How different are crowdfunders? Examining archetypes of crowdfunders

Lin, Yan; Boh, Wai Fong

2020

Lin, Y. & Boh, W. F. (2020). How different are crowdfunders? Examining archetypes of crowdfunders. *Journal of the Association for Information Science and Technology*, 71(11), 1357-1370. <https://dx.doi.org/10.1002/asi.24332>

<https://hdl.handle.net/10356/151583>

<https://doi.org/10.1002/asi.24332>

© 2019 ASIS&T. All rights reserved. This paper was published by Wiley in *Journal of the Association for Information Science and Technology* and is made available with permission of ASIS&T.

Downloaded on 26 Apr 2023 22:58:50 SGT

How Different are Crowdfunders?

Examining Archetypes of Crowdfunders

Yan LIN

Assistant Professor

Shenzhen Audencia Business School,

Shenzhen University

5/F Science and Technology Building, Shenzhen University, No. 3688 Nanhai Road, Shenzhen,

Guangdong Province, P. R. China

TEL: (86) 755-2653 2303

E-mail: linyan@szu.edu.cn

Wai Fong BOH*

Professor

Nanyang Business School

Nanyang Technological University

Blk S3, B2A-14, Nanyang Avenue, Singapore 639798

Tel: (65) 6790 6196

Fax: (65) 6792 2313

E-mail: awfboh@ntu.edu.sg

* Corresponding Author

Abstract

We unpack the complexities of the crowdfunder community by identifying different archetypes of crowdfunders funding technology projects on *Kickstarter.com*. Drawing on the extant literature on innovation adoption and opinion leadership, we propose two dimensions of crowdfunders that capture the heterogeneity in crowdfunders' behavior: opinion leadership and interest specialization of crowdfunders. Using a set of variables representing these two dimensions, our analysis revealed five distinct archetypes of crowdfunders: the *Vocal Actives*, the *Silent Actives*, the *Focused Enthusiasts*, the *Trend Followers*, and the *Star Seekers*, who each adopted distinct crowdfunding strategies. We established external and criterion-related validity of the cluster solutions in multiple ways. Our results suggest that the composition of crowdfunders is complex, even within a single platform.

Keywords: Crowdfunding, Cluster Analysis, Text Analysis

Introduction

Crowdfunding refers to the practice by which funding resources are pooled by people, usually via the Internet, to support efforts initiated by others (Belleflamme et al. 2014). It leverages the power of web-based architectures and Internet technologies to enable individuals to reach out to geographically dispersed strangers and individuals who might be interested and willing to support various charity, creative, entrepreneurial and lending-based endeavors in a collaborative manner (Hamari, Sjöklint, & Ukkonen, 2016). Crowdfunding has the potential to disrupt how organizations obtain funding by reaching out to diverse masses of individuals. Nowadays, crowdfunding has become an important funding source for creative projects. According to *Kickstarter*,¹ as of August 2019, more than 4 billion US dollars has been pledged by over 16 million backers to support 160,000 projects.

The growing popularity of crowdfunding has sparked interest in the research community. Prior research has a significant focus on the project level of analysis, examining project characteristics that determine the success of crowdfunding projects (e.g., Allison, Davis, Webb, & Short, 2017; Burtch, Ghose, & Wattal, 2013). A smaller set of studies have focused on the crowdfunder community. There are four streams of work in this area, examining (1) crowdfunder motivations for backing projects (Bretschneider & Leimeister, 2017; Cholakova & Clarysse, 2015); (2) how various institutional context factors – such as trust (Chen, Lai, & Lin, 2014) and loosening of information controls (Burtch, Ghose, & Wattal, 2015) – influence the behavior of crowdfunders; (3) how the behavior and decisions of crowdfunders influence other crowdfunders (i.e., herding effects) (Burtch et al., 2013; Zhang & Liu, 2012); and (4) various biases exhibited by crowdfunders, such as home bias (Lin & Viswanathan, 2015) and risk averseness (Paravisini, Rappoport, & Ravina, 2016).

Much of the existing research on crowdfunding seeks to understand if crowdfunding presents genuinely new ideas and behaviors, and attempts to determine if crowdfunding surfaces fundamentally new theoretical perspectives. Along these lines, our research asks the question of whether the well-accepted theory of consumer segmentation in innovation adoption (Rogers, 2003) is just as applicable in understanding crowdfunders who are evaluating creative digital product and service offerings. As crowdfunding platforms attract a large number of crowdfunders, the diversity of crowdfunders imply that it may be inaccurate to consider the market in the aggregate (Allenby & Rossi, 1998). Much prior research examining factors that determine the success of crowdfunding

projects assume all crowdfunders are influenced by the same project characteristics and do not consider the heterogeneity of project backers (e.g., Ahlers, Cumming, Günther, & Schweizer, 2015). Yet prior research shows that different individuals interpret the same information differently based on their backgrounds (Connelly, Certo, Ireland, & Reutzel, 2011). Segmentation of the crowdfunders thus become even more important in allowing project creators and platform owners to understand what kind of crowdfunders the platform might be attracting and how they process information differently.

Examining the composition of crowdfunders and their strategies on the crowdfunding platform thus offers a “demand-based” view of crowdfunding dynamics (Adner & Levinthal, 2001). This is analogous to the need for firms to gain an understanding of customer segments and their specific preferences, enabling firms to generate detailed and precise adjustments of their product features and marketing efforts (Smith, 1956; Zhu & Zhang, 2010). It is important to answer questions about: what is the composition of crowdfunders? Who would back a project and when? The answers to these questions will inform both project creators and future investors about whether the crowdfunders’ decisions can indeed serve as reliable indicators of market demand (Smith, 1956), especially when the crowdfunding community has been known to participate for various intrinsic and extrinsic reasons (Gerber, Hui, & Kuo, 2012; Zheng, Gong, & Pavlou, 2017).

Hence, our study aims to provide a systematic taxonomy of crowdfunders on a crowdfunding platform, by drawing on the literature on opinion leadership and technology adoption. Given the complexity of the crowdfunder community, our approach is exploratory in nature and we expect to uncover the underlying archetypes of crowdfunders. Our research questions are:

- (1) What are the archetypes of crowdfunders?
- (2) How do the archetypes differ in terms of their characteristics and project backing strategies?

We answer these research questions by examining crowdfunders funding technology projects on *Kickstarter.com*, American’s leading reward-based crowdfunding platform. We conducted exploratory cluster analysis and revealed five distinct archetypes of crowdfunders: the *Vocal Actives*, the *Silent Actives*, the *Focused Enthusiasts*, the *Trend Followers*, and the *Star Seekers*, who each adopted distinct crowdfunding strategies. Our empirical results not only provide a systematic understanding of crowdfunders but also provide insights into how the technology adoption life cycle can be enhanced as a framework to explain crowdfunder differences.

