How Different are Crowdfunders?
Examining Archetypes of Crowdfunders and Their Choice of Projects

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ABSTRACT

While current research treats all crowdfunders on the same platform as a homogeneous group, we argue that such an assumption may limit our understanding of the complexities of the crowdfunder community. In this paper, we begin to unpack the complexities of the crowdfunder community by identifying different archetypes of crowdfunders funding technology projects on *Kickstarter.com*, we identified four distinct types of crowdfunders: Active Backers, Trend Followers, the Altruistic, and the Crowd. Our results show that crowdfunders on the same platform are highly heterogeneous, with different motivations that are reflected in their strategies and behaviors. We further hypothesized and tested how the strategies and motivations of different crowdfunder archetypes further influence their choices of when and which projects to fund. In so doing, we not only reconcile conflicting results from the literature, but also synthesize differing theoretical perspectives that have been applied to understand the crowdfunding phenomenon.

Keywords: Crowdfunding, Social Influence, Signaling, Cluster Analysis, Choice Model

INTRODUCTION

Recent upheavals in global economic conditions have changed the landscape of financing for small businesses. Crowdfunding is becoming an important financing alternative for small businesses, as they increasingly face difficulties raising capital from traditional offline channels of credit, like angel capital providers, venture capitalists, and banks (Ahlers et al. 2012; Hemer 2011). Crowdfunding refers to the practice by which funding resources are pooled by people, usually via the Internet, to support efforts initiated by others (Ordanini et al. 2011). The market for crowdfunding did not exist until 2006, but it has grown very quickly since its inception. *Kickstarter*, America's leading crowdfunding platform for creative projects, has raised more than 800 million dollars by September 2013 even though direct payback in the form of equity or interest is prohibited under current regulations. Among all the successfully funded technology projects, nearly one fifth of them have raised more than 100 thousand US dollars. Some of the successful projects eventually became start-up companies (e.g. *Pebble,* a smartwatch manufacturer; *Ouya*, an android gaming console maker). According to industry reports by *Massolution*, the market size of crowdfunding has doubled each year in the past three years and is expected to grow to $5.1 billion in 2013 (Wang and Fesenmaier 2004).

The growing popularity of crowdfunding has also sparked interest in the research community. Due to the novelty of the phenomenon, much of the research done so far are still in working paper formats, or have only been published in conferences, with only a small percentage of the work published in journals. Nevertheless, this small but growing body of work is shaping our understanding of the crowdfunding phenomenon, highlighting critical theoretical perspectives that are relevant to help us gain further insights into crowdfunding.

Most research on crowdfunding so far focuses either on the entrepreneur's perspective or the crowdfunders' perspective. Many articles that focus on the entrepreneur's perspective seek to identify factors influencing the success of an entrepreneur in raising funds. Much of this work builds upon signaling theory (Spence 1973), mainly due to the problems of information asymmetry and adverse selection that all investors face when choosing which ventures to invest in – a problem widely acknowledged in the entrepreneurial finance literature (Leland and Pyle 1977). Due to the lack of information that investors have on entrepreneurs seeking funding from crowdfunding platforms, investors rely on signals that they can obtain about the venture. Lin, et al. (2013b), for example, examined how online friendship networks in *Prosper.com*, an online peer-to-peer lending marketplace, serve as signals of borrowers' credit quality, thus increasing the probability that lenders will be successfully funded. Giudici et al. (2013), similarly demonstrated how social capital of entrepreneurs influenced the probability of success of crowdfunding projects in 11 Italian crowdfunding platforms. Ahlers, et al. (2012), examining an equity crowdfunding context, focused on identifying signals, such as financial roadmaps, external certifications and internal governance, that predicted fundraising success of ventures.

Another group of studies focus on the crowdfunders' perspective, examining how crowdfunders make decisions about which projects to invest in. This group of studies draw on social influence theory, examining the extent to which crowdfunders are influenced by others' contribution behavior (e.g. herding behavior). Burtch et al. (2013), for example, found a crowding-out effect, where subsequent crowdfunders are less likely to fund the project because a decreased marginal utility is experienced by the crowdfunder who thinks that the additional contribution is less important to the project. Similarly, Kuppuswamy and Bayus (2013) find that subsequent crowdfunders' contributions are negatively related to previous crowdfunders' contributions. They attribute the findings to a bystander effect, whereby the diffusion of responsibility due to the presence of initial support and other available crowdfunders, fuel the typical crowdfunder's assumption that others will provide the necessary funds required for a project. These two studies stand in contrast to other papers that have found evidence of herding in crowdfunding platforms. Zhang and Liu (2012) found evidence of rational herding in *Prosper.com*, where crowdfunders engaged in observational learning, using lending decisions by other peers to infer borrowers' creditworthiness. Similarly, Colombo et al. (2013) found that early participation by crowdfunders encouraged additional participation by others in *Kickstarter*, and predicted crowdfunding success.

Already at this nascent stage of research on crowdfunding, research has started to uncover inconsistent findings regarding crowdfunders' behavior. We argue that the key factor contributing to such inconsistencies is the heterogeneity of the crowdfunders. While different crowdfunding platforms are clearly targeted for different purposes (e.g. for donations or equity), scholars have characterized crowdfunders differently even for the same crowdfunding platform. For example, Mollick (2013) assumes crowdfunders on *Kickstarter* are investors seeking return from the money they pledged. Kuppuswamy and Bayus (2013), on the other hand, explicitly assume crowdfunders on *Kickstarter* are donors, highlighting bystander effects that are typical of donor behavior. But as pointed out by a growing body of work (Gerber et al. 2012; Ordanini et al. 2011; Zvilichovsky et al. 2013), crowdfunders participate in crowdfunding for various motives. Gerber et al. (2012)'s interviews with *Kickstarter* participants reveal that people fund projects to get rewards, support creators and causes, and even simply to engage and contribute to the community.

To sum up, the goals of crowdfunders are heterogeneous (Mollick 2013). Given the complexities of crowdfunders' motivations in participating in crowdfunding platforms, it is important to recognize that even within the same crowdfunding platform, crowdfunders are not homogeneous. Two studies, in particular, have highlighted the questionable assumption that crowdfunders on the same platform are a homogeneous group with similar motivations for funding projects on a platform. Kim and Viswanathan (2013) identified experienced investors and investors who were also project creators, as two types of investors who stood out among the crowd and had significant influence on the crowdfunding behavior of other crowdfunders. Hahn and Lee (2013) also recognized that within the same crowdfunding platform, crowdfunders' behavior and strategies could be different. Hence, they identified five distinct archetypes of crowdfunders based on two dimensions of crowdfunders' behavior: the frequency with which they funded projects and the extent to which they backed projects in different categories (e.g. music versus technology). They found that projects with different compositions of crowdfunders differed in the success of their fund raising efforts. We build upon the fundamental premise of these two articles – that crowd funders on the same platform are heterogeneous in their motives; hence, their crowdfunding behavior and strategies differ.

Our first research objective is thus to incorporate the various perspectives explaining the motivations of crowdfunders and how that may influence their crowdfunding behavior and strategies. Using this approach, we try to identify different crowdfunder profiles and highlight the key characteristics of each type of crowdfunder profile. Recognizing the heterogeneity of the crowdfunder community and subsequently understanding the characteristics and behaviors of different crowdfunders have important theoretical and practical implications. Based on the crowdfunder profiles identified in the first stage of our research, our second research objective is to use the insights obtained about different crowdfunder archetypes to reconcile some of the contradictory findings that have appeared in the literature thus far. We build upon prior work that has examined both the herding behavior of crowdfunders and the signals important to entrepreneurs in two important ways. First, we seek to reconcile the differing findings regarding the herding behavior of crowdfunders by showing that only crowdfunders with certain profiles react to social influence and engage in some form of herding behavior. Second, we synthesize both the social influence and signaling theoretical perspectives typically used in prior research examining crowdfunders' behavior versus entrepreneurs' crowd funding success respectively. We do so by highlighting how crowdfunders with different profiles will react in distinct ways to various project quality signals, and how certain types of crowdfunders may, on their own, serve as a signal influencing the crowdfunding decisions of other crowdfunders.

THE CROWDFUNDING PHENOMENON

Crowdfunding is derived from the concept of crowdsourcing, in which a task is outsourced as an open call to the public, or the crowd (Afuah and Tucci 2012). Belleflamme et al. (2012) define crowdfunding as an open call, mostly through the Internet, for the provision of financial resources either in form of donation or in exchange for a future product or some form of reward and/or voting rights. This definition recognizes the Internet as an important component in this phenomenon. Raising funds by drawing on small contributions from the crowd is nothing new, but the development of Web 2.0 technology has turned the Internet into a new venue for fund raising. Web 2.0 technology allows fundraisers to reach a large number of users more easily than in the past. Potential barriers created by non-presence are mitigated by the rich information now presented via multimedia such as texts, pictures, videos, and hyperlinks. Online payment also makes monetary transactions easier to execute than in the past (Schwienbacher and Larralde 2010). Hence, crowdfunding can be thought of as a form of fund raising through the Internet and the embedded IT artifact makes it suitable for IS research (Orlikowski and Iacono 2001).

The literature discusses different forms of crowdfunding. Mollick (2013) suggests a typology of four types of crowdfunding, which clearly characterizes the nature of crowdfunding platforms currently available: the patronage, lending, reward-based, and equity-based models. The patronage model can be classified as donation-based crowdfunding, where funders act as philanthropists and the funding behavior is driven mainly by altruism (Galak et al. 2011). An example is *Kiva.org*, a microfinance platform where small loans are made to low-income individuals to alleviate poverty. The lending model refers to peer-to-peer lending platforms, where small loans are made in hope for a certain rate of return. A commonly known example is *Prosper.com*, a platform where individuals can request personal loans and offer a fixed rate of return to potential lenders (Lin et al. 2013b; Zhang and Liu 2012). The reward-based model, as the name suggests, typically offer some form of reward for funders, although the reward may range from a simple acknowledgment in the movie, a sticker of the initiative, or even a prototype of the product (Kuppuswamy and Bayus 2013; Mollick 2013). This model incorporates a wide variety of creative projects, ranging from music, games, to design and technology. Examples of this model include *Kickstarter* (http://www.kickstarter.com) and *Indiegogo* (http://www.indiegogo.com/). Finally, equity-based model offers funders a small equity stake in the future company in return for their funding contributions (Ahlers et al. 2012). This type of crowdfunding platform has yet to be widely popularized, mainly due to regulators' apprehension about the uncertainties of regulating such a market. Existing examples includes *Seedrs* (*http://www.seedrs.com/*) and *Crowdcube* (*http://www.crowdcube.com/*) in the UK.

