project, our affiliation network now includes timing, with directional links from earlier backers to later ones. The inclusion of this temporal data has now changed our network to a directed network, where the flow of influence from earlier backers to later backers is modeled. Furthermore, the use of the larger data set addresses issues with limited sample size and potential category limitations.

We identified 10 central backers based on the directional backer network in Demohour and present the results of their impact on project outcomes in Table 7. The 10 central backers identified by the centrality measures were early contributors to the projects, contributing within the first 29% of the project duration. The results validate our previous findings. We find that central backers have an impact on the different project outcomes by (1) increasing the likelihood of success (β=1.25, $p<.01$), (2) increasing the percent funding (β=1333.64, $p<.01$), (3) decreasing the goal rate (β=-.11, $p<.01$) and (4) increasing the number of backers (β=220.36, $p<.01$). Given that the results were reproduced even after accounting for backing sequence, we conclude that central backers can influence a crowdfunding project's outcomes and thus serve as an important determinant that should be considered by platforms and creators. [Insert Table 7]

DISCUSSION

Our research shows that network methods based on backing actions can be used to demonstrate influence and we provide evidence that backers in central positions within the backer network of a crowdfunding platform have an impact on crowdfunding project outcomes. Crowdfunding research tends to omit accounting for the influence of specific backers within the network. Our study offers a practical solution to address this by showing that the formation of an affiliation network based on backers' past actions and the measurement of each backer's centrality can be used to identify influential backers. The mere backing actions of these central backers can have a significant impact on crowdfunding project outcomes and thus should be accounted for when modeling crowdfunding success. As such, information on the past actions of backers is valuable not only to platforms but also to project creators and other backers.

We notice that goal amount has a negative effect on the project's funding. This is possibly due to the fact that backers feel that large goals are unreasonable and intimidating, thus discouraging potential backers from contributing in the first place. Lagazio and Querci (2018) found that individuals who participate in crowdfunding want to see the project being realized and if the goal is too large, backers will not participate in the funding as the project is judged as unlikely to reach its goal.

Our findings on different sources of digital buzz affecting central and non-central backers differently highlight another fundamental difference between these two different segments. We note that central backers are impacted by forums and blog posts - sources of media that tend to be longer and require more message elaboration by the individual due to the nature of the information presented in these forms. Even simple forum posts such as talking about the existence of the project or starting a thread on the project can generate sufficient interest in the project that will affect the actions of central backers. On the other hand, online and social media show an overall significant impact on non-central backers. This may be due to the possibility that these media, existing in short excerpts or in pictures and video, require less message elaboration and are created to generate attention. This is supported by previous research that have shown that the spread of social information through online and social media, such as tweets, have a positive impact on crowdfunding success (Thies et al., 2016). Simple tweets such as showing that you are a backer of the project and providing a link to the project have been shown to be impactful enough. Other research have also found that projects that have more online likes through social media platforms affect a backer's perception of project quality which will in turn affect the success of the crowdfunding project (Bi et al., 2017). This discrepancy may be attributed to the fact that unlike non-central backers, these central backers are more motivated to invest time and effort in the crowdfunding platform and thus will put in more effort to engage in message elaboration.

On a managerial level, project creators holding more in-depth knowledge on these backing actions can seek out backers that are central within the backer network. Once these backers are identified, project creators can target them in order to generate more positive outcomes for the crowdfunding project. Crowdfunding platforms should on this asset by providing an easy way for backers to locate and observe each other. This transparency of backer information is important and can affect the platform and its user network adversely if removed. As information provided increases, there will be a positive effect since allowing access to information can result in the spread of social influence within the user network that will generate positive project outcomes. Benefits accrued from network effects can expand depending on the amount and scope of information that is freely available. However, there is also the negative impact of information transparency stemming from privacy concerns (Burtch et al., 2015). From a backer's perspective, the positive effects of the backer network will be offset by the negative effects of privacy after a certain threshold when information on backers becomes so invasive that any benefits accrued by the backer are effectively canceled out. This becomes a delicate balancing act for platforms since privacy issues may lead backers to withdraw from the platform.

Our study's findings suggest that it is in the interest of crowdfunding platforms to identify the inflection point where the positive effects of the network will be offset by the negative impact of privacy issues. This maintains a balance of encouraging the development of the network while at the same time managing privacy concerns. We propose that managers can consider two methods to obtain a balance between the two. One possible method relates to the quality of the information provided. Crowdfunding platforms can allay privacy concerns by identifying users not by usernames but by a serial number. Centrality scores can be shown in these profile pages and a suitable metric label such as 'influence points' can be created. This suggestion allows information that assists in the formation of the backer network to be present while preserving the anonymity of the individual. As such, backers can follow central backers on the platform. Similarly, crowdfunding platforms or project creators can target these central backers by encouraging them to back projects due to their positive impact on other backers.