Literature

Crowdfunders as Consumers

Crowdfunders in reward-based crowdfunding may be compared to consumers as they can pre-order products (Belleflamme, Lambert, & Schwienbacher, 2014). The literature has long recognized that consumer heterogeneity has important implications. Market segmentation is a fundamental concept of modern marketing driving firms' marketing strategy (Allenby & Rossi, 1998). Especially for new ventures, customer segmentation plays a key role in driving the initial business model design and product development (Aulet, 2013).

A Typology of Crowdfunders

A taxonomy of consumers that has gained dominance in the technology adoption and marketing domains is one where individuals are classified into two main groups: the “early adopters” and the “imitators” (Van den Bulte & Joshi, 2007), based on two prominent theoretical frameworks: opinion leadership (Katz, 1957) and innovation diffusion (Moore, 2014; Rogers, 2003). Drawing on this literature, we propose an initial taxonomy of crowdfunders.

As many crowdfunding projects are experimental and involve substantial risk in that the projects might eventually fail to deliver the rewards and products (Mollick, 2014), the crowdfunder projects represent innovations that need to scale the innovation adoption curve. According to the technology adoption literature, the early market consists of “technology enthusiasts” and “visionaries”, who appreciate the innovation and its benefits, and are willing to explore the use of innovations to solve problems even when the innovations are immature. The mainstream market, on the other hand, includes relatively risk-averse individuals and firms who will only adopt innovations that are proven amongst peers and have well-established feasibility and a substantial installed base of prior adopters (Moore, 2014; Van den Bulte & Joshi, 2007).

These two groups map to the opinion leaders and follower groups defined by the opinion leadership literature. According to the opinion leadership literature, opinion leaders are “individuals who are likely to influence other persons in their immediate environment” (Katz & Lazarsfeld, 1955, p. 3), due to the high esteem and trust others place in them. Opinion leaders derive their influence from their informal status as a highly informed individual about a specific subject matter (Watts & Dodds, 2007).

Hence, we propose that there exists a group of early adopters or opinion leaders in the

crowdfunding platform who tend to back projects early in the funding lifecycle. They consist of techies, visionary users, and trendsetters, who are more confident and willing to experiment, and they are likely to be more knowledgeable due to their activeness in backing projects in the crowdfunding community. In addition to early adopters, we expect there will be a group of followers, who are also the mainstream customers according to Moore (2014). This group also maps to the “imitators” described in the opinion leadership literature. Compared to early adopters, this group tend to be pragmatic users or followers who are less confident and have a tendency to follow others in adoption decisions (Moore, 2014). This group is also likely to be less experienced and knowledgeable, and less active in funding projects.

The presence of these two groups is consistent with the herding effect found in crowdfunding platforms (e.g., e.g., Kuppuswamy & Bayus, 2017; Zhang & Liu, 2012), suggesting that crowdfunders tend to be influenced by others’ decisions. 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). Such herding phenomenon occurs because potential crowdfunders derive additional information by observing others’ decisions (Banerjee, 1992; Bikhchandani, Hirshleifer, & Welch, 1992). 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 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., 2015, p. 7).

Given that there are a number of domains in the technology area (e.g. hardware and software), the question that arises is whether the leader and follower groups were in specific domains, or whether there exist leader and follower groups that cut across the entire technology sector. Prior research has highlighted that both leader and follower groups can be monomorphic or polymorphic (Merton, 1968). Monomorphic opinion leaders are experts influential in one or two limited domains, and their influence does not diffuse to other domains (Grewal, Mehta, & Kardes, 2000). We thus expect crowdfunders who have significant interest in limited domains to become monomorphic early adopters of a specific domain. Polymorphic opinion leaders, on the other hand,

exert influence in generalized topics or a variety of domains that may not be related to one another (Myers & Robertson, 1972). Just as there are polymorphic and monomorphic opinion leaders, we expect that there are also polymorphic and monomorphic followers, as individuals may choose to invest only in specific limited categories, and they may wish to become followers in such limited categories. Hence, we propose the following propositions summarized in Table 1:

P1: There are polymorphic early adopters and polymorphic followers – who have interests in diverse domains.

P2: There are monomorphic early adopters and monomorphic followers – who have interests in a single domain.

Insert Table 1 about Here

Much prior research used demographic characteristics of consumers, such as age, gender, and education, to distinguish between early adopters and followers (MacVaugh & Schiavone, 2010). Our research, however, classifies crowdfunders based on their behaviors, as their behaviors are the best reflections of their innovation adoption tendencies (Paravisini et al., 2016).

Opinion Leadership

We identify two relevant dimensions that are closely related to the segmentation between early adopters and followers: crowdfunders' confidence levels and activeness.

Confidence. In line with our characterization of crowdfunders as early adopters and followers, we expect that crowdfunders' confidence levels will affect whether they become leaders or followers (Taylor, 1977). In the face of uncertainty, people tend to follow the actions of others, 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. We thus expect that early backers of projects will tend to be more confident of their backing decisions, believe more strongly in their own evaluations, and would be less concerned about the beliefs of others (Barber & Odean, 2001). The actions of such early adopters effectively convey their own private information to the rest of the group, thus allowing followers to observe the actions of early adopters and follow accordingly (Bernardo & Welch, 2001). This group may also have fewer concerns about backing bigger projects that may require a bigger investment amount.

Activeness. Individuals' level of activeness on the Kickstarter platform also helps to

differentiate between early and late backers of projects (Chan & Misra, 1990). Early adopters are often highly involved and very interested in the product (Van den Bulte & Joshi, 2007). Crowdfunders who are active in funding activities likely have the experience and expertise to evaluate projects and are more likely to notice new innovative projects on the platform (Kircher & Postlewaite, 2008).

Interest Concentration

Opinion leadership can span multiple areas or be specific to one domain. Our propositions also highlight a key differentiating factor – the diversity of crowdfunders’ interests – differentiating between monomorphics – specialists with limited interests, and polymorphics – generalists with diverse interests (Merton, 1968). According to Rogers (2003), polymorphism is “the degree to which an individual acts as an opinion leader for a variety of topics”, while monomorphism “is the tendency for an individual to act as an opinion leader for only a single topic” (pp. 314). Prior research has argued that interest concentration can indicate whether the crowdfunder is knowledgeable and experienced in certain areas (Hahn & Lee, 2013; March, 1991), and can be associated with considerable diversity in patterns of participation (Inbar & Barzilay, 2014). Distinguishing between monomorphics and polymorphics can help us identify opinion leaders whose influence span multiple areas (King & Summers, 1970; Silk, 1966).