We focus on the third model of crowdfunding platform – rewards based model for several reasons. The importance of the crowdfunding phenomenon arises from the fact that crowdfunding has been touted as an important financing alternative for entrepreneurs to access seed funding compared to traditional offline alternatives (Hemer 2011). While one may expect that equity-based crowdfunding platforms are more likely to fulfill the role of the alternative financing source for most entrepreneurs, the uncertainty associated with such platforms and the increasing popularity of rewards-based crowdfunding platforms, both for entrepreneurs and crowdfunders, have crystallized the key role that the latter type of platforms have in the crowdfunding space. Belleflamme et al. (2012), along with others, show that rewards-based crowdfunding presents many other benefits, in addition to raising funds for the entrepreneur. Crowdfunding serves as a way to price discriminate between two types of consumers (those who pre-order the product vs. those who buy the final product)

(Belleflamme et al. 2012). The success of a rewards-based crowdfunding project also generates hype around a new product and presents a way for entrepreneurs to market their products to early adopters of their products (Burtch et al. 2013; Schwienbacher and Larralde 2010). For the entrepreneur, pre-orders not only provide an indication of demand for the product, but also provide additional legitimacy to entrepreneurs who can show that their ideas have been supported through a democratic selection process by the crowd (Lehner 2012). Such information is especially useful for entrepreneurs who wish to seek funds from venture capitalists later on in their entrepreneurial journey.

RESEARCH SITE

Our research site is *Kickstarter.com*, the world's leading reward-based crowdfunding platform for creative projects. *Kickstarter* was founded in 2009 and has become one of the world's most influential crowdfunding platforms for supporting creative projects. As at 2013, a total of $933 million has been pledged by 5.4 million people to support 54,000 projects. *Kickstarter* aims to be as open as possible for creative projects, specifying only a few restrictions for projects. The platform only employs simple checks on each submitted project to ensure that they satisfy basic requirements. This makes it an ideal site for our research, as it allows us to examine a platform that has projects with a wide variety of characteristics.

To create a project, the creator specifies a goal for the project, such as launching a new album, or manufacturing a new product. The creator also has to specify the monetary goal of the project (i.e. the amount of money the project seeks to raise) and the duration of the project, ranging from 3 days to 3 months. *Kickstarter* provides various means for project creators to pitch their ideas. Project creators can provide detailed textual description of the project embedded with pictures and hyperlinks. Most project creators also make a video for the project. To provide further incentives to potential contributors, project creators can specify different levels of rewards to contributors. A reward can be as little as an acknowledgement on the website and as large as a prototype of the final product. When the project is launched, crowdfunders can review the project page and make their pledging decisions. The platform adopts an all-or-nothing mechanism, in which all previously pledged money will be returned to crowdfunders if the project does not reach its funding goal. If the project reaches its funding goal within its pre-specified period, the project will receive the total amount pledged (even if it exceeds the targeted amount) after *Kickstarter* deducts a 5% fee. *Kickstarter* also provides channels for interaction, monitoring, and crowdfunder community development for project creators and crowdfunders. Project creators usually post updates of their projects while crowdfunders post questions, suggestions, and comments.

We focus on the projects listed in the technology category of the *Kickstarter* site for the following reasons. First, projects in the technology category often offer pre-orders of a product prototype, and *Kickstarter* typically require such projects to produce a manufacturing plan and a clear delivery date for the stated rewards when starting a *Kickstarter* project (Mollick 2013). Hence, we believe that the technology category includes a large portion of projects that have significant potential of becoming a technology venture firm after a successful fund raising effort. One of the most successful examples is *Oculus Rift*, a virtual reality headset for video gaming, which raised more than $2 million, 10 times its original goal and is now an incorporated company. Second, prior research has also shown that projects in the technology category tend to be less susceptible to geographical constraints in the funding source, attracting the majority of funds from outside the home region (Kim and Hann 2013). This highlights that projects in this category has the promise of overcoming the problem typically faced by most technology ventures – that seed capital investments are often geographically concentrated. Given that technology entrepreneurship has been cited to be an important source for technical change and disruptive innovation (Schumpeter 2008), and given the promise of crowdfunding to overcome geographical constraints, we chose to focus only on projects in the technology category. We believe that it is imperative for both technology entrepreneurs and potential venture capitalists to know what makes up the composition of crowdfunders that they are attracting through the use of a rewards-based crowdfunding platform such as *Kickstarter*. We believe that the findings can also inform research on technology entrepreneurship.

STUDY 1: AN EXPLORATORY STUDY ON PROFILES OF CROWDFUNDERS

To determine the profiles of crowdfunders, we first examine the literature discussing the motivations of crowdfunders participating in crowdfunding platforms. While the crowdfunding phenomenon is relatively new, it relates to three familiar models that researchers have previously examined: donations collected by charity, online communities and crowd sourcing (Ordanini et al. 2011). Based on research in these areas, we identified a set of extrinsic and intrinsic motivations that may drive crowdfunders' participation in crowdfunding websites.

Altruism. Galak et al. (2011)'s research on *Kiva.org* suggests that some crowdfunders give money for prosocial reasons. Even on rewards-based crowdfunding platforms, prior research suggests that participants fund projects to support creators and causes, thus affirming certain values that participants held. Gerber et al. (2012, p. 7), for example cited an interviewee who funded technology projects so as to "support people who are seeking alternative ways of raising funds to maintain creative control". The finding that altruism plays a critical role motivating participation in online communities and crowdsourcing platforms has also been well-established in the literature (e.g., Lakhani and Von Hippel 2003).

Social Benefits. Prior research on online communities show the importance of reciprocity (Wasko and Faraj 2005), and a sense of community and involvement (Preece 2000) in sustaining the online community. Preliminary research on crowdfunding also shows that crowdfunders are motivated partly by the "community benefit" they derive as supporters of the project and the desire to be engaged in a creative community (Gerber et al. 2012).

Rewards. Prior research has also shown that a significant proportion of crowdfunders are driven by extrinsic motivations such as the rewards offered by the projects seeking funding. Kuppuswamy and Bayus (2013, p. 18) even noted that "many consumer-investors believe that the *Kickstarter* web site is essentially a retail platform in which project creators are pre-selling products". Prior research has also highlighted that extrinsic motivation stemming from the desire to win award money often motivate participation in crowdsourcing platforms (Lakhani and Wolf 2003).

Reputation. Another type of extrinsic motivation for many participants of online and crowdsourcing communities is the reputation benefits and recognition that can be derived from active participation in the community. Lerner and Tirole (2002) highlighted reputation and peer recognition to be a key driver of voluntary efforts in open source projects. Research on firm-hosted user communities also found that participants were motivated by firm recognition (Jeppesen and Frederiksen 2006).

Study 1 Data

We collected data on all technology projects listed from April 1, 2013 to August 1, 2013 on *Kickstarter.com*. A total of 2,022 projects were captured during the data collection period. 118 non-US projects were dropped, given that these constituted only a small portion of the projects and investors may regard non-US projects differently than US projects. 1,904 projects were used for further analysis. 182,291 crowdfunders (they are referred as backers on *Kickstarter*) were identified from the collected project data. For some projects, crowdfunder information was not accessible because *Kickstarter* only discloses backer information for projects that have more than 5 backers. The lack of such information, however, is not expected to have a significant impact on our study, as we believe that the projects that are not able to achieve more than 5 backers are likely funded only by friends and family of the project creator. We collected the backer profile information of the 182,291 crowdfunders who backed the 2,022 projects we collected during the 4 months of data collection.

To examine the profile of crowdfunders supporting technology projects in *Kickstarter*, we adopted an inductive and exploratory approach for conducting cluster analysis. One may use cluster analysis to test theoretically developed typologies. For example, Hahn and Lee (2013) used only two dimensions – number of project categories backed and backing frequency – to theoretically derive and test a typology of crowdfunder archetypes who invest in all *Kickstarter* categories. While we use prior literature to guide our selection of variables to include in the cluster analysis, our aim is to discover empirically driven typologies by using a broad range of variables that might be useful to classify the strategies and behaviors of crowdfunders in the Kickstarter technology category.

We used the crowdfunder motivations identified based on the literature, listed in the previous section, to guide our selection of variables. We do not explicitly measure the motivations of the crowdfunders, as the underlying motives of crowdfunders can only be gathered through interviews and surveys. Instead, we make use of the historical backing behavior of crowdfunders to determine what behavioral profiles and crowdfunding strategies the typical crowdfunder exhibits, and infer their overall motivational profile from a portfolio of variables that represent crowdfunders' behavior.

For each crowdfunder, we constructed seven variables.

(1) **Reward %** is the percentage of projects in the crowdfunder's portfolio that offer the final product as a reward to backers. Rewards offered on *Kickstarter* take non-monetary forms, ranging from t-shirts and thank-you mementoes to early access to a prototype or finished product. Project creators are allowed to customize their own funding levels and corresponding reward categories based on *Kickstarter* guidelines. We coded projects as offering reward if: (a) backers were allowed to pre-order the product, or (b) backers

would receive the final product or a prototype, or (c) backers would be given a licence for using the software or subscribe to it when others would be charged for usage.

(2) **Ave Goal** is the arithmetic mean of the funding goal of all projects backed by the focal crowdfunder. The average funding goal of projects backed by the crowdfunder can be seen as a proxy of the average risk of the projects, as projects with higher goal are at higher risk of not reaching their goals, consistent with prior research showing evidence that projects with higher goals are less likely to be successfully funded (Mollick 2013; Zvilichovsky et al. 2013). Further, projects with larger goals tend to be more ambitious in their product offerings. The average goal of all the backed projects thus reflects the general risk preference of the focal crowdfunder.

Both Reward % and Avg Goal would allow us to determine whether a crowdfunder is driven more by altruism or reward.

(3) **# Projects Backed** is the number of projects backed by the crowdfunder on *Kickstarter*, regardless of whether the project is in the technology category. This variable measures the experience of the focal crowdfunder and how active the crowdfunder is on *Kickstarter*.

(4) **# Projects Created** is the number of projects created by the crowdfunder on *Kickstarter* across all categories. This variable measures the project creation experience of the crowdfunder, which is important in identifying a small but important community of individuals who back projects while also creating projects (Zvilichovsky et al. 2013).

(5) **# Comments** is the number of comments posted by the crowdfunder. Crowdfunders are allowed to post comments. Typical comments involve inquiries of the shipment of the product and feedback on the delivered product. Others are suggestions for improvement for the product. Crowdfunders are also allowed to interact with each other. The number of comments posted by crowdfunders measures how active the crowdfunder is, not only in backing projects, but also in actively contributing to a particular project that she has

backed. Such individuals may potentially serve the role of "lead users", a small group of users who have strong needs for further innovation of the product and can foresee innovation earlier than the rest of the users, and they actively provide feedback to help improve the product (Jeppesen and Frederiksen 2006; Von Hippel 1986).

