The heterogeneity of crowdfunders

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2017

Lin, Y. (2017). The heterogeneity of crowdfunders. Doctoral thesis, Nanyang Technological University, Singapore.

http://hdl.handle.net/10356/69547

https://doi.org/10.32657/10356/69547

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A thesis submitted to the Nanyang Technological University

in partial fulfilment of the requirement for the degree of

Doctor of Philosophy

2016

ACKNOWLEDGEMENTS

I am very grateful to those who have provided help for the development of this thesis.

First, I would like to express my sincere gratitude to my supervisor – Dr. Boh Wai Fong, for her patience, guidance, and support during the whole process of my Ph.D. study. Dr. Boh introduced me to the field of Information Systems. Over the past four years, she has not only taught me step-by-step on how to conduct high-quality academic research, but also offered me various opportunities to work on projects, gain teaching experience, and participate in overseas conferences. She is kind, patient, and always willing to help. I am also thankful for the insightful comments, suggestions, and ideas she has offered to this thesis. Her self-motivation, dedication to research, and wisdom have made her a role model I will look up to in my future research life.

I am also deeply indebted to all the faculty members at Nanyang Business School and the ITOM department who have taught and helped me to lay a solid foundation for my future career. Dr. Hong Ying-yi introduced me to the field of psychology. She is always patient, attentive, and curious about new ideas and phenomena. The excellent methodology classes offered by Dr. Chiu Chi-yue, Dr. Clive Lennox, Dr. Wu Yuan, and Dr. Olexander Chernyshenko equipped me with various tools for my future research. Seminar classes offered by Dr. Ang Soon, Dr. Christina Soh Wai Lin, Dr. Sia Siew Kien, Dr. Goh Kim Huat, Dr. Damien Joseph, and Dr. Adrian Yeow Yong Kwang broadened my horizons in both the IS domain and Management in general.

I am fortunate to meet a group of friends during these four years in Singapore. Their help, suggestions, and company have made this experience enjoyable. Thanks also go to all my friends back in Mainland China, Hong Kong, Taiwan, and other places in the world. Thanks for listening to my complaints, tolerating me and being there for me.

I would also like to take this opportunity to thank all the staff at Nanyang Business School for their administrative support: Quek Bee Hua, Karen Barlaan, Amarnisha Mohd, Hu Tsai Ting, Julia Teng Huay Chiun, and many other officers. I am deeply impressed by their hard work, patience, and professionalism.

I would also like to thank Ma Kai for his help with data collection and cleansing. I am also grateful to Nanyang Technological University for providing financial assistance and the Singaporean people for providing such a welcoming and comfortable study environment.

This thesis is dedicated to my mother – who has always been supportive unconditionally throughout the years, and to my late father – who had spent a lot of time and effort on my education.

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ABSTRACT

Crowdfunding refers to the practice by which funding resources are pooled by people, usually via the Internet, to support efforts initiated by others. Prior research tends to treat crowdfunders on a particular platform as a homogeneous group, adopting a certain strategy or behavior. However, the Internet allows crowdfunding to reach out to a much wider audience than traditional fundraising channels. The possibility that different crowdfunders may exhibit different behaviors and funding strategies has important implications for theory building and practice. This dissertation unpacks the complexities of the crowdfunder community based on the premise that crowdfunders on the same platform are a heterogeneous rather than a homogeneous group. In the first essay, I draw upon the opinion leadership literature and begin to explore the complexities of crowdfunder community by identifying different archetypes of crowdfunders funding technology projects in *Kickstarter,* one of the world's most prominent reward-based crowdfunding platforms. I identified five distinct types of crowdfunders: the *Vocal Actives*, the *Silent Actives*, the *Focused Enthusiasts*, the *Trend Followers*, and the *Star Seekers*. Based on the understanding that crowdfunders are heterogeneous, the second essay examines the effects of one of the most visible and important dimensions of crowdfunder heterogeneity – crowdfunder experience. Drawing upon the Elaboration Likelihood Model (ELM), I investigate two broad sets of information a potential crowdfunder might rely on to overcome the information asymmetry

problem: the signals embedded in the project content and the social information derived from observing other crowdfunders' decisions and comments. I show that a crowdfunder's ability to process information increases with his/her experience. Experienced crowdfunders are more likely to process information via the central route and rely more on the content of information. In contrast, inexperienced crowdfunders are more likely to process information via the peripheral route and rely more on cues. Overall, I show that crowdfunders on the same platform adopt different strategies and behaviors, and discuss how this informs theory building and practice.