Crowdfunding platforms have the potential to create a long tail of crowdfunders with special interests (Anderson, 2004). The Internet has significantly reduced transaction costs and search costs for niche projects that would have difficulty discovering its demand offline. Hence, crowdfunding platforms might attract individuals that have special interest in specific project types. We thus include crowdfunders’ interest concentration in our analysis.

Methodology

Data

Our research focuses on technology projects in *Kickstarter*, the world’s leading reward-based crowdfunding platform for creative projects. We focus on technology projects for several reasons. First, technology projects often offer pre-orders of a product prototype. It is thus highly relevant to examine if consumer segments predicted by the technology adoption lifecycle apply. Further, digital entrepreneurship has been cited to be an important source for technical change and disruptive innovation. A large portion of technology projects have significant potential of

becoming a technology venture firm after a successful fundraising effort (Mollick, 2014), and digital ventures are growing in importance and dominance. Our findings can thus inform research on digital entrepreneurship – where digital technologies and entrepreneurship intersect by understanding the role that reward-based crowdfunding plays in the process of technology entrepreneurship. Finally, while it may be natural to find different archetypes of crowdfunders on a broad reward-based platform like *Kickstarter*, it would be interesting to examine whether there are meaningful archetypes of crowdfunders even within a single technology category, or perhaps we may find the technology category dominated by individuals of a specific profile.

Our dataset comprises all technology projects listed from January to November 2014 in *Kickstarter*.² For each project in the technology category, we collected all the relevant information provided on the project campaign page and the backer information. A total of 6,044 projects were captured during the data collection period. 4,249 US projects were used in this study.³ 331,421 crowdfunders (or backers)⁴ were identified from the project data. As *Kickstarter* did not disclose the exact time when a crowdfunder backed a project, we regularly captured the backer information on all projects and used these multiple snapshots to work out an estimation of the time when a crowdfunder backed a project. Given the sheer volume of data, we were able to collect a snapshot of all projects' backer information once every 4-7 days.

Similar to prior research (Paravisini et al., 2016), we made use of crowdfunders' historical backing records, which reflect backers' behaviors and funding strategies. Our analysis relies on the assumption that crowdfunders' characteristics are reflected in their behaviors. Hence, our main analysis examines crowdfunders whose behaviors are evident through multiple backing decisions. We conducted a separate analysis on backers who only had one or two backing record(s). This allows us to base our main analysis on crowdfunders with enough backing instances to reveal patterns in their behavior, and prevented us from reading too much into limited instances of an individual's behavior. In total, we identified and examined 21,429 crowdfunders who had more than two backing instances and 309,992 crowdfunders who had only one or two backing instances. While on the surface, the number of repeated crowdfunders is a small fraction of all the crowdfunders who participated in crowdfunding, nearly half of the funds were provided by these crowdfunders and repeated backers contribute 65% of the funding dollars on *Kickstarter* (Burtch, Ghose, & Wattal, 2016).⁵

Variables

For each individual, we constructed the following variables.

(1) **Ave Log Backers** refers to the number of backers cumulated ($NumBacker_k$) at the time when the crowdfunder made the backing decision for each project k in the crowdfunder's portfolio set C . These numbers were averaged to reflect the average number of existing backers on all projects backed by crowdfunder. The variable was calculated as:

$$Ave Log Backers = \left[\sum_{k=1}^N Log(NumBacker_k) \right] / N$$

(2) **Ave Log Goal** refers to the average project goal of all projects backed by the crowdfunder. Higher project goal size has been shown to be negatively associated with project funding success, and have more uncertainties in terms of delivery (Mollick, 2014). Hence, less confident crowdfunders are less likely to back such projects. For a crowdfunder who had backed N projects in his or her portfolio, the variable was calculated as:

$$Ave Log Goal = \left[\sum_{k=1}^N Log(Goal_k) \right] / N$$

(3) **Ave Log Median Reward**. *Kickstarter* projects allow project creators to specify different rewards for different crowdfunder contribution amounts. The amount contributed by the crowdfunder can be influenced by backers' confidence. Since the amount of crowdfunder's contribution is not disclosed, we used, as a proxy, the average size of contribution required for each project backed. For each project k in the crowdfunder's portfolio, we first calculated the median⁶ contribution amount based on the project's reward categories ($Median Reward_k$). *Ave Log Median Reward* was then calculated as:

$$Ave Log Median Reward = \left[\sum_{k=1}^N Log(Median Reward_k) \right] / N$$

(4) **Ave Log Creator Social Capital**. Prior research has shown that the social capital of the project creator serves as a key signal to potential crowdfunders (e.g., e.g., Colombo, Franzoni, & Rossi - Lamastra, 2015; Lin, Prabhala, & Viswanathan, 2013), which may be less salient to experienced and confident crowdfunders who tend to believe more strongly in their own evaluations. Hence, we used the number of projects backed by the project creator, which is shown on the project page, to proxy the social capital of the project creator (Colombo et al., 2015). For

each project k in the crowdfunder's portfolio set C , we identified the number of projects backed by the project creator at the time the crowdfunder pledged his or her money to the project ($Num\ Creator\ Backed_k$). We then averaged the number across all projects backed (N), calculating the *Average Log Creator Social Capital* as:

$$Ave\ Log\ Creator\ Social\ Capital = \left[\sum_{k=1}^N Log(Num\ Creator\ Backed_k) \right] / N$$

(5) **# Log Tech Projects Backed** refers to the number of technology projects backed by the crowdfunder on *Kickstarter*. This indicates the activeness of crowdfunders, and their experience.

(6) **# Log Comments** is the number of comments the crowdfunder had contributed to the technology projects s/he has backed. *Kickstarter* only allows existing backers to post comments. Active individuals are more likely to seek information and engage in word-of-mouth behavior (Venkatraman, 1988).