The above three variables, # Projects Backed, # Projects Created, and # Comments indicate the level of involvement of the crowdfunder in *Kickstarter*, and can provide insights into the sense of community and social benefits, as well as reputation related benefits that crowdfunder may be deriving from participating in the crowdfunding platform.

(6) **Ave Backers** measures the average number of backers of all projects in the crowdfunder's portfolio. Prior literature has recognized social influence as an important factor that shapes crowdfunders' behavior. A larger number of project backers could either signal better project quality (Zhang and Liu 2012), or discourage other project backers from choosing to fund the project (Burtch et al. 2013; Kuppuswamy and Bayus 2013).

(7) **#Variety** refers to the number of project categories backed by the crowdfunder. There are a total of 13 project categories on *Kickstarter*, ranging from Art, Comics to Technology etc. Variety captures the breadth of interest of the crowdfunder. This variable provides an indication of whether the strategy adopted by the crowdfunder is one of concentration or diversification of categories, and may signal to other crowdfunders whether the focal crowdfunder is a specialist or generalist (Hahn and Lee 2013), which may have implications for those concerned about their reputation.

Variable descriptions are summarized in Table 1. Table 2 shows the descriptive statistics and correlations. Out of the seven variables we identified above, four of the variables - # Projects Backed, # Projects Created, # Comments and # Variety – were collected from the backer profile pages in Kickstarter. These variables thus reflect all projects that the crowdfunder has backed on Kickstarter, since the crowdfunder has started backing projects in

Kickstarter. The remaining variables – Reward %, Avg Goal, and Avg Backers – reflect the project characteristics that the crowdfunder has backed on Kickstarter during the four-month collection period from April to Aug 2013, for the technology category.

Insert Tables 1 and 2 about Here

Study 1 Methodology

We employed an exploratory cluster analysis to identify meaningful clusters. Cluster analysis is a statistical technique for grouping entities such that entities in the same group are more similar to each other than to those in other groups (Aldenderfer and Blashfield 1984). Cluster analysis has been used by Information Systems researchers to study different phenomena (Joseph et al. 2012; Malhotra et al. 2005). We used a two-stage procedure where a hierarchical clustering was employed to determine the number of clusters for subsequent *k*-means clustering (Ketchen and Shook 1996). This approach is advocated by many researchers and is shown to increase validity of the clustering solutions (Milligan 1980; Punj and Stewart 1983). We followed Bensaou and Venkatramans (1995)'s approach: (1) All analyzed variables were standardized; (2) Euclidean distance was used for calculating the distance matrix; (3) Ward's minimum variance method was used for cluster agglomeration.

8000 user observations were randomly selected for hierarchical cluster analysis[1]. To determine the number of clusters, we first inspect the dendrogram. which indicated a four-cluster solution (Ketchen and Shook 1996). Next, we plot the within-group sum of squares against the number of clusters, where the appropriate number of clusters is found at the kink of the plot. We further performed *k*-means analysis on the *entire* sample of data to validate these results and to assign group membership for all backers. Details of this analysis are

[1] We were not able to use hierarchical clustering for the entire population given the large number of observations (182,291 backers). It is computationally challenging, if not impossible to compute the cluster membership in most leading statistical software such as SAS and Stata. In order to address this computation limitation, we rely on numerous random samples in our first-stage of hierarchical clustering. Drawing random samples from the data will provide a representative snapshot of the types of backers while adhering to statistical principles. Details of the procedure and other robustness checks are presented in Appendix A.

provided in Appendix A.

Study 1 Results

The cluster analysis reveals that there are four archetypes of crowdfunders backing technology projects in *Kickstarter*. Table 3 provides the mean and standard deviation for the seven variables included in the cluster analysis, for each cluster, depicting the composition of the crowdfunder community. We describe each of the clusters below.

Insert Table 3 About Here

Cluster 1: Active Backers. Crowdfunders from Cluster 1 comprise 9.27% of the sample. This group stands out from the rest of the crowdfunders in the several aspects. First, they tend to back a large number of projects (46.81 projects on average, compared to an average of 4-6 for other clusters). Second, they are more likely to create projects compared to other groups of crowdfunders (5.64% of crowdfunders in this cluster have created projects, compared to 1.17% in other clusters). Third, crowdfunders in this cluster also have a tendency to post more comments, compared to those in other clusters (22.90 comments on average, compared to less than 2 comments on average for other clusters). Finally, the interests of this cluster of crowdfunders tend to be broader, as they invest in 7.81 categories, on average, whereas the other clusters tend to focus on fewer than 3 categories on average.

This group of crowdfunders are clearly more active and involved in the community, not only in backing projects, but also in creating projects and providing comments to project creators and other crowdfunders. They are likely to be crowdfunders who are highly motivated by the social and reputational benefits arising from participating on the crowdfunding platform. We label this group of crowdfunders the Active Backers.

Cluster 2: Trend Followers. Crowdfunders from Cluster 2 comprise 23.62% of the sample. This group tends to be more risk adverse, backing projects that have a smaller average goal size (USD74,359), especially compared to the first and fourth cluster. Their risk adverseness is also evident in their tendency to back projects that have a large number of backers (9,410), compared to the other clusters (ranging from 1,085 to 3,713). It appears that this group of crowdfunders tends to back less risky projects that are also highly popular with a lot of backers. We thus label this group the Trend Followers.

Cluster 3: the Altruistic. Crowdfunders in Cluster 3 comprise 12.28% of the sample. This group of crowdfunders stands out from other clusters for their emphasis on backing projects that tend not to provide rewards. Moreover, these individuals are less risk adverse as they tend to back projects with significantly higher average goal (~USD158k), compared to other clusters (whose average goals range from USD75k to 95k). These individuals also tend to back projects with significantly fewer number of backers (1,085), compared to other projects, indicating that these individuals are not going for the highly popular projects. Given that this group of individuals is not driven by rewards, and appear to be less concerned about project risk and popularity, this group of individuals may be driven more by altruism for participating in *Kickstarter*. Hence, we label this cluster the Altruistic.

Cluster 4: the Crowd. Our cluster analysis reveals one last cluster that comprises 54.83% of the sample. This group is moderate in all aspects that they were measured on, not standing out in any particular aspect. Like Clusters 1 and 2, they tend to be focused on rewards. They tend to be relatively risk adverse, backing projects with smaller goals, on average (USD78,590), comparable to that of Cluster 2. They tend to back a significantly smaller number of projects and in fewer categories. They do not tend to create projects (comparable with Cluster 2), and they are not particularly likely to leave comments (comparable with Clusters 2 and 3). This group is neither more likely to back the most popular projects with the largest number of mean backers (like Cluster 2), nor are they more likely to back the least popular projects the smallest number of mean backers (like Cluster 3). Given the moderate aspects of this group, we label this group the Crowd. As the Crowd comprises about 50% of the entire sample of backers, the natural question is whether there are secondary clusters or sub-archetypes within this group. For the sake of completeness while not distracting the reader from the main message of this paper, we present an auxiliary analysis of the Crowd in Appendix B - further breaking down the composition of this large group of crowdfunders.

Study 1 Summary

In summary, our exploratory analysis shows that the crowdfunder community is not homogeneous. In our analysis, we found Active Backers, which can be thought of as investors who are looking for high quality projects, consistent with the conceptualization of crowdfunders by researchers like Mollick (2013). This group of crowdfunders also appear to form an active community within *Kickstarter*, emphasizing the social and reputation benefits that active participants may derive from such a platform. We also found an altruistic cluster, which appear to be backing projects to support a cause and for altruistic reasons more than for rewards, similar to the conceptualization of crowdfunders in Kuppuswamy and Bayus (2013). Interestingly, we also found a group we call Trend Followers, which appear to be more risk adverse and explicitly taking on a strategy of targeting popular projects. This group may be motivated more by rewards and less by social and altruistic reasons. The rest of the crowd appears to be moderate in most characteristics; hence they may represent crowdfunders who are still exploring the platform and may have yet to develop a clear strategy towards the crowdfunding platform. These results suggest that the composition of crowdfunders is complex.

STUDY 2: EXAMINING HOW DIFFERENT PROFILES OF CROWDFUNDERS MAKE FUNDING DECISIONS

As highlighted in the introduction section, prior research on Crowdfunding has highlighted two distinct theoretical perspectives that are important in understanding the crowdfunding phenomenon: signaling theory and social influence. Given the different profiles of crowdfunders found in Study 1, we expect that social influence and signaling effects would play out differently amongst the different crowdfunder archetypes. To better understand the crowdfunders, we create a set of hypotheses that consider how different crowdfunder archetypes react to different signals and to the behavior of other crowdfunders.

Moreover, our first study used the historical backing information of crowdfunders on *Kickstarter* to determine four distinct profiles of crowdfunders exhibiting different behaviors and strategies. We then inferred the motivations of the crowdfunders from their behavior. In this second study, we further test the accuracy of our profile classifications by considering how different crowdfunder motivations would drive their evaluation of each project differently, taking into account the availability of various project information and contribution behavior of other crowdfunders that may differ across time for each project.

Study 2 Hypotheses

Responding to Signals

In a seminal article by Spence (1973), he examined how signaling can solve the problem of asymmetric information faced by parties engaged in a transaction. He based his work on the pioneering study of Akerlof (1970) who examined the second hand car buying market, showing that high quality car sellers withdraw from the market if they cannot communicate the quality of the cars sold, leading to a market of "lemons". Spence (1973) highlighted that signals can be used to communicate quality, if the signals: (1) can be altered by the communicating party; and (2) the marginal cost of obtaining the quality signal is lower for the party holding the higher quality product compared to those with lower quality products. He applied the theory to the case of job-market signaling, where more productive employees invest in education as a signal of their quality, and employers are willing to pay more for employees who possess education as a signal. Researchers later extended the theory, showing its applicability in multiple settings ranging from shipping cartels (Podolny and Scott Morton 1999) to the biotechnology sector (Stuart et al. 1999).

The applicability of signaling theory to entrepreneurial finance is well-established by prior research, as investors face similar information asymmetry problems when evaluating start-ups (Hsu 2004). Prior research has thus examined how start-ups use signals such as board and founder characteristics to signal quality of the venture to potential investors such as angel investors or venture capitalists (e.g., Cosh et al. 2009). Crowdfunders are even more likely to depend on signals to evaluate the quality of projects, as they lack the financial sophistication, as well as expertise and experience of professional investors in evaluating and valuing new ventures (Freear et al. 1994). Moreover, the signals that they depend on are likely to be different from those used by professional investors, as they lacked the knowledge and it would be more costly for them to obtain the same information that professional investors have access to (Ahlers et al. 2012).