CHAPTER 1 INTRODUCTION

Crowdfunding refers to the practice by which funding resources are pooled by people, usually via the Internet, to support efforts initiated by others (Ordanini, Miceli, Pizzetti, & Parasuraman, 2011). It is becoming an important financing alternative for small businesses, as they usually face difficulties raising capital from traditional offline channels of credit, like angel investors, venture capitalists, and banks (Ahlers, Cumming, Guenther, & Schweizer, 2015). The market for crowdfunding did not exist until 2006, but it has been growing very quickly since its inception. *Kickstarter*, America's leading crowdfunding platform for creative projects, has raised more than 2 billion dollars by December 2015 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 each raised more than 100 thousand US dollars. Some of the successful projects eventually became start-up companies (e.g. *Pebble*, a smartwatch manufacturer and *Ouya*, an android gaming console maker). According to a report published by *Massolution*, the global crowdfunding market enjoyed a 167% growth from 6.1 billion US dollars in 2013 to 16.2 billion US dollars in 2014 and is expected to reach 34.4 billion US dollars in 2015 (Massolution, 2015).

The growing popularity of crowdfunding has also sparked interest in the research community, where a small but growing body of work is shaping our understanding of the crowdfunding phenomenon. Despite the growing body of work, we still do not have a good understanding of the crowdfunder community, and how they make funding decisions. While prior research in entrepreneurial finance has made in-depth investigations into how investors like venture capitalists and angel investors make investment decisions in new ventures (Baum & Silverman, 2004; Franke, Gruber, Harhoff, & Henkel, 2008; Kirsch, Goldfarb, & Gera, 2009; Roure & Keeley, 1990), these findings are unlikely to apply to the crowdfunding community, who differ from the venture capitalists and angel investors in many ways. Crowdfunders do not possess the financial sophistication and experience of angel investors or venture capitalists to evaluate new ventures, and they also lack the ability to extensively research and assess the new ventures and compare across potential investments (Ahlers et al., 2015; Freear, Sohl, & Wetzel, 1994). Given that new crowdfunding projects are often precursors to new ventures, which are characterized by extreme uncertainty and high failure rates (Xu, 2015), it is unclear how a group of inexperienced crowdfunders can exercise the “wisdom of the crowd” in screening new projects (Bruton, Khavul, Siegel, & Wright, 2015) and come up with optimal decisions with regard to which project should be funded.

Prior research also has a tendency to characterize crowdfunders on a particular platform as adopting a certain strategy or behavior or be driven by certain motivations (Allison, Davis, Short, & Webb, 2015; Cholakova & Clarysse, 2015; Collins & Pierrakis, 2012). For example, crowdfunders on microfinance sites like *Kiva.org* are typically characterized to be prosocial in their motivations, suggesting that lenders pay attention to intrinsic factors such as the desire to help others altruistically or to feel good about oneself when making crowdfunding decisions (Allison et al., 2015). Cholakova and Clarysse (2015) highlights that crowdfunders on reward-based platforms are often driven by intrinsic motivations to support projects, while crowdfunders on equity-based platforms focus on extrinsic and financial motivations (Collins & Pierrakis, 2012). Mollick (2014), on the other hand, assumes that crowdfunders on *Kickstarter* are investors seeking returns from the money they pledged.

Meanwhile, some researchers have pointed out that a single platform, such as *Kickstarter*, consists of multiple communities that vary considerably with respect to members' interests, participation patterns, and impact on the platform (Inbar & Barzilay, 2014). Yet we have little understanding of how crowdfunders might differ from one another in terms of their funding behaviors and strategies (Hahn & Lee, 2013). It is important for researchers to understand not only the number of participants participating in a crowdfunding platform but also the composition of the crowdfunders (Belleflamme, Omrani, & Peitz, 2015). Such an understanding is critical for understanding how the crowdfunding market works, how entrepreneurs can effectively leverage on the crowdfunding platform, and how to better design crowdfunding platforms to meet the needs of both entrepreneurs and crowdfunders.

Furthermore, understanding the composition of the crowdfunder community and the differences among crowdfunders will allow researchers to understand which theories are more applicable to a particular crowdfunding platform. Prior research has found that findings of crowdfunding behaviors tend to differ depending on the type of crowdfunders on the platform under examination. For example, focusing on crowdfunders who might be motivated more by obtaining financial returns on peer-to-peer lending platforms, Zhang and Liu (2012) find evidence of rational herding, where crowdfunders engage in observational learning, using lending decisions by other peers to infer borrowers' creditworthiness. On the other hand, focusing more on crowdfunders who might be motivated more by altruism and for donating to a cause, Burtch, Ghose, and Wattal (2013) examine a crowd-funded marketplace for online journalism projects and find that a higher number of initial crowdfunders are likely to lead to lower level of participation by other crowdfunders. This might be due 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 contradicting findings reflect the possibility that the composition of crowdfunders on a platform is likely to drive the applicability of different theories. If the crowdfunders are composed of highly heterogeneous individuals, it might make it difficult for researchers to tease out the noise and figure out the underlying mechanisms driving crowdfunders' behavior. Hence, it becomes critical for research to first understand the composition of crowdfunders and understand what might be the underlying drivers of different crowdfunders' backing decisions, as this would help researchers understand the applicability of different theories on a crowdfunding platform based on the composition of crowdfunders.