The second possible method relates to formulating the network without information being disclosed. Platforms can create an artificial network and use simple identification criteria to identify central backers. Our paper explores an organically formed network that is developed largely without control from the platform. However, since privacy is a concern and platforms may not want to release information on backers, platforms can choose to artificially form their own backer network. Individuals can be identified by crowdfunding platforms as star backers and can be listed on the platform itself. Individuals that are active in each category can be identified and segmented into further subcategories and backers can observe their backing decisions. Platforms that can manage this will be able to benefit from network externalities.

CONCLUSION

With increased data availability on all elements in an online platform, we now have access to previously hidden data and the tools to organize them in meaningful ways. This information has been underutilized by both practitioners as well as academics, but it is precisely this information that may have an unobserved impact on outcomes that we are interested in. The potential to exploit network targeting strategies has become an opportunity that crowdfunding platforms should explore given their impact on key crowdfunding outcomes that are paramount to the efficacy of the platform. Our paper suggests a method that can be used to locate influential platform users – centrality within the backer affiliation network. Our results show that these central backers do have a sizable impact on crowdfunding projects and platforms should leverage on this by implementing certain systems that increase the ease in which backers can link up with other backers while ensuring anonymity. This would benefit all three stakeholders in the crowdfunding ecosystem as it will not only allow backers to identify projects they may be interested in but also increase the likelihood of crowdfunding success and increasing funding amounts for the project creator while improving the efficiency and profitability of the platform itself.

Despite the seemingly appealing idea of simply using the number of projects to determine influence, our findings indicate that backers who indiscriminately back many projects do not have influence over project outcomes. Practitioners should be aware of this and target backers accurately so as not to allocate resources on backers that will not contribute significantly to the crowdfunding project's success. Similarly, the notion that not all central backers have uniform influence has also been shown in our findings. Practitioners need to be wary that targeting too many central backers may not be as effective as targeting a small group of top central backers as they may wield a disproportionate amount of influence and thus targeting these backers would be more cost efficient and generate the most benefits to practitioners.

In terms of the avenue needed to reach these central backers, our paper further provides information on the sources of digital buzz that can influence these central backers. Project creators and crowdfunding platform managers will be able to target these central backers via blogs and forums to reach them. As such, investments into increasing the word of mouth spread by these sources of digital buzz will provide incremental benefits to the crowdfunding projects.

We hope that our study helps cement the importance of networks in online platforms and initiate more research into this underexplored domain.

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Figure 1 Conceptual Model of Crowdfunding Success