Research on crowdfunding has thus begun to investigate what types of signals crowdfunders respond to, in determining the success of crowdfunded projects. A key signal that has been identified in several papers is the social capital of the project creator. Lin et al. (2013b) found that lenders on *Prosper.com* used the online friendships of borrowers as signals of credit quality, as friends have more information on the borrower than other non-friend borrowers. In particular, they found that friends who crowdfunded other projects on *Prosper.com* were a better quality signal than friends who did not otherwise participate in the crowdfunding platform. In addition to lending-based platforms, the use of the social capital of project creators as a project quality signal have also been established in *Kickstarter* (Colombo et al. 2013; Mollick 2013) and in 11 Italian crowdfunding platforms (Giudici et al. 2013).

Building upon this prior work, we draw upon signaling theory to hypothesize how different profiles of crowdfunders are likely to pay attention to the social capital of project creators when backing projects. Based on our analysis of the crowdfunders in Study 1, all crowdfunders, other than the Altrusitic group, appear to be motivated by rewards, and to seek projects that are likely to be successful (i.e. reach their pre-specified goal). Consistent with prior research (Colombo et al. 2013; Mollick 2013), we thus expect these crowdfunders to pay attention to signals of project quality.

There are, however, qualitative differences between the Active Backers group and the other two groups – the Trend Followers and the Crowd. Active Backers tend to have more experience and are more knowledgeable as they have experience of backing many projects. Their active participation thus allows them to learn more about the ins and outs of the platform, and learn about what types of projects tend to be more successful (Gompers et al. 2010). Zviliehovsky et al. (2013) found that those project creators who have backed many projects are more likely to create successfully funded projects, showing that some form of learning takes place when crowdfunders back multiple project, and through the process learn about evaluation and monitoring of the projects.

The expertise and knowledge that Active Backers have, relative to the Crowd and the Trend Followers, imply that they are well-positioned to understand and interpret more complex information that may be available about the project. As highlighted by prior researchers, investors typically use a range of information to evaluate new ventures, including financial roadmaps such as preplanned exit strategies, external certifications such as awards, government grants and patents, internal governance such as board structure and founder characteristic as well as risk factors such as the presence of disclaimers (Agrawal et al. 2013; Ahlers et al. 2012). Some of this information would be stated in the project description text provided by project creators, or can be found online by an experienced crowdfunder. This implies that crowdfunders with more experience will be in a better position to make sense of a multitude of information that may be more ambiguous than a simple signal of project quality embedded in the social capital of the project creator.

Prior research suggests that the importance of signals diminish when other information become available (Higgins et al. 2011; Podolny and Scott Morton 1999; Stuart et al. 1999). Podolny and Scott Morton (1999) studied the impact of the social status of entrants (a signal) on the predation behavior of incumbents in shipping cartels. Their study reveals that entrants with high social status are significantly less likely to be preyed on by the incumbent cartels than entrants with low social status, as cartel members use social status as a signal to determine if the entrant will be a cooperative cartel member. They further find that the effect of social status declines with the age of the entrant firm. The interpretation is that as the firm becomes older, the firm's visible history provides further information regarding the level of cooperativeness, rendering social status less important. Drawing on similar arguments, we propose that Active Backers are able to rely on a more complex and detailed set of information about projects they are backing, given their expertise and experience evaluating crowdfunded projects. Hence, they are less likely to rely on the simple signal of project quality conveyed in the social capital of the project creator. Hence, we hypothesize:

H1a: Crowdfunders comprising the Crowd are likely to back projects whose project creators have higher social capital.

H1b: Crowdfunders comprising the Trend Followers are likely to back projects whose project creators have higher social capital.

H1c: Crowdfunders comprising the Active Backers are less likely to back projects whose project creators have higher social capital, compared to the Crowd and the Trend Followers.

Compared to the other three clusters, crowdfunders comprising the Altrustic group, are expected to fund projects out of the wish to support causes and for altruistic reasons (Gerber et al. 2012). They are thus less likely to pay attention to whether the project can successfully raise funds, as they are unlikely to expect a return from their pledges. Hence, we do not expect crowdfunders in the Altruistic group to be responsive to any form of project signals.

Social Influence

Prior research has established that the behavior of other crowdfunders have a significant influence on the funding decisions of crowdfunders, as the information on prior contribution behavior is generally readily available on crowdfunding websites. Prior research, however, shows two contrasting effects that may arise from the influence of other crowdfunders' behavior: observational learning resulting in herding, versus bystander effects resulting in delayed actions. We believe that segregating the crowdfunders into different profiles will allow us to reconcile the contradictory findings with regards to the possible effects of the other crowdfunders' behavior, and allow a more fine-grained understanding of the types of crowdfunders participating in the crowdfunding platform.

One group of prior studies clearly identify that herding behavior arises in crowdfunding platforms (Colombo et al. 2013; Zhang and Liu 2012). Herding describes a scenario where individuals decide to follow others and imitate group behaviors rather than make decisions based on the information they possessed, due to the perceived uncertainty and perceptions of their own ignorance (Baddeley 2010). The key mechanism underlying herding is observational learning (Bikhchandani et al. 1998), where people tend to follow the actions of others in situations of uncertainty, as they assume that the actions of others convey the appropriate behavior (Sherif 1935) and information about the quality of products that may not be directly observable. In their investigation of herding behavior on lending-based crowdfunding platform, Zhang and Liu (2012) have found that crowdfunders are influenced by others' decisions because they believe that others possess additional information of the quality of the project that is unknown to them. Crowdfunders may assume that those projects that are highly popular, especially those that attract much crowdfunders' attention earlier in their listing are likely to be successful as a sizeable number of early backers have "already scrutinized the project, liked it, and trusted its proponent and her ability to manage the project" (Colombo et al. 2013, p. 7).

We expect that among all the crowdfunders, the Trend Followers are most susceptible to herding behavior. The Trend Followers are highly risk-adverse and have a disproportionate emphasis on popular projects, showing that they are most likely to pay attention to others' behavior and imitate others' behavior when there is significant attention paid by early crowdfunders on particular projects. This implies that the Trend Followers are likely to back projects later in the projects' life cycle, after they have had a chance to observe other crowdfunders' behavior, and they are likely to back projects only at the point when the project has accumulated a large number of backers. Hence, we hypothesize:

H2a: Crowdfunders comprising the Trend Followers are likely to back projects that are at their later funding stage.

H3a: Crowdfunders comprising the Trend Followers are likely to back projects that have accumulated a large number of backers.

Another group of studies point out that in crowdfunding platforms, bystander effects (Kuppuswamy and Bayus 2013), or substitution effects (Burtch et al. 2013) may arise. In such scenarios, crowdfunders are influenced by the behavior of other crowdfunders, but in the opposite direction as that predicted by herding behavior. Prior contribution behavior of crowdfunders discourage, rather than encourage further contributions, because crowdfunders assume that others will provide the necessary funding to the project – due to a diffusion of responsibility. In *Kickstarter.com*, Kuppuswamy and Bayus (2013) found that bystander effects diminish only as the project approaches its closing date.

We expect that such bystander effect will take root only amongst individuals who are contributing to crowdfunding projects for the purpose of supporting a cause. The underlying psychology of individuals who are subject to the bystander effect is that they view support of a project as a responsibility, rather than as a process of selecting a project likely to become successful. This is consistent with the behavior of the Altruistic group. We thus expect such individuals are likely to support a project only late in the project's funding stage, as they step in only when they realize a project may not reach its goal. This is similar to our expectations of Trend Followers, but we expect the Altruistic group to back projects that have accumulated fewer rather than more backers. Hence:

H2b: Crowdfunders comprising the Altruistic group are likely to back projects that are at their later funding stage.

H3b: Crowdfunders comprising the Altruistic group are likely to back projects that have accumulated a smaller number of backers.

We believe that Active Backers, in contrast to other crowdfunders, will be less likely to pay attention to the behavior of other crowdfunders. As highlighted above, Active Backers accumulate a wealth of experience and knowledge from evaluating many prior projects. Hence, they are likely to depend on their own ability and analysis to make predictions of which projects are likely to be successful. They are thus not likely to pay attention to the behavior of other crowdfunders, and they are likely to make their backing decisions early in the project's funding process, since they do not have to wait to observe other crowdfunders' actions and behavior. Hence, we hypothesize:

H2c: Crowdfunders comprising the Active Backers are likely to back projects that are at their earlier funding stage.

Reconciling the Signaling and Social Influence Perspectives

Our study also reconciles the signaling and social influence perspectives by highlighting that the behavior of other crowdfunders may also serve as a project quality signal for others, if one factors in the type of crowdfunder whose behavior is observed. This is similar to the concept of "rational herding" discussed by Kim and Viswanathan (2013). They highlight that early investments serve as a signal of quality for later investments, if early investments are made by expert investors –who also create projects and who are experienced investors. Rational herders are not only concerned about the presence of herding, but they decipher the underlying reasons that give rise to the herd and pay attention to whether herding individuals do indeed have better private information than they do (Zhang and Liu 2012).

Prior research shows that there exists a group of early adopters of products who tend to be more influential on others (Moore 1991). Ghose, Burtch, & Wattal (2013) further showed that crowdfunders do pay attention to detailed information of other crowdfunders, such as the amount of contributions provided, especially for large amounts of contributions. Zvilichovsky et al. (2013) further showed that project owners who also backed a significant number of projects appeared to constitute a sub-community of backers that other backers paid attention to. The actions of backing projects helped to increase project owners' network visibility and hence credibility, enabling them to achieve higher funding rates for projects they created. These results, together with those of Kim and Viswanathan (2013) provide support that Active Backers, who actively back projects and who are also more likely to be project creators, play a particularly influential role in the *Kickstarter* community.

Even though they may not be labeled as experts in *Kickstarter*, each backer has his/her own profile page that lists the backer's backing history. Given that prior research has shown that the majority of investors, "although inexperienced, are rather sophisticated in their ability to identify and exploit nuanced differences between various signals within the same market" (Kim and Viswanathan 2013, p. 1), we expect that crowdfunders who care about predicting the success of projects they back (i.e. all groups except the Altruistic) will pay attention to the number of active backers who have already backed the project when deciding whether to back a project in question. Hence:

H4a: Crowdfunders comprising the Active Backers are likely to back projects that have accumulated a large number of Active Backers.

H4b: Crowdfunders comprising the Trend Followers are likely to back projects that have accumulated a large number of Active Backers.

H4c: Crowdfunders comprising the Crowd are likely to back projects that have accumulated a large number of Active Backers.

Study 2 Methodology

To test the above hypotheses, we adopt a choice model to represent how crowdfunders select a particular project to pledge their funds. We let Y_{ij} to represent the binary choice task of backing a particular project. Y_{ij} is coded as 1 if the crowdfunder decides to fund the particular project, and 0 otherwise. We recognize that at any one point in time there are multiple projects available for backing and to model the choice task, we first have to construct the temporal choice set which the crowdfunder is presented with and her eventual choice.