Prior research has started to pay attention to the heterogeneity in a crowdfunding platform. Several studies 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 (2014) identify experienced investors and investors who are also project creators, as two types of investors who stand out among the crowd and have a significant influence on the crowdfunding behaviors of other crowdfunders. Hahn and Lee (2013) also recognize that within the same crowdfunding platform, crowdfunders' behaviors and strategies could be different. They identify five distinct archetypes of crowdfunders based on two dimensions of crowdfunders' behavior: the frequency with which they back projects and the extent to which they back projects in different categories (e.g. music versus technology). They find that projects with different compositions of crowdfunders differ in the success of their fundraising efforts. Inbar and Barzilay (2014) also propose four types of backers (they call communities) based on two similar dimensions: the number of projects backed and the number of project categories. They further examine how the compositions of different backer communities can affect fundraising success and find that focused backers have the highest impact on the fundraising success. I build upon the fundamental premise of these articles – that crowdfunders on the same platform are heterogeneous in their behaviors and strategies.

My research focuses on one of the world's most prominent reward-based crowdfunding platforms – *Kickstarter*. Reward-based crowdfunding offers many other benefits in addition to raising funds for the entrepreneur, such as price discrimination (Belleflamme, Lambert, & Schwienbacher, 2014), demonstration of market potential by attracting early adopters (Burtch et al., 2013; Schwienbacher & Larralde, 2010), and providing feedback to entrepreneurs (Xu, 2015). To examine crowdfunder heterogeneity, I employed two research projects reported in two essays in this dissertation. In the first research project, I started to unpack crowdfunder heterogeneity by identifying different archetypes of crowdfunders funding technology project on *Kickstarter*. My approach differs from other studies on crowdfunder heterogeneity (Hahn & Lee, 2013; Inbar & Barzilay, 2014) in that I do not start from a number of predefined clusters but instead employ an inductive exploratory approach to identify different types of crowdfunders. Doing so allows me to capture backer heterogeneity and examine backer typologies in a broader range of dimensions. Drawing upon the opinion leadership literature and using historical backing instances combined with other individual measures, I identified five distinct types of crowdfunders: the *Vocal Actives*, the *Silent Actives*, the *Focused Enthusiasts*, the *Trend Followers*, and the *Star Seekers*. Having identified these different types of crowdfunders, I further examine two questions related to the archetypes. First, I examined how these behaviors and strategies were associated with individual funding success. Second, by dividing the data into two periods, I also investigated the evolution of each archetype. The results show that significant heterogeneity exists among different crowdfunders both in terms of the funding strategies they adopt and the funding success of their strategies.

Having shown that significant heterogeneity exists among crowdfunders, in the second essay, I demonstrate how crowdfunder heterogeneity might affect theorizing on crowdfunder behavior. I focus on one of the most visible and important dimensions of crowdfunder differences – their experience. Synthesizing existing literature, I examine how crowdfunder experience might affect their reliance on two types of information provided on the project campaign page to overcome the information asymmetry problem: the signals embedded in the project description (Akerlof, 1970; Spence, 1973) and the social information they derive by observing other crowdfunders' decisions and comments (Banerjee, 1992; Bikhchandani, Hirshleifer, & Welch, 1992). Drawing upon the Elaboration Likelihood Model (Petty & Cacioppo, 1986a), I argue that experienced crowdfunders are more likely to process the information via the central route and rely more on the actual content of the project information. Inexperienced crowdfunders, on the other hand, are more likely to process information via the peripheral route and rely more on the cues that require less information processing.

In summary, I ask the following overall questions: How are crowdfunders different from one another? In addition, how do such differences affect their behaviors and strategies in funding projects?

The following part of this dissertation is organized as follows. In Chapter 2, I first present a brief introduction of the crowdfunding phenomenon. I then review the relevant crowdfunding literature and latest studies related to crowdfunder heterogeneity and highlight how my studies add to our understanding of the crowdfunder heterogeneity. I then report the two research projects in Chapter 3 and Chapter 4, respectively. Chapter 5 concludes by summarizing the main findings in the two studies.