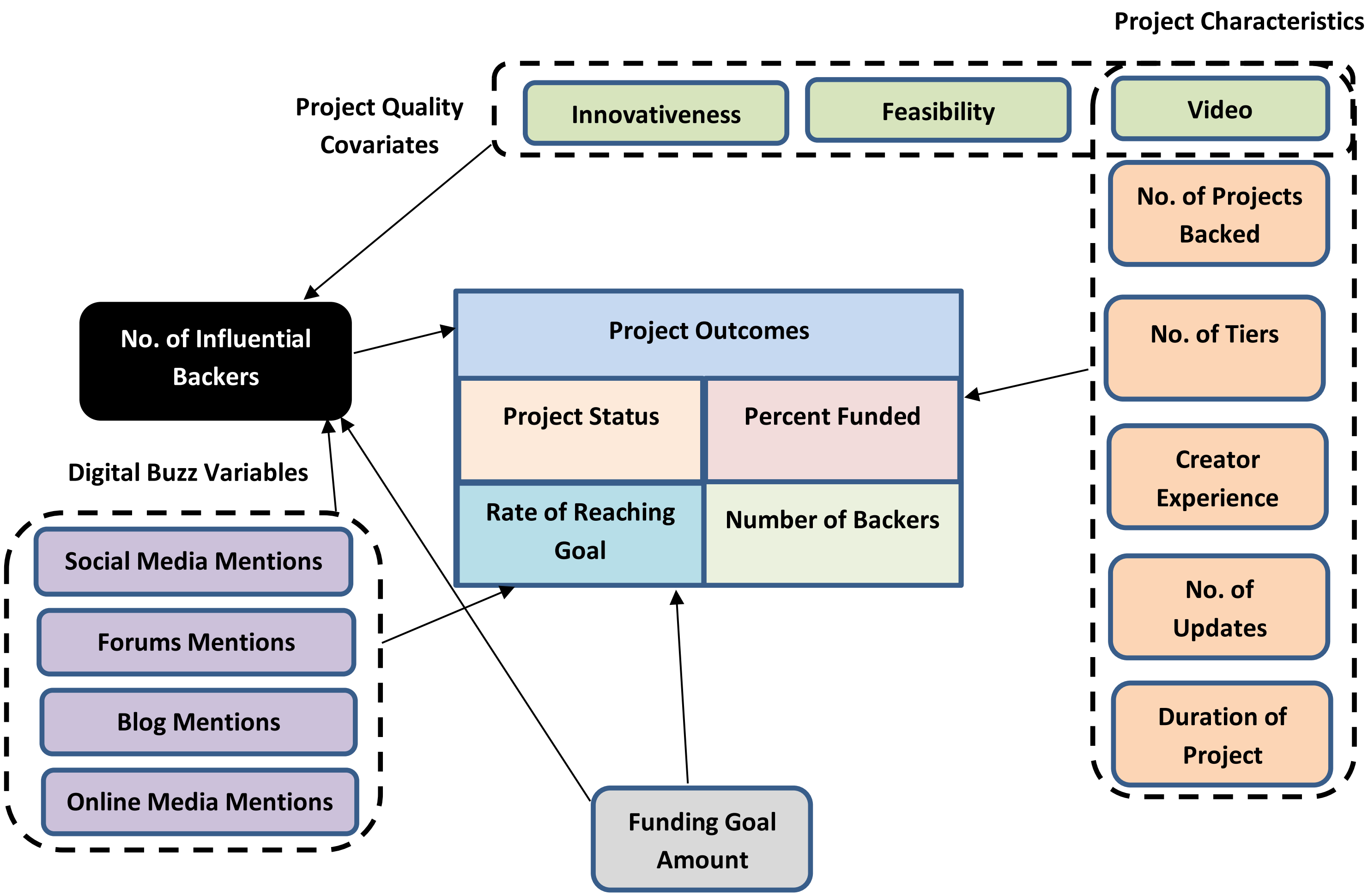

Figure 2 Transforming a two-mode affiliation network into a one-mode network

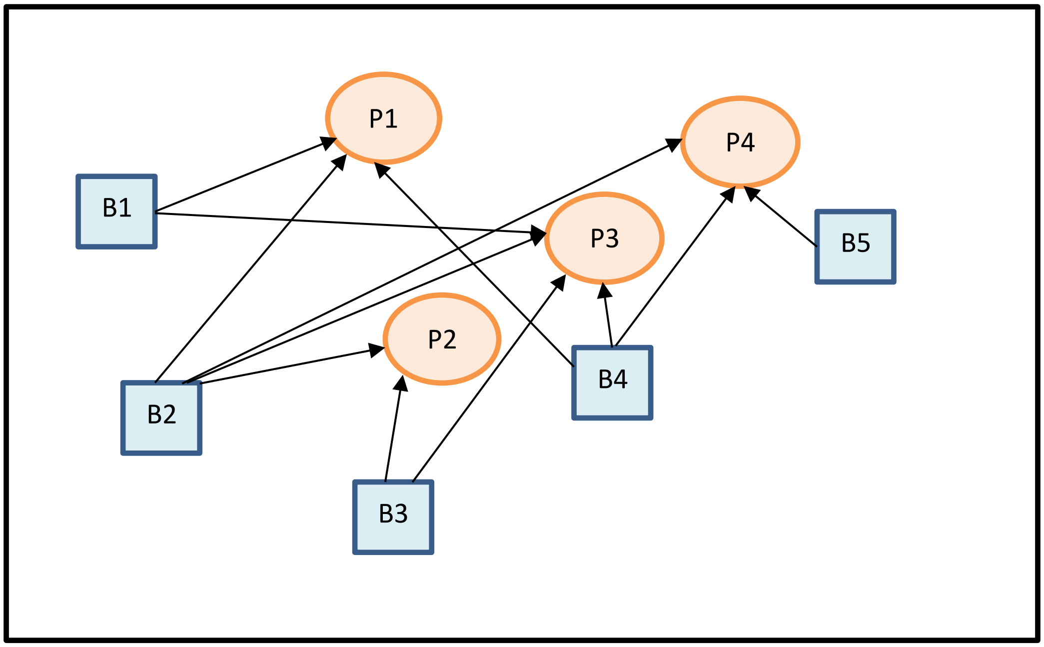

Fig 2a Two Mode Affiliation Network: *Backers and Projects as nodes with edges representing if a backer has backed that specific project.*