We begin building a choice task for each instance when a project is being backed. [2] For a particular project backing, we identify the possible set of alternatives, *i* that were available to the crowdfunder, *j* at the point in time of pledging. Here, *i* represents each *unique set* of alternatives that is present during the backing event. To determine this choice set, we first identify the relevant choices available for the particular individual at the point of pledging. Research in choice and preference construction suggests that individuals are most likely to compare items of similar attributes when making choices (Zeger et al. 1988). At any point in time, there are hundreds of ongoing projects which accepts funding and to realistically capture the choices available, we only consider alternative projects that were active (still accepting pledges) and of similar nature. A project is deemed to be similar in nature if it is in the same project category (i.e. Technology) and in the same sub-category (e.g. software or hardware). The construction of a choice set with similar competing projects

[2] We recognized that it is possible that a crowdfunder assesses a set of projects and decide not to back any single one. Such instances are not modeled here as there is no practical means for the researchers to detect such instances.

enhances the fidelity of the choice model (Lin et al. 2013a), as a crowdfunder faces cognitive limits in processing numerous projects available and is more likely to compare between those of similar nature. As we are interested in the factors that impact the likelihood with which a project is backed, we let μ_{it} to represent the marginal expectation of which a project is backed as seen in equation (1) below:

$$\mu_{it} = E(Y_{it}) \qquad (1)$$

The purpose of specifying the marginal expectation of success allows us to apply a population-average approach (Zeger et al. 1988) to model the factors that impact the take-up rate for a project in general while controlling for the choice set available.

We next represent the functional form of this choice model as follows:

$$Logit(\mu_{it}) = X_{ij}\beta + v_i \qquad (2)$$

Whereby X_{ij} represents the vector of independent variables (project and crowdfunder characteristics) that influences the choice task of pledging funds, β represents parameters of the functional form and v_i represents the stochasticity associated with the choice set available to the crowdfunder at the point in time of funding a particular project; $v_i \sim N(0,\sigma^2)$. This functional form suggests that the logit of the expected marginal probability with which a project will be backed (left-hand side of equation 2) is a function of the project and crowdfunder characteristics, X_{ij} and the unobserved effects, v_i as a result of the presence of a set of competing projects (right-hand side of equation 2). The introduction of the group effect v_i, allows us to partial out the effects of competing projects as well as possible temporal differences on the decision to pledge (or not pledge).

We estimate equation 2 using the Generalized Estimation Equation (GEE) approach as suggested by Zeger et al. (1988), given that choice task Y_i repeats across time and these repeated outcomes are likely to be correlated. For example, the same choice task might be presented to different individuals within a short span of time and circumstances surrounding the choice tasks are likely to be similar – hence outcomes are likely to be correlated. Given that the covariance structure of the specification is largely unknown, GEE will be an appropriate estimator as GEEs have consistent and asymptotically normal solutions even with misspecification of covariance structure as suggested in Greene (2003). In our model, we used the commonly specified exchangeable correlation structure for the estimation.

Dependent variable

The dependent variable of the model is a binary variable indicating whether or not the project is chosen by the crowdfunder. If the project is chosen by the crowdfunder, the variable is coded as 1, otherwise it is coded as 0.

Independent variables

Cluster membership dummies: Since we are interested in the behaviors of different types of crowdfunders, we included membership dummies in the model. The membership information of each backer is obtained from the cluster analysis. We created a dummy variable for each archetype of crowdfunder using “the Crowd” as the baseline: *Active Backer, Trend Follower* and *Altruistic*.

Funding stage indicator: We hypothesize that different types of crowdfunders tend to back projects at different funding stage. *Days Elapsed* measures the number of days elapsed since the project is launched when the crowdfunder was presented with the project.

Social capital: Prior research has shown that the social capital of the project creator serves as a key signal to potential project backers. Several prior studies have used the number of Facebook contacts of the project creator as an indicator of the project creator’s social capital (Giudici et al. 2013; Lin et al. 2013b). Not all project creators, however, show the number of Facebook contacts that they have (only half of the projects in our sample did). Moreover, prior research has shown that other than the social contacts established outside the crowdfunding platform – e.g. Facebook friends, a project creator may also develop social capital within the crowdfunding platform, and the key approach is via the backing of other projects (Colombo et al. 2013). Similarly Lin et al. (2013) also showed that having online friends who were themselves active in Prosper.com served as a more powerful signal of the lender's creditworthiness than having friends who were not active in Prosper.com. Given the difficulty associated with using the number of Facebook friends as the indicator of the project creator social capital due to the large amount of missing data, we proxy the social capital of the project creator by using the number of projects backed by the creator by the time she creates the project (Colombo et al. 2013). *Kickstarter* provides such information on the project page. We name the variable Project Creator Network.

Social influence: To test different crowdfunder archetypes' response to social influence, we created a variable # Backers Pledged, which measures the number of backers who had already pledged funds to the project when the focal crowdfunder is presented with the choice alternative. *Kickstarter* lists number of backers on the project page. This information can be directly observed by crowdfunders who are screening projects and forming their decisions. We also defined # Active Backers Pledged, which measure the number of Active Backers who had already pledged funding support for the project when the crowdfunder is presented with the project choice, to test hypotheses 4a, 4b and 4c.

Control variables: Following Mollick (2013), we controlled for two project level variables: natural logarithm of the project goal (*LogGoal*) and duration of the project (*Project Duration*), which have been found to relate to project success (Zvilichovsky et al., 2013).

Study 2 Results

Table 4 shows the descriptive statistics and inter-variable correlations while table 5 shows the results of the GEE estimation. Model 1 includes all the control variables. Models 2 to Models 5 show the inclusion of interaction terms, testing each set of hypotheses. The coefficients of the estimated models can be interpreted analogously to the standard logistic model (Aiken and West 1991; Zeger et al. 1988). As we used a large sample with more than 6,000,000 observations, one of the problems faced is the p-value problem, in which p-values quickly go to zero as sample size increases. Researchers argue that solely relying on the low p-value and the sign of the coefficient undermine the credibility of large-sample research (Lin et al. 2013a). To overcome this issue, we report the effect sizes for all the coefficients testing our hypotheses in Table 6.

Insert Tables 4, 5 and 6 about Here

Our first set of hypotheses is about the extent to which different crowdfunder archetypes react to the project quality signal of project creator network. Model 1 shows that the coefficient for *Project Creator Network* is positive and significant ($\beta = 0.0364$, $p < 0.001$). Every 10 projects backed by the project creator would increase the odds of the focal project being chosen by the crowdfunder by 43.9%. This suggests that in general, crowdfunders do pay attention to project creator network as a project quality signal.

Model 2 tests H1a to H1c. In Model 2, the coefficient for *Project Creator Network* is positive and significant ($\beta = 0.0392$, $p < 0.001$), indicating that projects where the creator had greater social capital are more likely to be chosen by the Crowd. Hence H1a is supported. Compared to the Crowd, Trend Followers were less likely to choose projects which had greater project creator network ($\beta = -0.0143$, $p < 0.001$), although on the whole they were still likely to choose projects which had greater project creator network ($\beta = 0.0249$, $p < 0.001$), thus supporting H1b. The results show that Active Backers were indeed less likely to back projects whose project creators have higher social capital compared to the Crowd ($\beta = -0.007$, $p < 0.001$). But Trend Followers were less likely to back projects whose project creators have higher social capital compared to the Active Backers (difference in $\beta = -0.0073$, $p < 0.001$), thus H1c was not supported.

Our second set of hypotheses is about whether different crowdfunder archetypes were likely to back projects in the early or later stage of the funding process. First, Model 1 shows that the coefficient for Days Elapsed is negative and significant ($\beta = -0.0122$, $p < 0.001$), suggesting that in general, crowdfunders tend to back projects that are at their earlier funding stage. This is also consistent with Kuppuswamy and Bayus (2013)'s observation that projects tend to get a large number of supporters in the first few days. We used Model 3 to test H2a to H2c. Our results show that the interaction term *Days Elapsed * Trend Follower* is significantly positive ($\beta = 0.0332$, $p < 0.001$), hence increasing the coefficient of *Days Elapsed* to 0.0177 ($p < 0.001$) for the Trend Followers. This indicates that Trend Followers are likely to back projects that are in later stages of the funding process, thus providing support for H2a. To test H2b, we examine the coefficient for the interaction term *Days Elapsed * Altruistic, which* is not significant ($\beta = 0.0007$, $p>0.10$). This suggests that the Altruistic are as likely as the baseline group (the Crowd) to back projects in the earlier stages of the funding process ($\beta = -0.0155$, $p < 0.001$). H2b is thus not supported. Finally, we tested H2c by examining the coefficient for the interaction term *Days Elapsed * Active Backers, which* is negative and significant ($\beta = -0.0031$, $p < 0.001$), further decreasing the negative coefficient of the baseline group to -0.0186 ($p < 0.001$), showing that Active Backers are the most likely amongst all four clusters to back projects that are at their earlier funding stage, thus providing support for H2c.

Our third set of hypotheses are about the extent to which different crowdfunder archetypes make project backing decisions based on information about the number of existing backers of the project at the point when they were evaluating the project. Model 1 indicates that the coefficient for *# Backers Pledged* is close to 0, although it is significant, indicating that crowdfunders in general do not have a preference over number of backers. H3a and H3b are tested using Model 4. The results show that Trend Followers are likely to back projects that have accumulated a large number of backers ($\beta = 0.0001$, $p < 0.001$). Hence, H3a is supported although the effect size is small - every 1000 backers accumulated would increase the odds by 10.5%. The Altruistic group is likely to back projects that have accumulated a smaller number of backers (β = - 0.0003, $p < 0.001$), providing support for H3b.

Finally, our fourth set of hypotheses test the extent to which the number of Active Backers already backing the project would affect the backing decisions of different crowdfunding archetypes. Model 1 shows that crowdfunders, in general, do favor projects that have accumulated a large number of Active Backers. The coefficient for *#Active Backers Pledged* is positive and significant (β = 0.0038, $p < 0.001$) – every 100 active backers would increase the odds of the project being backed by exp (0.0038 * 100) -1 = 46.2 %. Model 5 shows the results testing H4a to H4c. The results show that Active Backers (β = 0.0037, $p < 0.001$), Trend Followers (β = 0.0066, $p < 0.001$), and the Crowd (β = 0.0034, $p < 0.001$), are all more likely to back projects that have a larger number of existing Active Backers, providing support for H4a, H4b and H4c.

DISCUSSION

We probed the interaction effects based on the recommendations of Aiken and West (1991). Figures 1a-1d show the graphical plots for all four sets of interactions tested.