(7) **Interest Concentration (HHI)**. While prior research has examined the level of interest concentration of crowdfunders, they tend to examine interest concentration across broad categories predefined by the crowdfunding platform (e.g. Art, Technology, Dance, Comics are some example predefined categories). There is, however, significant heterogeneity in topics within a single category (Roma, Petruzzelli, & Perrone, 2017). Hence, we conducted a topic analysis using Latent Dirichlet Allocation (LDA) to analyze the rich textual descriptions provided by project creators to discover subcategories within the technology category.⁷ The topic analysis showed that technology projects can be classified into five distinct topic areas: *Electronics & Design*, *Software Applications*, *Hardware*, *New Technologies*, and *Patronage* projects. The topic analysis assigned each project a set of topic loadings on each of the five topics, showing how much the project was related to the topic. For a crowdfunder who had backed N projects, we first calculated the average topic loading of all the projects backed by the individual:

$$Topic_i = \frac{\sum_{j=1}^N Loading_{ij}}{N}, i = 1, 2, \dots, 5$$

Where $Loading_{ij}$ is the topic loading of project j on topic i . We then used the average topic loading to calculate the Herfindahl-Hirschman Index (HHI) for the individual:

$$HHI = \sum_{i=1}^5 Topic_i^2$$

We use HHI to measure the extent to which a crowdfunder's interest is concentrated on one

topic, or is diversified across multiple topics.

For variables (1) to (6), we used the natural logarithm of the original value to mitigate the impact of extreme values.

Table 2 provides descriptive statistics and correlations for all the variables.

Insert Table 2 about Here

Cluster Analysis

We employed cluster analysis to discover meaningful clusters and to test the proposed typology. We randomly divided crowdfunders into two samples of equal size. This allowed us to conduct cluster analysis on one half, and use the other half of the sample for testing to ensure the external validity of our cluster solution (Ketchen & Shook, 1996). There are two basic types of clustering algorithms: hierarchical and nonhierarchical (Ketchen & Shook, 1996). Hierarchical algorithms progress by building a tree-like structure where small clusters are nested within larger clusters via a series of agglomerative steps that combine small clusters into larger clusters. Nonhierarchical algorithms generate clusters by partitioning data into a predetermined number of clusters without hierarchical relationships (Hair, Black, Babin, Anderson, & Tatham, 2009; Ketchen & Shook, 1996).

As both hierarchical and nonhierarchical clustering each has its advantages and disadvantages (Ketchen & Shook, 1996), we followed the recommendations of researchers (Ketchen & Shook, 1996; Malhotra, Gosain, & Sawy, 2005) by employing both approaches to analyze our data. First, we employed hierarchical cluster analysis following Bensaou and Venkatraman (1995)'s approach: (1) All analyzed variables were standardized; (2) The Euclidean distance matrix was calculated; and (3) Ward's minimum variance method was used for cluster agglomeration. The computation of distance matrix for hierarchical clustering is computationally intensive for a large sample size. Hence, for both samples, we drew a sub-sample of 2000 crowdfunders (about 20% of the split-half sample) for the analysis, resampling several times and varying the number sampled (using 1500 and 2500 crowdfunders) to ensure consistent results. As in prior research (Malhotra et al., 2005), we determined the number of clusters by inspecting the dendrogram and the agglomeration coefficients. Both samples suggested a five-cluster solution.

Next, we employed the nonhierarchical K-means cluster algorithm on the same samples to

test the robustness of the five-cluster solution (Malhotra et al., 2005), as the consistency (i.e., reliability) of a cluster solution should be evaluated by performing cluster analysis multiple times using multiple methods (Ketchen & Shook, 1996). Plotting the within cluster sum of squares against the number of clusters, we determined that a five-clusters solution fits the data best. For both samples, the Cohen's Kappa between the solution from the hierarchical and the nonhierarchical cluster analysis is about 0.6, suggesting sufficient consistency. Hence, the K-means algorithm was further applied to the full data, and ran multiple times to ensure robustness of results.

Results

Insert Table 3 about Here

Clustering results were consistent across the two samples. Table 3 provides, by cluster, the mean and standard deviation for the seven variables included in the cluster analysis for both samples. Values that differentiate the cluster from others were highlighted with bold and underline. To provide an intuitive understanding of the clustering results, Table 4 summarized the characterization of the clusters based on their relative position (high, moderate, or low) in each of the dimensions. We named the clusters based on their distinct behavioral profiles reflected in the variables that differentiate them from other clusters. For the sake of brevity, we describe the results from the first half of the sample. The hold-out sample shows similar results.

Insert Table 4 about Here

Silent Actives: This cluster comprises 21.7% of the sample. They are active in backing projects, reflected in the relatively higher number of technology projects backed (*# Log Tech Projects Backed* = High). However, they tend not to contribute comments to the projects (*# Log Comments* = Low). They tend to pay less attention to the creator's social capital (*Average Log Creator Social Capital* = Low). These crowdfunders seem to be generalists, as they tend to back a wide range of technology projects (*HHI* = Low). They tend to back projects early when the number of crowdfunders is small (*Average Log Backers* = Low), suggesting that they pay less attention to other crowdfunders' decisions. In addition, they tend to fund projects with a relatively large goal

(*Average Log Goal* = High) and that require relatively large contributions (*Ave Log Median Reward* = High). Overall, this group appears to include polymorphic crowdfunders who are more confident and moderately active.

Vocal Actives: This cluster comprises about 10% of the sample. Similar to the *Silent Actives*, they are actively backing projects, reflected in both the high number of projects backed (*# Log Tech Projects Backed* = High) and the high number of comments posted (*# Log Comments* = High). They pay attention to project signals (*Average Log Creator Social Capital* = Moderate). *Vocal Actives* tend to back projects earlier compared to other clusters (*Average Log Backers* = Low), although they tend to back slightly later than the *Silent Actives*. Similar to the *Silent Actives*, they tend to fund projects with a relatively large goal (*Average Log Goal* = High), that require relatively large contributions (*Ave Log Median Reward* = High) and they tend to be generalists backing a range of technology projects (*HHI* = Low). Overall, this group appears to include polymorphic crowdfunders who are confident and highly active.

Focused Enthusiasts: The third cluster comprises 15.5% of the sample. They are the only group that typically focus on projects in specific topic areas (*HHI* = High). They are moderate in all other aspects. This cluster appears to represent the monomorphic crowdfunders.

Trend Followers: This cluster comprises 25.9% of the sample. They tend to back projects that have already accumulated a large number of project backers (*Average Log Backers* = High), that have a relatively small funding goal (*Average Log Goal* = Low) and that require smaller contributions (*Ave Log Median Reward* = Low). They appear to be less active compared to the *Actives* (*# Log Tech Projects Backed* = Moderate; *# Log Comments* = Low), but they pay attention to project signals (*Average Log Creator Social Capital* = High). They are generalists backing a wide range of technology projects (*HHI* = Low). In sum, their funding strategy suggests that the *Trend Followers* are the polymorphic, less confident crowdfunders in the market.