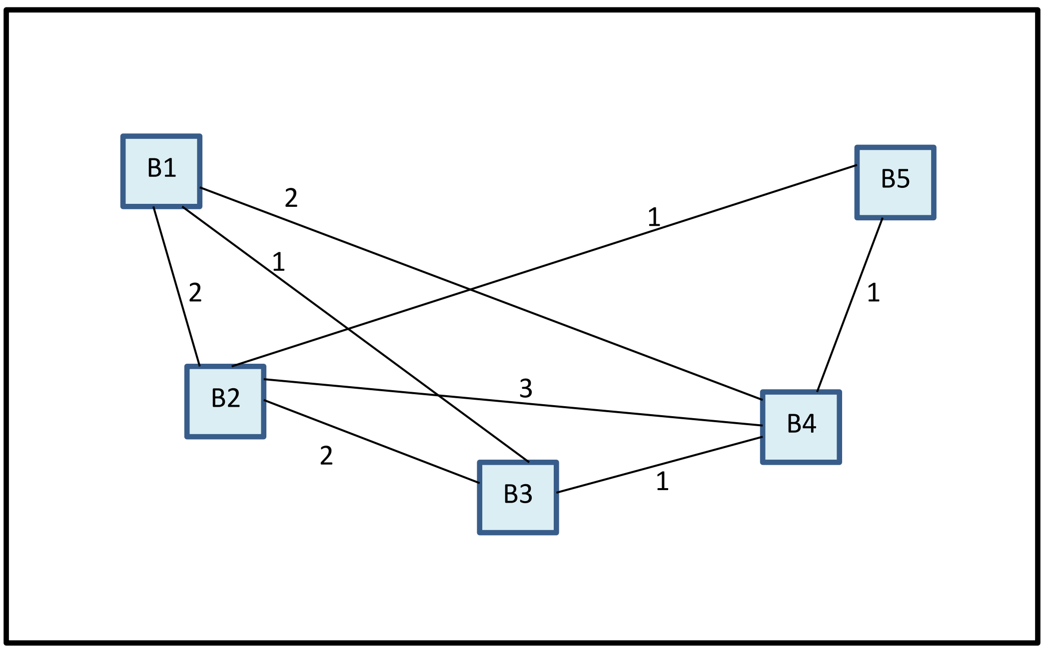

Fig 2b Projection into a one-mode network: *Backer nodes are selected and are linked to each other if they backed the same project, with the number of shared projects as the weights of the edges.*

Figure 3 Presence of Central Backers on Project Outcomes

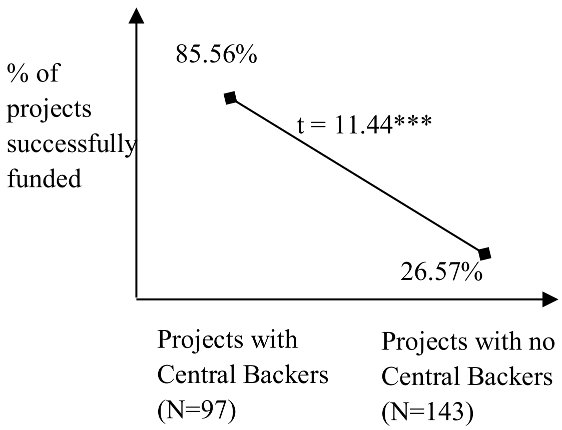

Fig 3a Presence of Central Backers on Funding Status: *Projects with Central Backers show a higher likelihood of success*

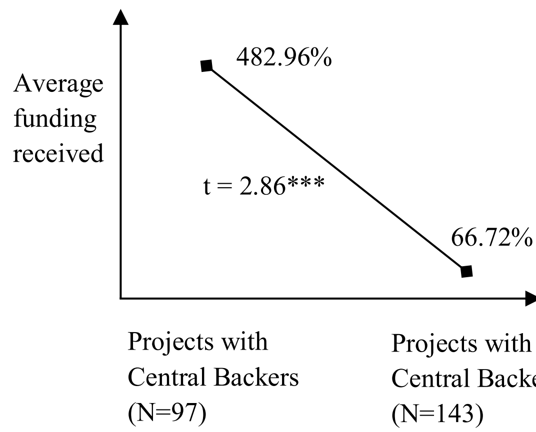

Fig 3b Presence of Central Backers on Percent Funded: *Projects with Central Backers generate higher funding*

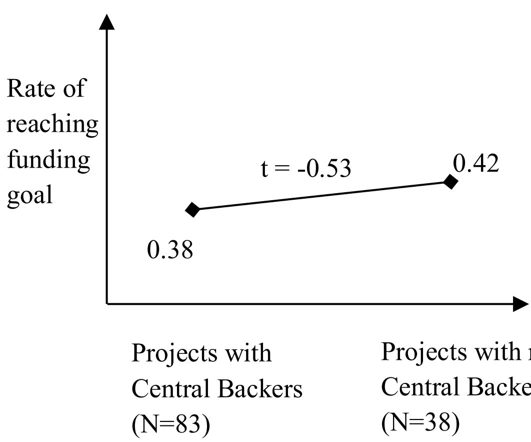

Fig 3c Presence of Central Backers on Goal Rate: *Projects with Central Backers are slightly faster in reaching its funding goal*