Insert Figures 1a-1d About Here

We first tested the extent to which different crowdfunder archetypes reacted to project quality signals – namely, the project creator network within the crowdfunding platform. The results for this set of hypotheses, shown in Figure 1a, showed rather surprising results. We had expected the Crowd and Trend Followers to exhibit the most reliance on the project quality signals, the Active Backers to exhibit relatively less reliance on the signals and the Altruistic not to be affected by the project quality signals. The results in Figure 1a, however, showed that the Altruistic group's choice of projects was the most sensitive to Project Creator Network, whereas Trend Followers were only slightly influenced by Project Creator Network. This might be because the Project Creator Network in the crowdfunding platform might be less of a project quality signal, and more of an indicator of accumulated social obligations of the project creator. Our results show that the Altruistic, who invest for reasons other than a successful investment, appear most sensitive to the social capital of the project creator, showing that they do recognize and ensure those project creators who actively back other projects obtained reciprocal backing for their project . In turn, the Trend Followers paid relatively less attention to the Project Creator Network, showing that they emphasized more objective characteristics and paid less attention to ensuring reciprocal support for project creators who also actively supported other projects.

The second and third set of hypotheses tested the extent to which different Crowdfunder archetypes reacted to social influence by exhibiting herding versus bystander effects. We tested these effects in two ways. First, we examined how different Crowdfunder archetypes differed in their tendency to invest early versus late in the project funding phase (Figure 1b). Second, we examined how different crowdfunder archetypes differed in the extent to which they paid attention to the number of backers that had already pledged funds to the focal project (Figure 1c). For Trend Followers, we expected them to invest later in the funding stages, and that they would be sensitive to the number of existing backers, which were supported by our findings. For the Altruistic, they were indeed insensitive to the number of existing backers, although they tended to invest earlier in the funding stages (contrary to our expectations). This shows that the Altruistic, although they invest to help those who have yet to reach their funding goals, did not wait till the project deadline to invest. Rather, they did not care for whether others were investing in the projects they were interested in. For Active Backers, we found that they invested earlier in the funding stages, as we expected, and they were also not highly sensitive to the number of existing backers. Finally, our fourth set of hypotheses examined whether the number of active backers who had already pledged funds served as an indicator to other crowdfunders. As shown in Figure 1d, all four groups of crowdfunders, even the Crowd, paid attention to the existing number of active backers on a project, when deciding whether to back a project.

Implications for Research

The findings of this research have significant theoretical implications. First, the findings of study 1 suggest that assuming the homogeneity of the crowdfunding community may not accurately capture the complexity of the crowdfunding phenomenon. Our study suggests that crowdfunders differ from each other in various dimensions. By arbitrarily assuming their role as investors or donors, researchers may narrow their scope and fail to identify important aspects of this complex phenomenon. Expanding the conceptualization and operationalization of crowdfunders with different behavioral strategies driven by different sets of motivations enriches our understanding of crowdfunders and allows us to explain crowdfunders' behaviors in a more nuanced manner.

Furthermore, expanding the conceptualization of crowdfunders allow us to enrich and reconcile theories that explain the crowdfunding phenomenon. We identified two theoretical perspectives that prior research have used to examine the crowdfunding phenomenon to both explain the success of crowdfunded projects and the behavior of crowdfunders: the signaling and social influence perspectives. Our expanded conceptualization of crowdfunders first allowed us to reconcile the contradicting findings about whether crowdfunders exhibited herding or bystander behavior. By highlighting that the fundamental premise underlying either the herding or the bystander behavior had to do with the motivation driving the behavior of crowdfunders, we showed that it was crowdfunders who consciously followed trends, that were more susceptible to herding behavior, while crowdfunders who were more altruistic, invested to help project creators. This shows that recognizing the fundamental differences between different types of crowdfunders is important to understanding which theoretical perspectives are applicable to the appropriate group of crowdfunders, allowing us to apply the correct theoretical perspectives more accurately.

In addition, by differentiating between different groups of crowdfunders, it also allowed us to enrich theory by first, enriching our understanding of the impact of signals, as we examine how different types of crowdfunders, themselves, served as a key signal for other crowdfunders. Distinguishing an important category of crowdfunders known as the active backers gave us the opportunity to enrich theory by synthesizing both the social influence and signaling theoretical perspectives. We showed that the number of active backers backing a project provided an impetus to other crowdfunders to back a project as this served as a project signal to other crowd funders. We thus showed the theoretical importance of differentiating between different types of crowdfunders and of understanding the underlying strategies, behavior and motivation of crowdfunders in developing theories that may help us to understand the crowdfunders. It will thus be critical for future researchers to bear in mind that the crowdfunders on the same platform are not homogenous and this heterogeneity will need to be factored in when theorizing about the behaviors of the crowdfunders.

Implications for Practice

This study also provides significant practical implications for a wide variety of parties who may have an interest in monitoring crowdfunding platforms. First, to both projects seeking funds and professional investors who may use the success of rewards-based crowdfunding projects as indicators of quality that influence their subsequent investment decisions, it is important to understand the composition of crowdfunders that are backing projects on such crowdfunding platforms. We show that the crowdfunders backing technology projects who have significant potential of becoming technology ventures subsequently, are heterogeneous in their motivations. But more importantly, the majority of the investors are not donors or individuals driven by altruism. This group constitutes only a small percentage of the crowdfunders. Most of the other crowdfunders are driven by rewards. This shows that such rewards based platforms may be a good source of serious crowdfunders who are seeking to support projects offering real products as a reward. This provides more legitimacy to the use of successful fund raising on such a platform as an indicator for future demand.

Second, our study findings also provide a greater understanding of the crowdfunders and provide an understanding of the strategies that they may wish to adopt. Our results show that the endorsement of active backers is regarded as signal of project quality. Hence, it is crucial for project initiators to attract these people in the initial funding period of their projects. The presence of active backers may also provide some information to potential professional investors, as not all backers are equal. Professional investors may wish to examine the composition of backers of the projects that are seeking funding from them, to determine the proportion of active backers, who may be a better signal of quality than simply whether the project has been successfully funded in a platform like *Kickstarter*.

Our results also provide implications to crowdfunding platform managers. The heterogeneity of the crowdfunders, their differing strategies and signaling value to other crowdfunders imply that crowdfunding platform managers may wish to consider providing more information about crowdfunders, so as to increase transparency to users of their platform.

Our results also have significant implications to policy makers. Our results show that crowfunders of reward-based platform have evolved, such that they play different roles and have a different and complex set of motivations. Although some crowdfunders have gained significant amount of experience, others are still amateur and rely on those who are more experienced. This may imply that it continues to be important to protect those who lack experience, even as crowdfunding evolves, so that they are not misled.

Limitations

Our study is not without limitations. The first limitation is related to our empirical quantitative approach. Within the archival empirical framework, we were not able to verify the motivations inferred from crowdfunders' exhibited behavior. We encourage further qualitative or survey research to substantiate the findings.

The second limitation is that our research focuses on data collected over a relative short period of time. Although we believe that such time period is enough for our research -- since the longest duration of a project is 3 month -- we admit that the dynamics of the archetypes of crowdfunders may change with time. As learning takes place and platform policies change, some types of crowdfunders may evolve into other types of crowdfunders. For example, Trend Followers may evolve into Active Backers when they have accumulated significant amount of experience. The design of our study did not address such an issue. Longitudinal follow on studies could address this. The third limitation pertains to our research site. Although we have picked the most influential rewards-based crowdfunding platform, focusing solely on this platform has drawbacks. First, we were not able to triangulate our findings with other platforms. Second, there may exist other types of crowdfunders in other platforms that we have not yet unveiled.

CONCLUSION

The growing popularity and significant impact of crowdfunding calls for a closer examination of this complex phenomenon. In this paper, we take a first step by identifying different types of crowdfunders. Our results show that crowdfunders are highly heterogeneous, with different motivations that are reflected in their strategies and behaviors. Our choice model results further show that the different strategies and motivations of different crowdfunder archetypes influence their choices of which projects to fund. Our results show that researchers may have to be cautious when theorizing and modeling about the behaviors of the crowdfunders since they are not a homogeneous group.

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Table 1. Variables for Cluster Analysis

Variable	Description
Reward %	Percentage of projects in the crowdfunder's portfolio that offer the final product as a reward to crowdfunders.
Ave Goal	Arithmetic mean of the goal (amount of money the project seeks to raise) of all projects backed by the focal crowdfunder.
# Projects Backed	Total number of projects backed by the crowdfunder.
# Projects Created	Total number of projects created by the crowdfunder.
# Comments	Total number of comments posted by the crowdfunder.
Ave Backers	Average number of backers of all the projects in the crowdfunder's portfolio.
# Variety	Number of project categories backed by the crowdfunder.

Table 2. Descriptive Statistics and Correlations

	Mean	S.D.	1	2	3	4	5	6
Reward %	0.87	0.32						
Ave Goal	88,982	460,431	-0.06**					
# Projects Backed	8.97	21.27	-0.03**	0.03**				
# Projects Created	0.02	0.31	-0.03**	0.01**	0.04**			
# Comments	3.48	51.45	-0.01**	0.02**	0.14**	0.05**		
Ave Backers	4,183	3,649	0.32**	-0.01**	-0.02**	-0.02**	-0.01*	
# Variety	2.83	2.21	-0.08**	0.03**	0.60**	0.08**	0.09**	0.01**

Notes: * Correlation is significant at .05 level; ** Correlation is significant at .01 level.