Star Seekers: The last cluster (comprising 26.8% of the sample) has many similarities with *Trend Followers* in that they tend to back projects that have many other backers (*Average Log Backers* = High), with extremely large funding goals (*Average Log Goal* = High) and that require relatively large contributions (*Ave Log Median Reward* = High). They pay less attention to project signals (*Average Log Creator Social Capital* = Low). They appear to be less active (*# Log Tech Projects Backed* = Moderate; *# Log Comments* = Low) and tend to be generalists backing a wide range of technology projects (*HHI* = Low). Overall, *Star Seekers* appear to be less confident and

less active, but they appear to focus solely on highly popular “superstar” projects (Doshi, 2014).

We took special care in validating our cluster solution to ensure that we have arrived at a reliable, meaningful and useful set of clusters. According to Ketchen and Shook (1996, p. 447, p. 447), the goals of validation is to ensure that the cluster solution has (1) external validity and (2) criterion-related validity. Below, we discuss the results of the validity tests.

External Validity

External validity means that the cluster solution is representative of the general population of interest (i.e., crowdfunders backing technology projects in *Kickstarter*). We conducted the external validity check in two ways, as described below.

Split-half Sample. As recommended by prior research (Ketchen & Shook, 1996; Punj & Stewart, 1983), we split the data into two samples. The data in the second half serves as a hold-out sample to compare against the cluster results from the original solution. As shown in Table 3, clustering results from the two samples show similar patterns. The percentage of individuals in each cluster is similar across the two samples, showing a stable solution with similar distribution of observations across samples (Hair et al., 2009), establishing external validity.

Splitting into Two Time Periods. As an alternate approach, we separated the backing instances observed into two time periods: Period 1 ranges from January to June 2014, whereas Period 2 ranges from July to November 2014. We then conducted two separate analyses on the two periods using the same approach we described previously. The results from both periods are consistent with our main results.⁸

Criterion-related Validity – Linking Clusters to Crowdfunding Success

Criterion-related validity means that the clustering solution is useful for predicting important outcomes (Ketchen & Shook, 1996; Punj & Stewart, 1983). It is often assessed through significant tests with external outcome variables that are not used in the cluster analysis but are theoretically related to the clusters, such as performance. Accordingly, we examined how the different funding strategies and behaviors reflected in our cluster analysis were associated with the crowdfunders’ funding success (i.e., backing projects that have been successfully funded).

We constructed a dataset at the funder-project level to formally investigate the funding success rate of different types of crowdfunders. For each case in which Crowdfunder i pledges money to Project j , we examined the dependent variable, Success_{ij} , which takes on a value of 1 if

Project j reaches its goal, and 0 otherwise. We estimated a logistic regression, where Crowdfunder i 's membership in one of the five types of crowdfunders (D_Silent_i , D_Vocal_i , D_Trend_i , D_Star_i , with the *Focused Enthusiasts* group as the baseline) and various project attributes as controls predicted $Success_{ij}$. Random effects were added at the individual level to control for unobserved individual attributes.

Insert Table 5 about Here

Table 5 shows the results for both samples used in the main analysis. (results for control variables excluded due to space constraints).⁹ The regression results are consistent across the two samples. As expected, the *Star Seekers* were more likely to back successful projects, than crowdfunders in other clusters. Crowdfunders who specialize in specific domains (*Focused Enthusiasts*) achieve the second highest funding success rate, likely because they are knowledgeable about the projects they invest in. *Trend Followers* have lower funding success rate compared to *Focused Enthusiasts*, but their funding success rate is greater than the *Silent Actives* and *Vocal Actives*. The early adopter groups (*Silent Actives* and *Vocal Actives*) are less likely to back successful projects. The results are consistent with the observations that these early adopters are more confident and appear to pay less attention to projects' funding probability.

Backers with one or two backing instances

To provide a comprehensive view of crowdfunder behaviors, we conducted a separate analysis on the remaining 309,992 crowdfunders who had only one or two backing record(s) in our sample (among which 27,524 had two backing instances). Using the same approach as the main analysis, we divided the sample into two random samples. All the variables except *HHI* were used. As *HHI* indicates the diversity of topics based on projects backed, the variable has little meaning when we observe crowdfunders who back only one or two projects. Given the sheer number of observations, hierarchical clustering with a small sample might not provide a solution that is representative of the whole sample. Hence, we relied solely on K-means clustering for this analysis. Using a similar approach as described in the main manuscript, we found that the five-cluster solution best fit the data. Table 6 provides the clustering results.

Insert Table 6 about Here

We found a five-cluster solution. For the ease of interpretation, we also summarize the characterization of the clusters in Table 7.

Insert Table 7 about Here

The first cluster is similar to the *Star Seekers* found in our main analysis. Specifically, these crowdfunders are attracted to popular projects with relatively large goals (*Average Log Goal* = High) and are backed by many crowdfunders (*Average Log Backer* = High). These backers also tend to be one-time backers (*# Log Tech Projects Backed* = Low) who do not contribute comments (*# Log Comments* = Low). The second and third clusters appear similar to the *Trend Followers* we found in our main analysis. They tend to back projects when many people have backed the project (*Average Log Backer* = High), which makes them more similar to the profile of *Trend Followers* than the *Actives* in our main analysis. Among these *Trend Followers*, a small fraction (*Cluster 2*: 2.9%) also tend to contribute comments (*# Log Comments* = High). These vocal *Trend Followers* might have the potential to become *Vocal Actives* in the future.

Finally, while we identified two clusters (*Cluster 4* and *Cluster 5*) that backed projects relatively early compared to the other clusters (*Average Log Backers* = Low), these clusters did not appear similar to the early adopter groups in the main analysis. Rather, they are not active (*# Log Tech Projects Backed* = Low; *# Log Comments* = Low). They appear to be one-time backers who come to the platform to support a specific project. Interestingly, the fourth cluster tends to back projects initiated by those who have limited social capital (*Average Log Creator Social Capital* = Low), whereas the fifth cluster favors projects initiated by those who have high social capital (*Average Log Creator Social Capital* = Low). We speculate that these people might be family, friends or acquaintances of project creators (Agrawal, Catalini, & Goldfarb, 2015).

Discussion

In summary, we identified five archetypes of crowdfunders: *Silent Actives*, *Vocal Actives*, *Focused Enthusiasts*, *Trend Followers*, and *Star Seekers*. The *Silent Actives* and *Vocal Actives* map to the Early Adopter groups, as both groups are more confident and active in backing projects, and tend to back projects early. As the interest diversity of both groups are wide rather than narrow, both groups can be considered Polynomic Early Adopters. These early backers play an important

role as their early contributions help reduce uncertainty regarding the project and generate momentum as subsequent crowdfunders derive information from observing them (Banerjee, 1992). The *Trend Followers* and *Star Seekers* map to the Follower groups, as both groups tend to be less confident and back projects only later when substantial numbers of other crowdfunders have done so. Combined, they occupy about half of the total population. Both groups can also be considered Polynomic Followers as their interest diversity are wide rather than narrow. Overall, our results provide support and validation for Proposition 1 but not for Proposition 2. It appears that monomorphic crowdfunders make up only a minority of the sample (15.5%), and thus do not constitute a significant enough group to be further differentiated into early adopters and followers. This highlights that most technology project backers on *Kickstarter* have a general interest in the technology domain, and are not narrowly focused on specific types of technologies.