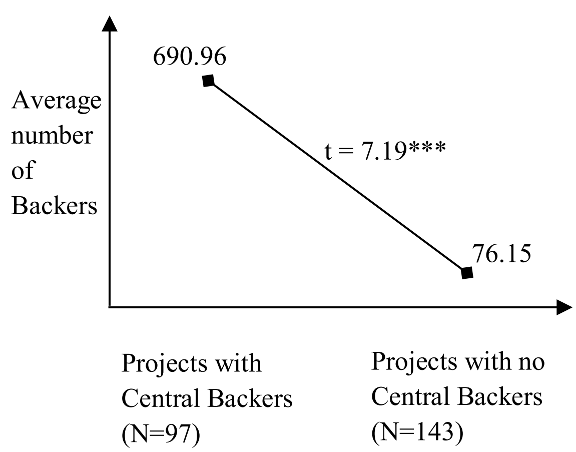

Fig 3d Presence of Central Backers on Number of Backers: *Projects with Central Backers have a higher number of backers*

Figure 4 Presence of Different Backers on Project Outcomes

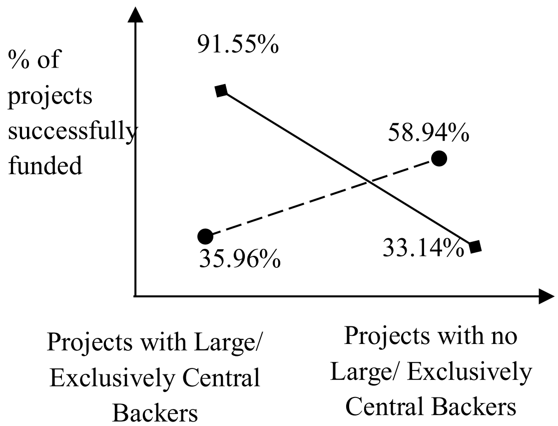

Fig 4a Presence of Different Backers on Funding Status: *Unlike projects with central backers, projects with large backers do not have a higher likelihood of success compared to projects with no large backers.*

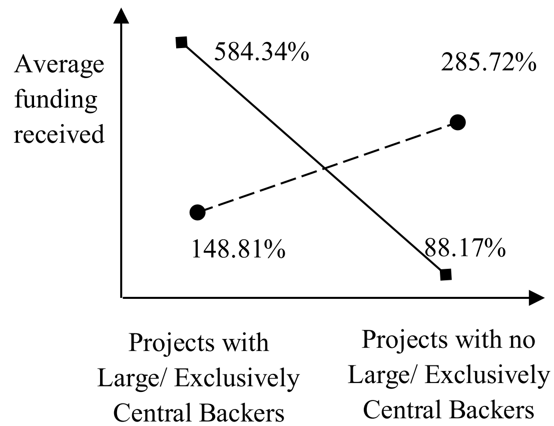

Fig 4b Presence of Different Backers on Percent Funded: *Unlike projects with central backers, projects with large backers do not generate higher funding compared to projects with no large backers.*

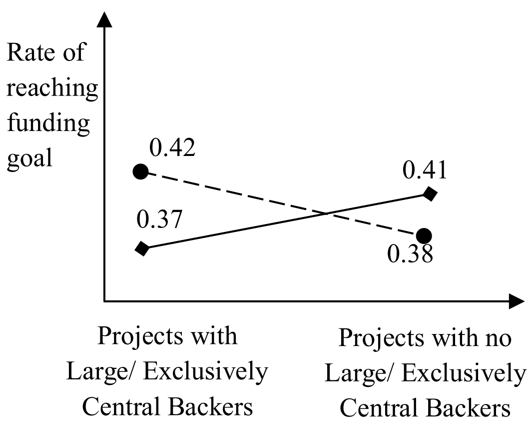

Fig 4c Presence of Different Backers on Goal Rate: *Unlike projects with central backers, projects with large backers do not reach its funding goal faster compared to projects with no large backers.*