CHAPTER 2 LITERATURE REVIEW

Crowdfunding is still a developing phenomenon and the literature on crowdfunding is growing rapidly. A number of early and recently published works together with a bulk of working papers have provided valuable insights into this novel phenomenon. In this chapter, I first offer a brief introduction to the crowdfunding phenomenon. Then I survey the crowdfunding literature, highlighting the importance of studying crowdfunder heterogeneity.

The Crowdfunding Phenomenon

The concept of crowdfunding is rooted in crowdsourcing, an act of outsourcing a task (e.g. idea generation, new product development, or logo design) to the "crowd" as an open call to leverage the power of the crowd (Afuah & Tucci, 2012; Howe, 2006). Ordanini et al. (2011) define crowdfunding as "an initiative undertaken to raise money for a new project proposed by someone, by collecting small to medium investments from several other people (i.e. a crowd)" (pp. 444). Belleflamme et al. (2014) offer a refined definition (pp. 588):

"Crowdfunding involves an open call, mostly through the Internet, for the provision of financial resources either in the form of donation or in exchange for the future product or some form of reward to support initiatives for specific purposes."

This definition recognizes the Internet as an important element in this phenomenon. In fact, raising funds by pooling small contributions from the crowd is nothing new. It is the Internet that revitalizes this old phenomenon in the modern day. Through the Internet, fundraisers can reach out to a much wider audience more easily than in the past. The Web 2.0 technologies allow fundraisers to present their ideas by using multimedia such as texts, pictures, videos, and hyperlinks. Online payment also makes monetary transactions much easier (Schwienbacher & Larralde, 2010). Many crowdfunding platforms also provide social networking functionalities such as a comment section and *Facebook* connection to further facilitate information flow and increase transparency to a certain extent.

Early examples of crowdfunding practices are anecdotal. Belleflamme et al. (2014) describe several selected crowdfunding cases where some companies or individuals started their own online crowdfunding campaigns to raise money after failing to get money from traditional sources. Nowadays, most crowdfunding activities take place on dedicated crowdfunding platforms. The literature highlights four models of crowdfunding (Mollick, 2014): (1) the donation-based crowdfunding (or the patronage model), (2) the lending-based crowdfunding (or peer-to-peer lending), (3) reward-based crowdfunding, and (4) the equity-based crowdfunding. In the donation-based model, funders act as philanthropists and the funding behavior is driven mainly by altruism (Galak, Small, & Stephen, 2011). An example is *Kiva* (*https://www.kiva.org*), a microfinance platform where small loans are made to low-income individuals to alleviate poverty. In the peer-to-peer lending-based model, funds are provided as loans to fundraisers in exchange for a certain rate of return. A commonly known example is *Prosper* (*http://www.prosper.com*), a platform where individuals can request personal loans and offer a fixed rate of return to potential lenders (Lin, Prabhala, & Viswanathan, 2013; Zhang & Liu, 2012). The reward-based model, as the name suggests, typically offers some forms of rewards to funders. The reward can be a simple acknowledgment in the movie, a sticker, or even a prototype of the product (Kuppuswamy & Bayus, 2015; Mollick, 2014). This model incorporates a wide variety of creative projects, ranging from music, games, to design and technology. Two prevalent examples of this model are *Kickstarter* (*http://www.kickstarter.com*) and *Indiegogo* (*http://www.indiegogo.com*). Finally, the equity-based model offers funders equity stakes in the future company in return for their contributions (Ahlers et al., 2015). Traditionally, public solicitation and advertising to attract investors are strictly regulated in many countries. Due to this, this type of crowdfunding platform has yet to be widely popularized as of now, mainly due to regulators' apprehension about the uncertainties of regulating such a market. Existing examples include *Seedrs* (*http://www.seedrs.com*) and Crowdcube (*http://www.crowdcube.com*) in the UK. Table 1 summarizes the four types of crowdfunding models.

Table 1 Different Crowdfunding Models

Model	Characteristics	Examples
Donation-based crowdfunding	• Crowdfunders give funds as donations or offer zero interest loans	• Kiva.org

	• Funders are driven by altruistic motives	• Gofundme.com
Lending-based crowdfunding (peer-to-peer lending)	• Borrowers request personal loans from investors (crowdfunders) • Returns are offered as interest to investors • Funders are mainly driven by economic motives	• Prosper.com • Lendingclub.com
Reward-based crowdfunding	• Projects creators seek financial support for creative ideas • Returns are offered as rewards, e.g., an acknowledgment, or a prototype of the product • Funders participate for different reasons	• Kickstarter.com • Indiegogo.com
Equity-based crowdfunding	• Startup companies raise money for expansion • Investors get returns from an exit event when the funded company is bought or floats on a stock exchange. Investors also receive dividends when the company distributes their earnings.	• Seedrs.com • Crowdcube.com