However, our analysis shows that amongst the polynomic crowdfunders, a simple two-segment framework differentiating the Early Adopters and Followers does not fully describe the heterogeneity amongst crowdfunders. Amongst the Early Adopter groups, we can further differentiate between the *Vocal Actives* and the *Silent Actives*. The *Vocal Actives* offer suggestions and feedback during the campaign, which can help project creators refine their projects (Colombo et al., 2015). They also reduce uncertainty about funding success for other potential crowdfunders and provide monitoring for the delivery of rewards by project creators.

Our findings suggest that there is scope for integrating the innovation adoption literature and the opinion leadership literature. The opinion leadership literature points out that opinion leaders are those who participate in the diffusion of information to other peers to influence the formation of their opinions in a particular domain (Watts & Dodds, 2007). The innovation adoption literature, on the other hand, characterizes early adopters by their behavior in terms of innovation adoption (Moore, 2014; Rogers, 2003). Our identification of the *Vocal Actives* and the *Silent Actives* groups highlight that opinion leaders might map to the *Vocal Actives*, and the combination of these two groups make up early adopters. Our research also highlights that while all early backers may act as “influentials” triggering imitating behavior, only the opinion leaders (*Vocal Actives*) play a role in generating word-of-mouth around the project.

Amongst the Followers, we identified two sub-groups: *Trend Followers* and *Star Seekers*. While both sub-groups represent pragmatic crowdfunders who are less confident and less active, strategies of these two sub-groups differ. *Trend Followers* try to avoid projects that have a bigger

project goal or request larger contributions, as these projects might face a greater risk of not being delivered or completed. The *Star Seekers* adopt a different approach. They tend to choose projects more strategically, focusing on demonstrated “superstars” that attract a large number of backers and that require large contributions. *Star Seekers* can be viewed as an extreme form of followers, as they invest only in large and popular projects, while *Trend Followers* tend to go for other smaller projects. Further analysis also shows that the strategies adopted by the follower groups are quite effective, in that they tend to back projects that achieve funding success, especially for *Star Seekers*.

These findings provide insights into the literature that discuss the potential for crowdfunding platforms to create a long tail of potential crowdfunders who invest in niche projects (Anderson, 2004). The long-tail effect appears to characterize *Trend Followers*, who appear to go for smaller niche projects – once other crowdfunders have shown sufficient interest in these projects. Yet our findings suggest that crowdfunding platforms also allow the emergence of large and popular projects that attract those who are only interested in supporting such superstar projects on the crowdfunding platform.

As expected, we identified a group of crowdfunders who were limited in their interests (monomorphic crowdfunders) – *Focused Enthusiasts*, but this group did not constitute a big enough group for further segmentation into early adopters and followers. Our results suggest that *Focused Enthusiasts*’ backing decisions are driven by the fit of the project domain to their interests, and they do not adopt either early adopter or follower strategies. This group does a good job of backing successfully funded projects, on par with *Trend Followers* and better than the *Early Adopters*. This suggests that their specialized interests might provide them with sufficient knowledge to identify worthwhile projects to back.

Finally, our analysis of crowdfunders who had only one or two backing record(s) provides more insights into crowdfunder archetypes. It shows that one-time backers appear likely to be either family, friends or acquaintances of project creators or people who participate in *Kickstarter* mainly to back popular projects they hear about (*Star Seekers*). The remaining crowdfunders making up those who back about 1-2 projects on *Kickstarter* appear to conform more to the profile of *Trend Followers*.

Theoretical Implications

Our clustering results suggest that the composition of crowdfunders is complex, even within a single technology category on one platform. The fact that no single group of individuals appears

to dominate highlights that the strategies of crowdfunders appear to be rather fragmented. Expanding the conceptualization of crowdfunders and understanding their behavioral strategies enriches our understanding of crowdfunders and allows us to explain crowdfunders' behaviors in a more nuanced manner. Our results show that while existing theories on opinion leadership and innovation adoption give us some guidance about the crowdfunder archetypes that might exist, the empirical results show a differentiated and richer set of archetypes.

The crowdfunder archetypes surfaced in our study provide evidence that crowdfunders within a single platform do not react uniformly to the same project information. We show that different groups tend to pay attention to different project information. For example, the *Star Seekers* pay attention to projects that are large and popular, while the *Trend Followers* go for smaller projects, but pay significant attention to the project creator's social capital. Recognizing the fundamental differences between different types of crowdfunders is important. It may also help us understand why there may be inconsistent results about the effects of some project signals in the literature. Future research should study in greater depth how different crowdfunder characteristics may drive crowdfunders to pay attention to different types of project information.

Practical Implications

For both *project creators* and *professional investors* who may use the success of reward-based crowdfunding projects as an indication of consumer demand, it is important to understand the composition of crowdfunders on the crowdfunding platform. Understanding the characteristics of these groups will guide project creators on how to position the project to appeal to these crowdfunders in the early stages. Our results also provide implications for *platform managers*. Our research provides insights into the most important backer groups platform managers should pay attention to, such as the *Vocal Actives* and *Silent Actives*, whose actions others might follow, and the *Focused Enthusiasts*. Further, the heterogeneity of the crowdfunders implies that crowdfunding platform managers may consider providing more information about crowdfunders to increase transparency to users of their platform. Lastly, for *crowdfunders* concerned about backing successfully funded projects, our study suggests that backing large and highly popular projects may be an effective strategy to achieve higher funding success.

Limitations

Our paper also has several limitations. First, while our research is motivated by the two-segment framework differentiating the Early Adopters and Followers, our study is exploratory in nature, and our findings provide insights into a richer set of archetypes available. The exploratory nature of these findings suggests the need for future research that is more confirmatory in nature to extend this research. Second, we conducted a criterion-validity check by examining the outcomes of decisions made by each cluster, but this analysis focused only on whether the projects backed were funded. We did not consider whether the project eventually delivered the products, which is a major risk concern for many crowdfunders. We encourage further longitudinal studies that consider the final delivery of the products. Third, while we identified early adopter and follower groups based on the behaviors exhibited on the *Kickstarter* platform, we were not able to determine the underlying reasons why the crowdfunders adopted different behaviors or strategies. Possible reasons due to media actions (Ordanini, Miceli, Pizzetti, & Parasuraman, 2011) or underlying reasons for backing (e.g. due to desire for product or altruistic reasons) (Bretschneider & Leimeister, 2017; Ryu, Kim, & Kim, 2016) have not been examined in our study, and are possible avenues for future research.