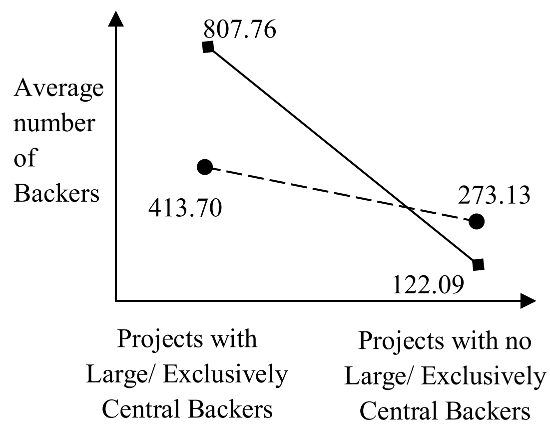

Fig 4d Presence of Different Backers on Number of Backers: *Although projects with large backers have more backers, however the magnitude of backer size is smaller than that of projects with central backers.*

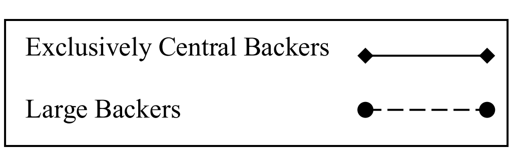

Table 1 Variable Definitions, Measures and Data Sources

Classification	Measures	Meaning	Source
Project Outcomes	Status	Project Success or Failure	Kickstarter Page
	% Funded	Percentage of the project goal Funded	Kickstarter Page
	Goal Rate	Time taken for the project to reach its goal	Kickspy
	No. of Backers	No. of backers contributing to the project that are not identified as central backers	Kickstarter Page
Network Variable	No. of Central Backers	No. of backers contributing to the project that score high on centrality measures	Web Crawler
Project Characteristics	Duration	Total duration of the project	Kickstarter Page
	Creator Experience	No. of other projects created by the project creator	Kickstarter Page
	Tiers	No. of project reward tiers	Kickstarter Page
	Updates	No. of updates by the creator for the duration of the project	Kickstarter Page
	Goal Amount	The amount the project is seeking to raise	Kickstarter Page
	No. of Projects Backed	The number of other projects backed by the project creator	Backer Information Page
Project Quality	Innovativeness	The novelty of the project from a technological and market standpoint	Ratings of the Project Page
	Feasibility	The likelihood of the project being a success in the market	Ratings of the Project Page
	Video	Presence of a video on the project page	Kickstarter Page
Digital Buzz Variables	Social Media	No. of mentions on social media pages for the duration of the project	Search of Twitter, Facebook and Google Plus
	Forums	No. of forum threads created for the duration of the project	Web Search of Forum Threads
	Online Media	No. of media page posts created for the duration of the project	Web Search of media pages
	Blogs	No. of blog mentions posted for the duration of the project	Web Search on Blogs

Table 2 Descriptive Statistics

			Correlation Matrix																	
Variable	**M**	**SD**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**
1.Duration (log)	3.41	.33	1.00																	
2.Goal amount (log)	8.86	1.66	.22	1.00																
3. Forums	2.21	2.92	-.03	.14	1.00															
4. Media	.54	1.35	.06	.24	.47	1.00														
5. Blogs	.85	2.08	-.02	.19	.48	.47	1.00													
6. Social	75.64	429.01	-.01	.11	.50	.54	.51	1.00												
7. No. of Central Backers	1.33	2.24	-.10	.09	.39	.09	.26	.05	1.00											
8. Tiers	10.43	6.62	.19	.38	.21	.25	.29	.18	.06	1.00										
9. Video	.83	.37	.03	.20	.15	.15	-.03	.07	.16	.23	1.00									
10. Updates	8.18	10.12	.09	.14	.35	.23	.29	.05	.40	.40	.10	1.00								
11. Innovativeness	3.46	2.09	.06	.34	.21	.25	.25	.19	.29	.33	.31	.26	1.00							
12. Feasibility	5.49	2.31	-.07	-.30	.08	-.05	-.02	-.09	.19	-.06	-.01	.05	-.18	1.00						
13. Creator Experience	1.72	5.97	-.17	-.11	.06	-.05	-.01	-.03	.33	-.15	.01	.01	.03	.13	1.00					
14. No. of Backed Projects	27.7	61.06	-.05	-.05	.21	.03	.02	.005	.26	.01	-.01	.19	-.03	.12	.39	1.00				
15. Status	.50	.50	-.10	-.22	.39	.23	.31	.14	.51	.20	.004	.46	.16	.18	.17	.32	1.00			
16. Percent Funded	234.95	933.64	-.09	-.16	.12	.01	.04	.02	.33	.02	-.02	.23	.13	.09	.07	.11	.24	1.00		
17. Goal Rate	.20	.32	.06	.01	.19	.20	.19	.08	.21	.18	.07	.27	.19	.01	-.03	.16	.62	-.04	1.00	
18. No. of Backers	324.40	619.09	-.07	.21	.59	.54	.48	.45	.61	.25	.13	.36	.32	.08	.07	.14	.43	.40	.14	1.00