Literature

The literature on crowdfunding is growing at a rapid speed. Table 2 summarizes a selective body of published and working research articles. Researchers have asked and examined various research questions. In general, these research questions can be grouped into three perspectives: the project creator's perspective, the crowdfunder's perspective, and the platform's perspective. From the project creator's perspective, research has mainly focused on strategies project creators adopt to attract funding (Ahlers et al., 2015; Colombo, Franzoni, & Rossi-Lamastra, 2015; Galak et al., 2011; Gao & Lin, 2015; Giudici, Guerini, & Lamastra, 2013; Hu, Li, & Shi, 2015; Lin et al., 2013; Michels, 2012). From the crowdfunders perspective, research has looked at a broader set of questions, including crowdfunders' motivations (Allison et al., 2015; Cholakova & Clarysse, 2015; Gerber, Hui, & Kuo, 2012), crowdfunder dynamics (Burtch et al., 2013; Herzenstein, Dholakia, & Andrews, 2011; Koning & Model, 2013; Kuppuswamy & Bayus, 2015; Zhang & Liu, 2012), and crowdfunder biases (Agrawal, Catalini, & Goldfarb, 2015b; Burtch, Ghose, & Wattal, 2014; Greenberg, Gerber, Greenberg, & Mollick, 2016; Lin & Viswanathan, 2015). From the platform's perspective, research has mainly focused on the effects of different platform designs on crowdfunding outcomes and crowdfunder behaviors (Burtch, Ghose, & Wattal, 2015; Hildebrand, Puri, & Rocholl, 2016). All three sets of literature tend to assume that crowdfunders on the same platform are a homogeneous group. Having such assumption, the majority of the studies conduct project level analysis (e.g. Ahlers et al., 2015; Lin et al., 2013) or aggregate crowdfunder data at the project level (e.g. Burtch et al., 2013; Kuppuswamy & Bayus, 2015).

Table 2 Crowdfunding Literature

Citation	Type of Crowdfunding	Research Question	Method / Unit of Analysis	Findings
Agrawal et al. (2015b)	CF platform for artists	Does crowdfunding platforms diminish distance-sensitive costs?	Empirical / Artist–crowdfunder level	CF platforms do eliminate some distance related frictions but not all.
Ahlers et al. (2015)	Equity-based crowdfunding	What are the effective signals entrepreneurs use to attract funders?	Empirical / Project level analysis	Retaining equity and providing more detailed information about risks are effective signals.

Allison et al. (2015)	Prosocial-lending	How do lenders respond to intrinsic and extrinsic cues embedded in narratives?	Empirical / Project level analysis	Lenders respond positively to narratives highlighting the venture as an opportunity to help others, and less positively when the narrative is framed as a business opportunity.
Belleflamme et al. (2014)	Reward-based and equity-based crowdfunding	Compare reward-based with equity-based crowdfunding	Modeling	Conditions under which entrepreneurs prefer reward-based crowdfunding or otherwise.
Burtch et al. (2014)	prosocial-lending	Do cultural differences matter in lenders decisions?	Empirical / Country level	Lenders do tend to lend to those who are culturally similar to them.
Burtch et al. (2013)	CF platform for journalism	Do prior contributions encourage or discourage subsequent contributions?	Empirical / Project-day level	A partial crowding-out effect: prior contributions discourage subsequent contributions
Burtch et al. (2015)	Reward-based crowdfunding	How privacy control mechanisms influence crowdfunder behavior?	Experiment	Loosing information controls increases net fundraising.
Burtch, Ghose, and Wattal (2016)	Reward-based crowdfunding	How does concealing contributions influences subsequent contribution dynamics?	Empirical / Project-contribution level	Hiding contributions negatively influences subsequent contributions.
Cholakova and Clarysse (2015)	Equity-based and reward-based crowdfunding	What is the relationship between crowdfunders' intrinsic motivations and extrinsic motivations?	Survey / Individual level analysis	Crowdfunders in both reward-based and equity-based crowdfunding are primarily motivated by financial incentives.
Colombo et al. (2015)	Reward-based crowdfunding	How does social	Empirical / Project level	Project creators' Internal social capital