Endnotes

¹ <https://www.kickstarter.com/help/stats>

² Starting from December 2014, Kickstarter no longer discloses existing backer information on the project page. Hence, data after December 2014 was excluded.

³ We dropped data from non-US countries because (1) to use text mining tools, we need to focus on projects written in English, and projects from the US make up the majority of projects in English; and (2) focusing on projects from one country allows us to mitigate the impact of culture differences.

⁴ Crowdfunders are referred to as backers in Kickstarter. We use these two terms interchangeably.

⁵ Online Appendix A provides details on the distribution of backing instances per crowdfunder.

⁶ Using mean provides similar results.

⁷ Online Appendix B provides technical details on the topic analysis conducted.

⁸ Online Appendix C provides details of the external validity analysis of splitting into two time periods.

⁹ Online Appendix D provides the full results including the control variables.

References

- Adner, Ron, & Levinthal, Daniel. (2001). Demand Heterogeneity and Technology Evolution: Implications for Product and Process Innovation. *Management science*, 47, 611-628.
- Ahlers, Gerrit, Cumming, Douglas, Günther, Christina, & Schweizer, Denis. (2015). Signaling in Equity Crowdfunding. *Entrepreneurship Theory and Practice*, 39, 955–980.
- Allenby, Greg M, & Rossi, Peter E. (1998). Marketing Models of Consumer Heterogeneity. *Journal of Econometrics*, 89, 57-78.
- Allison, Thomas H, Davis, Blakley C, Webb, Justin W, & Short, Jeremy C. (2017). Persuasion in Cowdfunding: An Elaboration Likelihood Model of Crowdfunding Performance. *Journal of Business Venturing*, 32, 707-725.
- Anderson, Chris. (2004). The Long Tail. The Future of Entertainment Is in the Millions of Niche Markets at the Shallow End of the Bitstream. *Wired Magazine*, 170-177.
- Aulet, Bill. (2013). *Disciplined Entrepreneurship: 24 Steps to a Successful Startup*. New Jersey: John Wiley & Sons.
- Baddeley, Michelle. (2010). Herding, social influence and economic decision-making: socio-psychological and neuroscientific analyses. *Philosophical Transactions of the Royal Society B: Biological Sciences*, 365, 281-290.
- Banerjee, Abhijit V. (1992). A Simple Model of Herd Behavior. *Quarterly Journal of Economics*, 107, 797-817.
- Barber, Brad M, & Odean, Terrance. (2001). Boys will be boys: Gender, overconfidence, and common stock investment. *The quarterly journal of economics*, 116, 261-292.
- Belleflamme, Paul, Lambert, Thomas, & Schwienbacher, Armin. (2014). Crowdfunding: Tapping the Right Crowd. *Journal of Business Venturing*, 29, 585-609.
- Bensaou, Michael, & Venkatraman, Nirmala. (1995). Configurations of Interorganizational Relationships: A Comparison between US and Japanese Automakers. *Management Science*, 41, 1471-1492.
- Bernardo, Antonio E, & Welch, Ivo. (2001). On the evolution of overconfidence and entrepreneurs. *Journal of Economics & Management Strategy*, 10, 301-330.
- Bikhchandani, Sushil, Hirshleifer, David, & Welch, Ivo. (1992). A Theory of Fads, Fashion, Custom, and Cultural Change as Informational Cascades. *Journal of Political Economy*, 100, 992-1026.
- Bretschneider, Ulrich, & Leimeister, Jan Marco. (2017). Not Just an Ego-trip: Exploring Backers' Motivation for Funding in Incentive-based Crowdfunding. *The Journal of Strategic Information Systems*, 26, 246-260.
- Burtch, Gordon, Ghose, Anindya, & Wattal, Sunil. (2013). An Empirical Examination of the Antecedents and Consequences of Contribution Patterns in Crowd-Funded Markets. *Information Systems Research*, 24, 499 - 519.
- Burtch, Gordon, Ghose, Anindya, & Wattal, Sunil. (2015). The Hidden Cost of Accommodating Crowdfunder Privacy Preferences: A Randomized Field Experiment. *Management Science*, 61, 949-962. doi: 10.1287/mnsc.2014.2069
- Burtch, Gordon, Ghose, Anindya, & Wattal, Sunil. (2016). Secret Admirers: An Empirical Examination of Information Hiding and Contribution Dynamics in Online Crowdfunding. *Information Systems Research*, 27, 478 - 496.
- Chan, Kenny K., & Misra, Shekhar. (1990). Characteristics of the Opinion Leader: A New Dimension. *Journal of Advertising*, 19, 53-60. doi: Article