Notes: VIF was < 5 for all variables, ranging between 1.13 to 3.73

Table 3 Results from Kickstarter Crowdfunding Data

	Status		% Funded		Goal Rate		Backers	
	Status	No. of Central Backers	% Funded	No. of Central Backers	Goal Rate	No. of Central Backers	No. of Backers	No. of Central Backers
Central Backer Variable								
No. of Central Backers	.65(.17)***		158.72(38.22)***		-.04(.02)***		181.25(15.94)***	
Project Characteristics								
Duration (log)	-.04(.35)		-125.31(175.25)		.11(.08)		-108.76(73.11)	
Creator Experience	-.06(.03)*		-9.49(10.75)		-.01(.005)		-9.17(4.48)**	
No. of Backed Projects	.01(.004)***		.19(1.02)		.0001(.0004)		.001(.43)	
No. of Tiers	.06(.03)*		6.61(10.25)		-.01(.004)		7.60(4.28)*	
No. of Updates	.06(.02)***		13.73(6.87)**		-.003(.003)		-.73(2.87)	
Goal Amount (log)	-.63(.11)***	-.05(.08)	-116.22(37.52)***	-.05(.08)	.11(.02)***	.23(.07)***	12.24(15.65)	-.05(.08)
Project Quality Indicators								
Innovativeness		.30(.06)***		.30(.06)***		.18(.05)***		.30(.06)***
Feasibility		.28(.06)***		.28(.06)***		.22(.05)***		.28(.06)***
Video	-.06(.35)	.68(.37)*	-136.66(159.27)	.68(.37)*	.11(.08)	.73(.31)**	-96.46(66.44)	.68(.37)*
Digital Media Buzz Variables								
Forums	.01(.06)	.25(.05)***	-5.87(25.94)	.25(.05)***	-.01(.01)	.08(.03)**	29.45(10.82)***	.25(.05)***
Online Media	.13(.14)	-.15(.11)	10.40(53.14)	-.15(.11)	-.01(.02)	-.23(.08)***	144.15(22.17)***	-.15(.11)
Blogs	.36(.17)**	.13(.05)***	-45.15(35.50)	.13(.05)***	-.002(.01)	.06(.03)*	-1.81(14.81)	.13(.05)***
Social Media	.002(.002)	-.001(.0003)**	.16(.18)	-.001(.0003)**	-.000003(.0001)	-.0002(.0002)	.26(.07)***	-.001(.0003)**
Log-Likelihood	-355.59		-2247.44		-229.74		-2037.62	

*** p<0.01 **p<0.05 *p<0.1

Table 4 Alternative Backer Specifications & Robustness Checks for Kickstarter Data

Models	Source	Status	% Funded	Goal Rate	No. of Backers
1. Large Backer Model	Identifying the 10 backers who backed the most number of projects that do not score high on centrality	-.82(.20)***	-1.65(89.35)	-.02(.05)	51.20(44.62)
Log-Likelihood		-266.97	-2162.52	-111.62	-1995.84
2. Exclusively Central Backer Model	Identifying the 10 backers who score high on centrality but are not large backers	.66(.18)***	155.16(38.18)***	-.05(.02)***	182.42(15.83)***
Log-Likelihood		-304.48	-2195.14	-203.96	-1983.80
3. Non-Central Backer Model	Identifying 10 backers who do not score high on centrality	.60(.43)	81.9(192.51)	-.02(.08)	83.0(96.28)
Log-Likelihood		-152.23	-2039.42	-74.65	-1873.14

Table 5 Endogeneity Correction with an Instrumental Variable on an Alternative Model (Kickstarter)