		capital contribute to project funding success?	analysis	developed within the platform contributes to the project's funding success.
Doshi (2014)	Reward-based crowdfunding	How do superstar projects affect the crowdfunders?	Empirical / Project level analysis	Superstar projects increase the transaction volume in similar projects and result in an overall increase of transaction volume.
Galak et al. (2011)	Prosocial-lending	How do borrower characteristics engender lending?	Empirical / Project-funder level analysis	Lenders favor individual borrowers over groups and borrowers that are socially similar to them.
Gao and Lin (2015)	Lending-based crowdfunding	The relationship between linguistic styles of borrower-supplied texts and the quality of loans	Empirical / Project level	Linguistic features reveal valuable information about borrowers.
Giudici et al. (2013)	11 Italian CF platforms	How do individual's social capital and territorial social capital affect the success of the project?	Empirical / Project-funder level analysis	Individual social capital is correlated with project success but the effect is weakened when territorial social capital is considered.
Greenberg et al. (2016)	Reward-based crowdfunding	Are women entrepreneurs less likely to get supported?	Empirical and lab experiment	Projects founded by women outperform men in technology project category.
Hahn and Lee (2013)	Reward-based	How different the crowdfunders' funding behavior and strategy are from one another's?	Empirical/individual and project level analysis	Five types of crowdfunders are found
Hakenes and Schlegel (2014)	Reward-based crowdfunding	How is crowdfunding used for	Modeling	Firms set both the loan rate and the threshold too low,

		information aggregation?		inducing households to generate too much information.
Hildebrand et al. (2016)	Lending-based crowdfunding	How do adverse incentives affect lending activities?	Empirical / Project level analysis	Origination fees are adverse incentives that provide a wrong signal about project quality.
Hu et al. (2015)	Reward-based crowdfunding	What are the optimal product and pricing decisions in a crowdfundin g mechanism?	Modeling	When buyers are heterogeneous in their product valuations, the creator should offer a line of products with different levels of product quality.
Inbar and Barzilay (2014)	Reward-based crowdfunding	How different crowdfunder communities affect project funding performance ?	Empirical / Individual and project level analysis	Some communities have negative impact on project success.
Kim and Hann (2015)	Reward-based crowdfunding	How does geography affect the formation of crowdfundin g projects?	Empirical / Project level analysis	Small cities disproportionately benefit from crowdfunding.
Koning and Model (2013)	Donation-based crowdfunding	How do initial contribution s affect subsequent contribution s?	Field experiment	Initial contributions indeed affect subsequent contributions but different from what have been theorized.
Kuppuswamy and Bayus (2015)	Reward-based crowdfunding	What is the backer dynamics over the project funding cycle?	Empirical / Project-day level analysis	Backer dynamics follow a U-shape
Lin et al. (2013)	Lending-based crowdfunding	How do crowdfunder s overcome the information asymmetry problem?	Empirical / Project level analysis	Online friendships act as signals of credit quality.

Lin and Viswanathan (2015)	Lending-based crowdfunding	Does home bias still exist in crowdfunding?	Empirical and natural experiment / Lender-borrower level analysis	Home bias still exists in crowdfunding and rationality-based explanations cannot fully explain it.
Marom, Robb, and Sade (2015)	Reward-based crowdfunding	What is the gender dynamics in crowdfunding?	Empirical / Project level analysis	Crowdfunders tend to fund projects with the same gender.
Marom and Sade (2013)	Reward-based crowdfunding	Do entrepreneur descriptions matter in fundraising?	Empirical / Project level analysis	Project descriptions matter for project funding raising.
Michels (2012)	Lending-based crowdfunding	Do unverifiable disclosures help to reduce the cost of debt?	Empirical / Project level analysis	Unverifiable disclosures help.
Mollick (2014)	Reward-based crowdfunding	What factors are associated with the success of crowdfunding projects?	Empirical / Project level analysis	Personal networks and underlying project quality are associated with project funding outcomes.
Mollick and Nanda (2015)	Reward-based crowdfunding	How are crowdfunders different from field experts?	Survey	There is significant agreement between crowdfunders and experts.
Mollick and Kuppuswamy (2014)	Reward-based crowdfunding	Why entrepreneurs often form firms?	Empirical / Project level analysis	Entrepreneurs establish firms to gain legitimacy.
Xu (2015)	Reward-based crowdfunding	Do entrepreneurs learn from their projects?	Empirical / Individual level analysis	Crowdfunding provides valuable information to entrepreneurs.
Zhang and Liu (2012)	Lending-based crowdfunding	Does herding occur in lending-based crowdfunding and why?	Empirical / Project level analysis	Herding takes place in lending-based crowdfunding and it is a rational strategy adopted by crowdfunders.
Zvilichovsky, Inbar, and Barzilay (2015)	Reward-based crowdfunding	Does owner's backing history	Empirical / Project level analysis	Playing both sides of the market increases funding success.

		improve project funding success?		

Meanwhile, some researchers have pointed out that a single platform might consist of multiple communities that vary considerably with respect to members' interests, participation patterns, and impact on the platform. Hahn and Lee (2013) conceptualize four types of crowdfunders based on backing frequency and category concentration and investigate their impact on funding outcomes. Using data collected from *Kickstarter*, they identify five clusters, of which four are aligned with the proposed typology. They further find that projects with different crowdfunder compositions differ in their fundraising outcomes. Inbar and Barzilay (2014) also propose four types of crowdfunders (called communities) based on two similar dimensions: the number of projects the crowdfunder has backed and the number of different product categories the crowdfunder is interested in. They also examine how the composition of different backer communities can affect fundraising outcome and find that focused crowdfunders have the highest positive impact on fundraising success.