Table 3. Clustering Results

Variables	Mean (SD) of clusters				Pairwise comparisons using t tests with pooled SD (p adjustment: Holm)
	Cluster 1	Cluster 2	Cluster 3	Cluster 4	
Reward %	0.87 (0.25)	0.99 (0.05)	**0.06** **(0.16)**	0.99 (0.05)	1-2***, 1-3***, 1-4***, 2-3***, 2-4***, 3-4***
Ave Goal	95,650 (487,094)	**74,359** **(122,504)**	**158,479** **(1,195,119)**	78,590 (137,606)	1-2***, 1-3***, 1-4***, 2-3***, 2-4, 3-4***
# Projects Backed	**46.81** **(54.30)**	5.31 (6.14)	6.08 (7.54)	4.80 (5.55)	1-2***, 1-3***, 1-4***, 2-3***, 2-4***, 3-4***
# Projects Created	**0.10** **(0.90)**	0.01 (0.11)	0.03 (0.19)	0.01 (0.13)	1-2***, 1-3***, 1-4***, 2-3***, 2-4, 3-4***
# Comments	**22.90** **(164.75)**	1.25 (7.72)	1.81 (15.07)	1.54 (9.60)	1-2***, 1-3***, 1-4***, 2-3, 2-4, 3-4
Ave Backers	3,713.54 (3,004.79)	**9,410.75** **(2,429.33)**	**1,085.08** **(923.66)**	2,705.09 (1,968.65)	1-2***, 1-3***, 1-4***, 2-3***, 2-4***, 3-4***
# Variety	**7.81** **(2.11)**	2.46 (1.53)	2.75 (1.84)	2.17 (1.29)	1-2***, 1-3***, 1-4***, 2-3***, 2-4***, 3-4***
Population (%)	9.27%	23.62%	12.28%	54.83%	
	Active Backers	**Trend Followers**	**The Altruistic**	**The Crowd**	

***p < 0.001, **p < 0.01, *p < 0.05

Table 4. Descriptive Statistics and Correlations

	Mean	S.D.	1	2	3	4	5	6	7	8
1. Days Elapsed	18.35	12.52								
2. Project Duration	36.79	11.05	0.43							
3. Active Backer	0.19	0.39	0.01	0.00						
4. Trend Follower	0.16	0.37	-0.02	0.01	-0.21					
5. The Altruistic	0.03	0.16	0.00	-0.01	-0.08	-0.07				
6. Log Project Goal	9.96	1.52	0.14	0.22	0.00	-0.01	-0.02			
7. Project Creator Network	4.05	7.15	0.07	0.03	0.00	0.01	0.00	0.14		
8. # Backers Pledged	470.51	1701.28	0.10	0.00	0.00	0.01	0.00	0.08	0.11	
9. # Active Backers Pledged	47.34	124.73	0.03	0.02	-0.01	0.02	-0.01	0.13	0.12	0.83

Note: All correlations are significant at 0.01 level

Table 5. Choice Model Results

Variables	Model 1	Model 2	Model 3	Model 4	Model 5
Intercept	-5.7095***	-5.7380***	-5.5918***	-5.6121***	-5.6182***
Days Elapsed	-0.0122***	-0.0121***	-0.0155***	-0.0111***	-0.0119***
Project Duration	-0.0005	-0.0006	-0.0009*	-0.0004	0.0003
Log Project Goal	0.0953***	0.0965***	0.0918***	0.0908***	0.0921***
Project Creator Network	0.0364***	0.0392***	0.0357***	0.0375***	0.0376***
# Backers Pledged	0.0000***	0.0000***	0.0000***	-0.0001***	0.0000***
# Active Backers Pledged	0.0038***	0.0038***	0.0039***	0.0040***	0.0034***
Active Backer	0.0230***	0.0643***	0.0758***	-0.0358***	-0.0320***
Trend Follower	-0.5907***	-0.5011***	-1.2245***	-1.2481***	-1.4389***
Altruistic	0.3275***	0.2780***	0.3169***	0.4935***	0.5133***
Project Creator Network * Active Backer		-0.0070***			
Project Creator Network * Trend Follower		-0.0143***			
Project Creator Network * Altrustic		0.0091***			
Days Elapsed * Active Backer			-0.0031***		
Days Elapsed * Trend Follower			0.0332***		
Days Elapsed * Altrustic			0.0007		
# Backers Pledged * Active Backer				0.0000***	
# Backers Pledged * Trend Follower				0.0002***	
# Backers Pledged * Altrustic				-0.0002***	
# Active Backers Pledged * Active Backer					0.0003***
# Active Backers Pledged * Trend Follower					0.0032***
# Active Backers Pledged * Altrustic					-0.0019***
GEE Fit Criteria (QIC)	**914,292.58**	**913,935.12**	**912,601.70**	**892,289.67**	**891,424.29**

***p < 0.001, **p < 0.01, *p < 0.05

Table 6. Effect Size and Summary of Hypotheses Results

Model	Independent Variable of interest	Cluster	Coefficient	Hypothesis	Supported?	Effect Size (the odds of the project being chosen)
Model 2	Project Creator Network	Crowd	0.0392	H1a	Yes	Every 10[3] more projects backed prior creating the project would increase the odds by 48.0%.
		Trend Followers	0.0249	H1b	Yes	Every 10 more projects backed prior creating the project would increase the odds by 28.3%.
		Active Backers	0.0322	H1c	No	Every 10 more projects backed prior creating the project would increase the odds by 38.0%.
Model 3	Days Elapsed	Trend Followers	0.0177	H2a	Yes	Every 7 days past the project launch date would increase the odds by 13.2%.
		Altruistic	-0.0155	H2b	No	Every 7 days past the project launch date would decrease the odds by 10.3%.
		Active Backers	-0.0186	H2c	Yes	Every 7 days past the project launch date would decrease the odds by 12.2%.
Model 4	# Backers Pledged	Trend Followers	0.0001	H3a	Yes	Every 1000 backers accumulated would increase the odds by 10.5%.
		Altruistic	-0.0003	H3b	Yes	Every 1000 backers accumulated would decrease the odds by 25.9%.
Model 5	# Active Backers Pledged	Active Backers	0.0037	H4a	Yes	Every 100 Active Backers accumulated would increase the odds by 44.8%.
		Trend Followers	0.0066	H4b	Yes	Every 100 Active Backers accumulated would increase the odds by 93.5%.
		Crowd	0.0034	H4c	Yes	Every 100 Active Backers accumulated would increase the odds by 40.5%.

[3] These base numbers are chosen by rounding the value of one standard deviation to either 10, 100 or 1000, depending on which is nearer (as these are more interpretable to the lay person), or to the nearest calendar month/week/day.

Figure 1a. Project Creator Network and Probability of Project Choice by Clusters

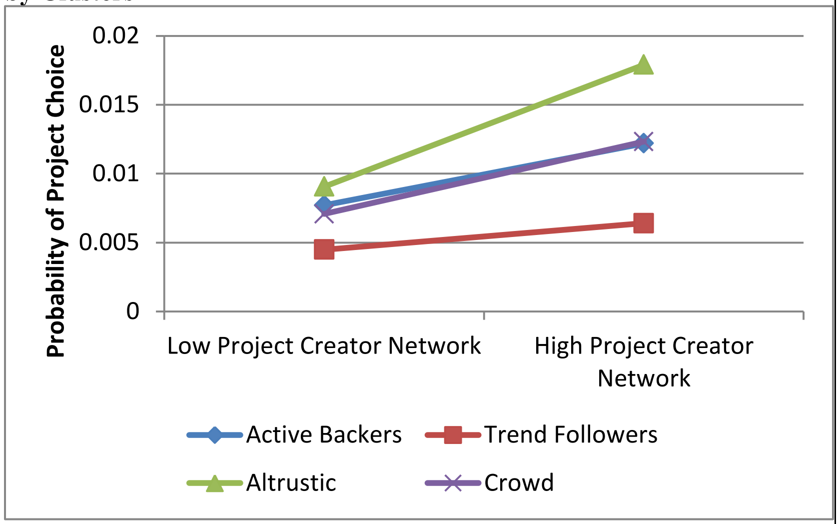


Figure 1b. Days Elapsed Since Project Creation and Probability of Project Choice by Clusters

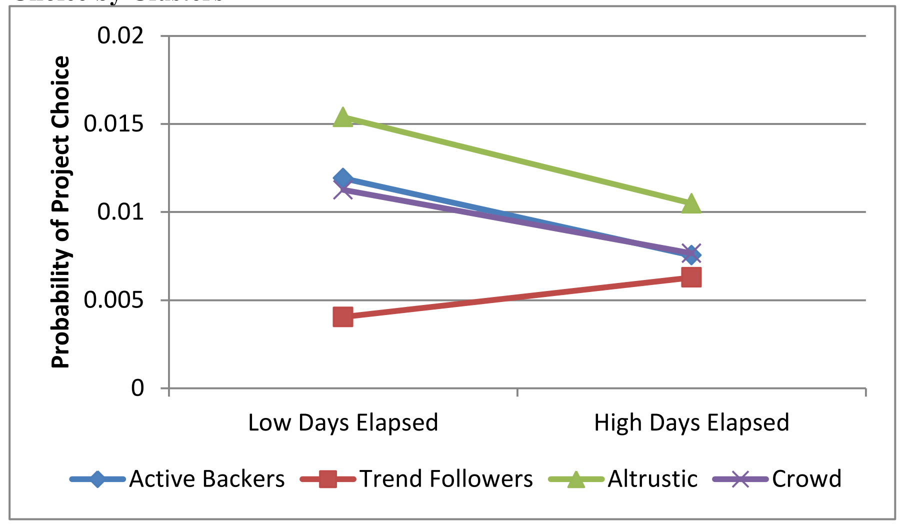


Figure 1c. # Backers Pledged and Probability of Project Choice by Clusters

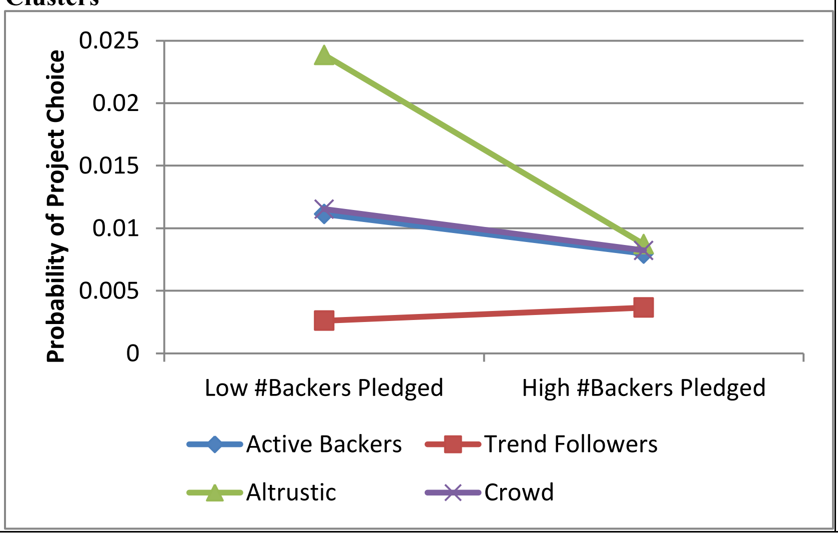
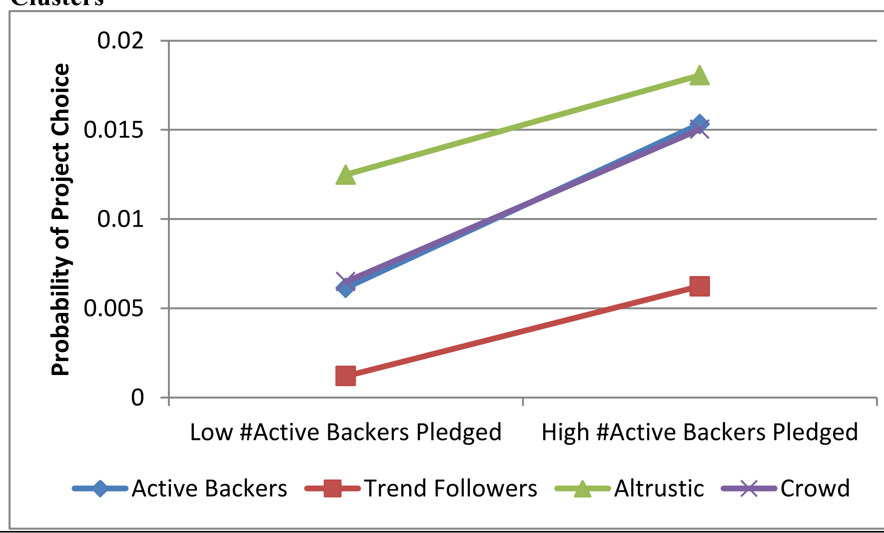