	Status		% Funded		Goal Rate		Backers	
	Status	No. of Central Backers	% Funded	No. of Central Backers	Goal Rate	No. of Central Backers	No. of Backers	No. of Central Backers
Central Backer Variable								
No. of Central Backers	.94(.14)***		*243.45(126.60)**		*-.11(.06)**		144.61(52.85)***	
Project Characteristics								
Duration (log)	.19(.31)	-.45(.28)	-91.54(183.45)	-.45(.28)	.08(.09)	-.52(.48)	-123.36(76.58)	-.45(.28)
Creator Experience	-.07(.03)***	.07(.02)***	-16.27(14.5)	.07(.02)***	-.001(.01)	.07(.03)**	-6.23(6.06)	.07(.02)***
No. of Backed Projects	.01(.004)	-.0004(.002)	.07(1.05)	-.0004(.002)	.000003(.0004)	-.002(.002)	.05(.44)	-.0004(.002)
No. of Tiers	.06(.02)**	-.04(.02)**	9.59(11.19)	-.04(.02)**	-.01(.01)	-.06(.03)**	6.31(4.67)	-.04(.02)**
No. of Updates	.02(.02)	.05(.01)***	9.00(9.67)	.05(.01)***	-.001(.003)	.03(.02)*	1.32(4.04)	.05(.01)***
Goal Amount (log)	-.55(.12)***	.14(.06)**	-124.83(39.83)***	.14(.06)**	.14(.04)***	.48(.14)***	15.97(16.63)	.14(.06)**
Video	-.31(.31)	.57(.25)**	-191.42(178.78)	.57(.25)**	.19(.11)*	1.03(.48)**	-72.78(74.63)	.57(.25)**
Instrumental Variable								
Competitive Intensity for Central Backers		.55(.11)***		.55(.11)***		.63(.19)***		.55(.11)***
Digital Media Buzz Variables								
Forums	-.07(.05)	.10(.04)**	-20.63(33.59)	.10(.04)**	-.01(.01)	.07(.06)	35.84(14.02)**	.10(.04)**
Online Media	.17(.12)	-.06(.09)	25.14(57.63)	-.06(.09)	-.03(.03)	-.15(.13)	137.78(24.06)***	-.06(.09)
Blogs	.18(.16)	.17(.06)***	-61.06(42.41)	.17(.06)***	.01(.02)	.10(.08)	5.07(17.71)	.17(.06)***
Social Media	.002(.002)	-.0004(.0003)	.21(.19)	-.0004(.0003)	-.00003(.0001)	-0003(.0004)	.23(.08)***	-.0004(.0003)
Wald's chi-square	79.46		32.67		30.71		355.84	

Note: The probability value for No. of Central Backers for % Funded and Goal Rate is 0.05

*** p<0.01 **p<0.05 *p<0.1

Table 6 Correlation of Backers Between Central Backers and Backers Scoring High on Individual Centrality Indices

Number of Central Backers	Individual Centrality Indices	Overlap
10	Degree	0.9
10	Closeness	0.9
10	Betweenness	0.7
20	Degree	0.8
20	Closeness	0.85
20	Betweenness	0.7
50	Degree	0.72
50	Closeness	0.72
50	Betweenness	0.56

Table 7 Results from Demohour Crowdfunding Data

	Status		% Funded		Goal Rate		Backers	
	Status	**No. of Central Backers**	**% Funded**	**No. of Central Backers**	**Goal Rate**	**No. of Central Backers**	**No. of Backers**	**No. of Central Backers**
Central Backer Variable								
No. of Central Backers	1.25(.21)***		1333.64(245.83)***		-.11(.02)***		220.36(15.80)***	
Project Characteristics								
Duration (log)	-.11(.08)		-233.91(261.03)		-.01(.02)		-109.97(16.78)***	
Creator Experience	.10(.09)		-343.20(263.69)		.04(.02)**		-12.43(16.95)	
No. of Backed Projects	.02(.01)**		-10.15(21.21)		.0003(.002)		-.18(1.36)	
No. of Tiers	.04(.01)***		235.48(40.40)***		.01(.003)**		15.31(2.60)***	
No. of Updates	.01(.002)***		28.91(3.72)***		.00003(.0002)		6.56(.24)***	
Goal Amount (log)	-.24(.03)***	.27(.11)**	-329.90(111.94)***	.27(.10)**	-.01(.01)	.45(.12)***	23.92(7.20)***	.27(.10)**
Project Quality Indicators								
Innovativeness		.58(.06)***		.58(.06)***		.43(.06)***		.58(.06)***
Feasibility		.42(.08)***		.42(.08)***		.18(.08)**		.42(.08)***
Video	.22(.09)**	-.65(.23)***	-217.33(313.59)	-.65(.23)***	.05(.03)*	-.69(.22)***	-24.88(20.16)	-.65(.23)***
Digital Media Buzz Variables								
Forums	.88(.38)**	.25(.33)	-900.09(695.13)	.25(.33)	.08(.05)	.18(.30)	42.23(44.69)	.25(.33)
Online Media	-.36(.45)	-.60(.60)	478.62(1094.90)	-.60(.60)	-.01(.08)	-.32(.52)	479.99(70.39)***	-.60(.60)
Blogs	.71(.14)***	.46(.13)***	-127.88(252.30)	.46(.13)***	-.08(.02)***	.36(.11)***	21.45(16.22)	.46(.13)***
Social Media	.43(.27)	-17.58(552.13)	363.87(1043.79)	-18.41(836.05)	.03(.09)	-17.79(594.31)	338.86(67.11)***	-18.41(836.05)
Log-Likelihood	-1025.61		-11276.18		-547.33		-8273.91	

*** p<0.01 **p<0.05 *p<0.1