I build on the premise of these two studies – that crowdfunders on the same platform are heterogeneous. I start to explore crowdfunder heterogeneity by identifying different types of crowdfunders, reported as my first research project. My approach to exploring crowdfunder heterogeneity differs from the aforementioned two studies on crowdfunder archetypes in the following important ways (Hahn & Lee, 2013; Inbar & Barzilay, 2014). First, I adopt an exploratory approach in identifying different types of crowdfunders. In doing so, I am not constrained to a fixed set of predefined clusters. Such an exploratory approach allows me to capture backer heterogeneity and examine backer typologies in a broader range of dimensions (i.e. risk preference, involvement, and interest).[1] Second, my study focuses on different behavioral patterns of these backers from the backer's perspective, hence providing insights into how crowdfunders make backing decisions, as this provides critical information about how the crowdfunding market works and how crowdfunders infer project quality based on the history of each crowdfunder.

Furthermore, understanding the composition of the crowdfunder community and the differences among crowdfunders will allow researchers to understand which theories are more applicable to a particular crowdfunding platform and reconcile some inconsistent findings. First, studies have shown that crowdfunder behaviors tend to differ depending on the type of crowdfunding platform under examination. Both Zhang and Liu (2012) and Herzenstein et al. (2011) find that herding takes place on lending-based crowdfunding, where crowdfunders are largely motivated by receiving financial returns. On the other hand, Burtch et al. (2013) find that existing crowdfunders crowd out subsequent crowdfunders in a crowdfunding marketplace for online journalism, a form of public good. This is might be due to a bystander effect, where altruistic crowdfunders believe others have already fulfilled the need for

[1] In fact, both Hahn and Lee (2013) and Inbar and Barzilay (2014) define crowdfunder heterogeneity along two dimensions: the number of projects backed by the crowdfunder and the types of projects backed by the crowdfunder.

public goods. These opposite findings suggest that crowdfunder behaviors might be different depending on their motivations. Such differences might also exist on the same platform, especially in the form of reward-based crowdfunding, where crowdfunders' motivations are more diverse (Allison et al., 2015; Cholakova & Clarysse, 2015; Gerber et al., 2012). Second, crowdfunder heterogeneity might also be an important factor to consider in studying crowdfunder behavior. This has been evident in the related literature. For example, in the marketing literature, Zhu and Zhang (2010) argue that consumer characteristics (e.g. Internet experience) affect their reliance on online reviews. They find that consumers with greater Internet experience are more likely to be influenced by online reviews. In the finance literature, Dhar and Zhu (2006) find that wealthier individuals, individuals employed in professional occupations, and individuals who trade more frequently are less likely to exhibit disposition effect, which is a tendency to realize gains sooner than recognize losses. Along with this line, in the second research project, I demonstrate how considering crowdfunder heterogeneity might affect theorizing on crowdfunder behavior by focusing on one of the most visible crowdfunder characteristics: crowdfunder experience.

Research Context

The context of my studies is reward-based crowdfunding. I focus on the reward-based crowdfunding because of its importance for innovation and entrepreneurial finance. The increasing popularity of reward-based crowdfunding platforms, both for entrepreneurs and funders, has crystallized their key role in the crowdfunding space. Belleflamme et al. (2014) along with others show that reward-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). The success of a reward-based crowdfunding project also generates hype around a new product, provides an indication of demand for the product to project creators, and also provides additional legitimacy for future fundraising (Burtch et al., 2013; Lehner, 2012). Such information is especially useful for entrepreneurs who wish to seek funds from venture capitalists later on in their entrepreneurial journey.

My research focuses on *Kickstarter*, 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 creative projects. As of 2016, nearly a total of $2 billion has been pledged by 10 million people to support 100,000 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 research, as it allows me 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 1 to 60 days. *Kickstarter* provides various means for project creators to pitch their ideas. Project creators can provide a detailed textual description of the project embedded with pictures, videos, 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 acknowledgment 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 the previously pledged funds would be returned to crowdfunders if the project did 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 on their projects while crowdfunders post questions, suggestions, and comments.