Figure 1d. # Active Backers Pledged and Probability of Project Choice by Clusters



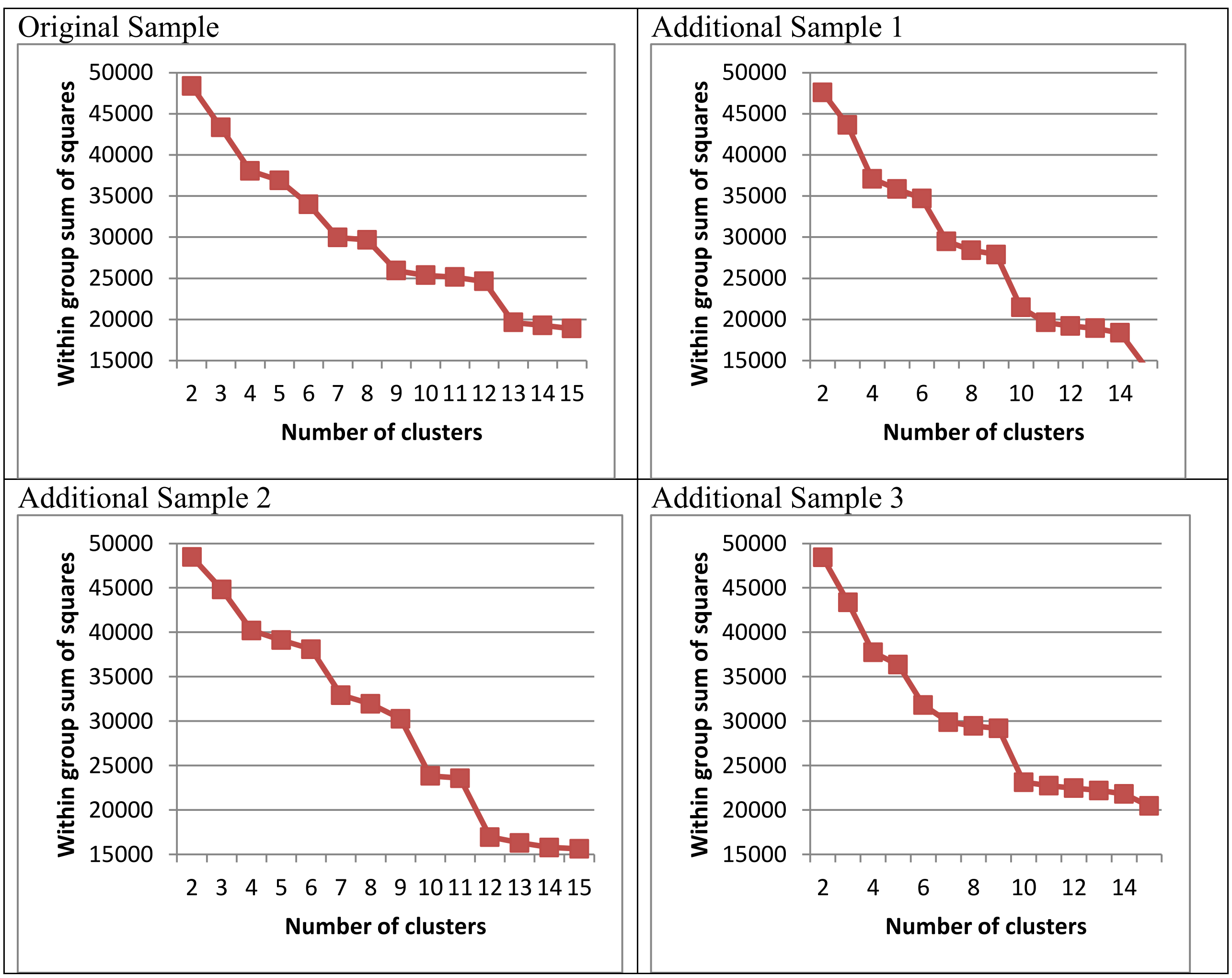
Appendix A. Robustness Tests for Cluster Analysis

We provide results of robustness tests for our cluster analysis. We used a two-stage clustering procedure recommended by Ketchen and Shook (1996). In the first stage, a hierarchical algorithm is used to determine the number of clusters (Ward's method with Euclidean distance). The number of clusters is then used for nonhierarchical clustering (*k*-means clustering). The rationale behind this is that nonhierarchical methods have several potential advantages over hierarchical methods although it is computationally intensive and thus cannot handle extremely large samples. The iterative process allowing multiple passes through the data ensures results are less impacted by outliers. Such a process also minimizes within-group variance and maximizes between-group variance (Ketchen and Shook 1996). On the other hand, nonhierarchical methods are more efficient and less computational intensive, which can be used to analyze large samples. However, nonhierarchical methods require the number of clusters stated a priori. Given the relative advantages, we use hierarchical methods as a prior step to determine the appropriate number of clusters, and we use nonhierarchical methods to classify the entire sample of observations.

Given the large number of backers in our dataset (182,291 observations), using hierarchical clustering for the entire population will be computationally challenging, if not impossible in most leading statistical software such as SAS and Stata. In order to address this computational limitation, we rely on numerous random samples in our first stage hierarchical clustering. Drawing random samples from the data provides a representative snapshot of the types of backers while adhering to statistical principles. To illustrate our efforts, in this appendix, we present another three distinct random samples from our dataset – all pointing towards a consistent 4-cluster solution. We employed hierarchical clustering on each sample and plotted the within-group sum of squares against number of clusters. As shown in Figure A1, the first distinct kink in the plot was found at the four-cluster solution for all three samples.

We used the results of the hierarchical clustering to determine the number of clusters to specify for the non-hierarchical, *k*-means clustering. *k*-means clustering is used to ensure both robustness of results and that all crowdfunders can be assigned to a cluster group. To examine the validity of the four-cluster solution for the *k*-means clustering, we compute the means of the attributes for the four-cluster solutions obtained from k-means clustering and compared them against that of the means obtained from the hierarchical Ward's clustering. The mean values of the attributes for both clustering methods are qualitatively similar for all four archetypes suggesting robustness in the clustering results.

Figure A1. Plot of Within-Group Sum of Squares and Number of Clusters for 3 Additional Random Samples



Appendix B. Composition of Cluster 4 – The Crowd

In this appendix, we provide a detailed analysis to break down the fourth cluster – the Crowd, which constitutes 54.83% of our sample. Employing the two step clustering procedure, the first hierarchical clustering step showed that a three-cluster solution best fits the data – as Figure A1 in Appendix A shows – the second kink is located at the seven-cluster solution.

Table B1 shows the clustering results from the *k*-means clustering procedure. As shown in the table, the Crowd can be further decomposed into three groups, each resembling one archetype in our primary categorization (Active Backer, Trend Follower and Crowd), but more moderate than the original archetype in all aspects, showing that they may be these archetypes in the making. We term them secondary Active Backers, Trend Followers and Crowd. Notably, we did *not* observe a secondary Altruistic group within this cluster. The reason for this is intuitive as one key characteristic of altruistic crowdfunders is that they do not expect rewards – a feature which will have precluded altruistic crowdfunders from appearing in the Crowd in the first place, given that the general crowd seeks reward for backing projects.

The secondary Active Backers comprise 22.18% of the primary Crowd. They resemble the original Active Backers in various aspects. First, the secondary Active Backers tend to back a large number of projects (12.5 projects on average, compared to around 2 projects for other subclusters), although the number is almost a quarter that of the Active Backers. Second, they are more likely to create projects (0.04 projects on average, compared to close to 0 for other subclusters). The number is also lower than that of the Active Backers, which is 0.10 on average. Third, they also have a higher tendency to post comments compared to other subclusters (4.95 comments on average, compared to less than 1 comments on average for other subclusters), but less than that of the Active Backers (22.90 comments on average). Finally, they have broader interest than the other subgroups since they invest in close to 4 categories, whereas the rest subclusters only invest 1 to 2 categories, but their interest is less broad than the primary Active Backers, who invest in 7.81 categories on average. The secondary Trend Followers comprise 32.28% of the primary Crowd. They tend to back projects that have a large number of backers (4,970), compared to the other subclusters (1,194 and 2,511 respectively), although this characteristic is less distinct compared to the primary Trend Followers (9,410). Finally, there remains a catch-all remaining category, that comprises 45.54% of the fourth cluster, that are moderate in all aspects that they were measured on. We thus label this group the secondary Crowd.

Table B1. Clustering Results of the Crowd

Variables	Mean (SD) of clusters			Pairwise comparisons using t tests with pooled SD (p adjustment: Holm)
	Cluster 1	Cluster 2	Cluster 3	
Reward %	1.00 (0.01)	0.96 (0.11)	1.00 (0.01)	1-2***, 2-3***, 1-3
Ave Goal	139,586.03 (215545.44)	58,192.30 (72387.1)	45,280.55 (46287.48)	1-2***, 2-3***, 1-3***
# Projects Backed	2.71 (2.28)	**12.50** **(6.88)**	2.53 (1.95)	1-2***, 2-3***, 1-3***
# Projects Created	0.00 (0.06)	**0.04** **(0.24)**	0.01 (0.08)	1-2***, 2-3***, 1-3**
# Comments	0.56 (2.61)	**4.95** **(19.47)**	0.56 (2.42)	1-2***, 2-3***, 1-3
Ave Backers	**4,970.08** **(905.24)**	2,510.66 (1651.75)	1,193.99 (813.66)	1-2***, 2-3***, 1-3***
# Variety	1.68 (0.83)	**3.94** **(1.09)**	1.65 (0.79)	1-2***, 2-3***, 1-3***
Population (%)	32.28%	22.18%	45.54%	
	Secondary Trend Followers	Secondary Active Backers	Secondary Active Backers	

***p < 0.001, **p < 0.01, *p < 0.05

In sum, similar archetypes occurred when we further decompose the primary Crowd into three subclusters. These subclusters resemble the primary ones in various aspects but are less distinct in their defining aspects. Such decomposition further substantiates our findings of the archetypes, and shows that they may be such archetypes in the making, as they gain more experience backing projects on *Kickstarter*.