- Chen, Dongyu, Lai, Fujun, & Lin, Zhangxi. (2014). A trust model for online peer-to-peer lending: a lender's perspective. *Information Technology and Management*, 15, 239-254.
- Cholakova, Magdalena, & Clarysse, Bart. (2015). Does the Possibility to Make Equity Investments in Crowdfunding Projects Crowd Out Reward - Based Investments? *Entrepreneurship Theory and Practice*, 39, 145-172.
- Colombo, Massimo G, Franzoni, Chiara, & Rossi - Lamastra, Cristina. (2015). Internal Social Capital and the Attraction of Early Contributions in Crowdfunding. *Entrepreneurship Theory and Practice*, 39, 75-100.
- Connelly, Brian L, Certo, S Trevis, Ireland, R Duane, & Reutzel, Christopher R. (2011). Signaling Theory: A Review and Assessment. *Journal of Management*, 37, 39-67.
- Doshi, Anil. (2014). The Impact of High Performance Outliers on Two-Sided Platforms: Evidence from Crowdfunding. Available at SSRN: <http://ssrn.com/abstract=2422111>.
- Gerber, Elizabeth M, Hui, Julie S, & Kuo, Pei-Yi. (2012). *Crowdfunding: Why People are Motivated to Post and Fund Projects on Crowdfunding Platforms*. Paper presented at the International Workshop on Design, Influence, and Social Technologies: Techniques, Impacts and Ethics.
- Grewal, Rajdeep, Mehta, Raj, & Kardes, Frank R. (2000). The role of the social-identity function of attitudes in consumer innovativeness and opinion leadership. *Journal of Economic Psychology*, 21, 233-252.
- Hahn, Jungpil, & Lee, Gwanhoo. (2013). *Archetypes of Crowdfunders' Backing Behaviors and the Outcome of Crowdfunding Efforts: An Exploratory Analysis of Kickstarter*. Paper presented at the Conference on Information Systems and Technology 2013, Minneapolis, Minnesota.
- Hair, Joseph F, Black, William C, Babin, Barry J, Anderson, Rolph E, & Tatham, Ronald L. (2009). *Multivariate data analysis* (7 ed.). New Jersey: Pearson.
- Hamari, Juho, Sjöklint, Mimmi, & Ukkonen, Antti. (2016). The sharing economy: Why people participate in collaborative consumption. *Journal of the association for information science and technology*, 67, 2047-2059.
- Inbar, Yael, & Barzilai, Ohad. (2014). Community Impact on Crowdfunding Performance. Available at SSRN: <http://ssrn.com/abstract=2524910>.
- Katz, Elihu. (1957). The Two-Step Flow of Communication: An Up-to-Date Report on an Hypothesis. *Public Opinion Quarterly*, 21, 61-78.
- Katz, Elihu, & Lazarsfeld, Paul. (1955). *Personal influence*: New York: Free Press.
- Ketchen, David J, & Shook, Christopher L. (1996). The Application of Cluster Analysis in Strategic Management Research: An Analysis and Critique. *Strategic Management Journal*, 17, 441-458.
- King, Charles W, & Summers, John O. (1970). Overlap of Opinion Leadership across Consumer Product Categories. *Journal of Marketing Research*, 7, 43-50.
- Kircher, Philipp, & Postlewaite, Andrew. (2008). Strategic firms and endogenous consumer emulation. *The Quarterly Journal of Economics* 621-661.
- Kuppuswamy, Venkat, & Bayus, Barry L. (2017). Does my contribution to your crowdfunding project matter? *Journal of Business Venturing*, 32, 72-89.
- Lin, Mingfeng, Prabhala, Nagpurnanand R, & Viswanathan, Siva. (2013). Judging Borrowers by the Company They Keep: Friendship Networks and Information Asymmetry in Online Peer-to-Peer Lending. *Management Science*, 59, 17-35.
- Lin, Mingfeng, & Viswanathan, Siva. (2015). Home Bias in Online Investments: An Empirical Study of an Online Crowd Funding Market. *Management Science* 62, 1393 - 1414.

- MacVaugh, Jason, & Schiavone, Francesco. (2010). Limits to the diffusion of innovation: A literature review and integrative model. *European Journal of Innovation Management*, 13, 197-221.
- Malhotra, Arvind, Gosain, Sanjay, & Sawy, Omar A El. (2005). Absorptive Capacity Configurations in Supply Chains: Gearing for Partner-Enabled Market Knowledge Creation. *MIS Quarterly*, 29, 145-187.
- March, James G. (1991). Exploration and exploitation in organizational learning. *Organization Science*, 2, 71-87.
- Merton, Robert King. (1968). *Social Theory and Social Structure*. New York: The Free Press.
- Mollick, Ethan. (2014). The Dynamics of Crowdfunding: An Exploratory Study. *Journal of Business Venturing*, 29, 1-16.
- Moore, Geoffrey A. (2014). *Crossing the Chasm: Marketing and Selling High-Tech Products to Mainstream Customers* (3 ed.). New York: Harper-Collins.
- Myers, James H., & Robertson, Thomas S. (1972). Dimensions of Opinion Leadership. *Journal of Marketing Research*, 9, 41-46. doi: 10.2307/3149604
- Ordanini, Andrea, Miceli, Lucia, Pizzetti, Marta, & Parasuraman, A. (2011). Crowd-Funding: Transforming Customers into Investors through Innovative Service Platforms. *Journal of Service Management*, 22, 443-470.
- Paravisini, Daniel, Rappoport, Veronica, & Ravina, Enrichetta. (2016). Risk aversion and wealth: Evidence from person-to-person lending portfolios. *Management Science*, 63, 279-297.
- Punj, Girish, & Stewart, David W. (1983). Cluster analysis in marketing research: Review and suggestions for application. *Journal of marketing research*, 20, 134-148.
- Rogers, Everett M. (2003). *Diffusion of Innovations* (5 ed.). New York: The Free Press
- Roma, Paolo, Petruzzelli, Antonio, Messeni, & Perrone, Giovanni. (2017). From the crowd to the market: The role of reward-based crowdfunding performance in attracting professional investors. *Research Policy*, 46, 1606-1628.
- Ryu, Sunghan, Kim, Keongtae, & Kim, Young Gul. (2016). *Reward Versus Philanthropy Motivation In Crowdfunding Behavior*. Paper presented at the 20th Pacific Asia Conference on Information Systems, Chiayi.
- Sherif, Muzafer. (1935). A study of some social factors in perception. *Archives of Psychology*, 187.
- Silk, Alvin J. (1966). Overlap among Self-Designated Opinion Leaders: A Study of Selected Dental Products and Services. *Journal of Marketing Research*, 3, 255-259.
- Smith, Wendell R. (1956). Product differentiation and market segmentation as alternative marketing strategies. *Journal of marketing*, 21, 3-8.
- Taylor, James W. (1977). A Striking Characteristic of Innovators. *Journal of Marketing Research*, 14, 104-107. doi: Article
- Van den Bulte, C., & Joshi, Y. V. (2007). New Product Diffusion with Influentials and Imitators. *Marketing Science*, 26, 400-421. doi: 10.1287/mksc.1060.0224
- Venkatraman, Meera P. (1988). Investigating Differences in the Roles of Enduring and Instrumentally Involved Consumers in the Diffusion Process. *Advances in Consumer Research*, 15, 299-303.
- Watts, Duncan J, & Dodds, Peter Sheridan. (2007). Influentials, Networks, and Public Opinion Formation. *Journal of Consumer Research*, 34, 441-458.
- Zhang, Juanjuan, & Liu, Peng. (2012). Rational Herding in Microloan Markets. *Management Science*, 58, 892-912.

- Zheng, Alvin, Gong, Jing, & Pavlou, Paul A. (2017). On Using the Lottery in Crowdfunding Platforms: 'Crowding in' the Masses But 'Crowding out' Success. Available at SSRN: <https://ssrn.com/abstract=2916807>.
- Zhu, Feng, & Zhang, Xiaoquan. (2010). Impact of Online Consumer Reviews on Sales : The Moderating Role of Product and Consumer. *Journal of Marketing*, 74, 133-148. doi: 10.1509/jmkg.74.2.133