Projects listed on *Kickstarter* are divided into different categories.[2] I focus on the projects listed in the technology category for the following reasons. First, projects in the technology category often offer pre-orders of a product prototype, and *Kickstarter* typically requires such projects to produce a manufacturing plan and a clear delivery date for the stated rewards when starting a *Kickstarter* project (Mollick, 2014). Hence, technology category includes a large portion of projects that have significant potential of becoming a technology venture firm after a successful fundraising effort. One of the most successful examples is *Oculus Rift*, a virtual reality headset for video gaming, which raised more than $2 million, ten times of 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 & Hann, 2015). This highlights that projects in this category have 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, I chose to focus only on projects in the technology category. 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

[2] They are: Art, Comics, Crafts, Dance, Design, Fashion, Film & Video, Food, Games, Journalism, Music, Photography, Publishing, Technology, and Theater.

use of a reward-based crowdfunding platform such as *Kickstarter*. The findings can also inform research on technology entrepreneurship.

CHAPTER 3 EXAMINING ARCHETYPES OF CROWDFUNDERS

Introduction

Existing studies tend to treat crowdfunders as a homogeneous group and thus tend to conduct project level analysis (Mollick, 2014). Several studies have pointed out that there are significant differences among crowdfunders (Hahn & Lee, 2013; Inbar & Barzilay, 2014; Kim & Viswanathan, 2014). In this chapter, I begin to explore the heterogeneity of crowdfunders. There is a strong reason that heterogeneity might exist, even within the same platform. Modern crowdfunding activities are all Internet-mediated. Crowdfunding platforms allow crowdfunding campaign to attract a much wider audience than traditional fundraising campaigns. Everyone with Internet access can participate in crowdfunding activities regardless of culture, ethnicity, age, and expertise. Hence, it is likely that crowdfunders might exhibit different behaviors and adopt different strategies.

The marketing literature and finance literature have suggested that individuals are indeed different in terms of their investing strategies (Clark-Murphy & Soutar, 2005) and purchasing strategies (Currim, 1981). There is, however, limited literature on how crowdfunders might be different. Furthermore, both sets of literature in finance and marketing cannot be readily applied to the crowdfunding context, especially in the case of reward-based crowdfunding, where crowdfunders' motivations are more diverse (Gerber et al., 2012).

To address this gap, I employ an inductive exploratory approach to developing crowdfunder archetypes by using a comprehensive set of crowdfunder attributes. Exploring the heterogeneity and developing archetypes have a long tradition in the IS literature (Nickerson, Varshney, & Muntermann, 2013). According to Nickerson et al. (2013), developing archetypes can provide conceptual knowledge for further theory building. In exploring bidder heterogeneity in the online auction context, Bapna, Goes, Gupta, and Jin (2004) also argue that “a robust taxonomy can then be used to perform *ex-post* theory building, shedding light on what drives real online bidders to make their bidding decisions” (pp. 23). Given that crowdfunder heterogeneity is largely underexplored, this study will be the first step to unpack the complex crowdfunder community. The results will also shed light on the behavior of crowdfunders for further theory building.

An Exploratory Study on Profiles of Crowdfunders

To examine the profiles of crowdfunders supporting technology projects in *Kickstarter*, I conducted an inductive and exploratory analysis. There are two approaches to developing a taxonomy (Nickerson et al., 2013). First, one might develop typologies based on theory or conceptualization by identifying relevant dimensions and characteristics within each dimension through sound logical reasoning. This is usually followed by empirical analyses to evaluate, verify, and modify the proposed typologies. For example, Hahn and Lee (2013) used 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* projects. Second, one might employ an inductive exploratory approach by directly analyzing the empirical data, which is the case of Bapna et al. (2004). In their research on bidder heterogeneity in the online auctions, they employed an inductive exploratory approach to identify different bidders with different bidding strategies. My approach is similar to Bapna et al. (2004)'s. The aim here is to discover empirically driven taxonomies by using a broad range of variables that might be useful to classify the strategies and behaviors of the crowdfunders. I do not begin with a pre-specified typology of crowdfunders. Instead, I allow the interesting patterns to emerge. There are several reasons for employing such research approach. First, crowdfunding is a developing phenomenon and research in the field is still growing. The current literature tends to assume that crowdfunders are a homogenous group adopting similar strategies and exhibiting similar behaviors (e.g. herding). Hence, there is limited knowledge about the dimensions in which crowdfunders might be different. The inductive approach is especially suitable for unexplored phenomena as both the characteristics and number of clusters can be derived from the data (Fiedler, Grover, & Teng, 1996). Second, crowdfunding is characterized by its complexity and its popularity among ordinary Internet users. Employing an inductive approach allows me to explore the richness of the complex phenomenon and provide "conceptual knowledge" by discovering relationships among different concepts (Nickerson et al., 2013; Sabherwal & King, 1995) that can be used for *ex-post* theory building (Bapna et al., 2004).

In the following part of this chapter, I first report the exploratory cluster analysis I did to identify different crowdfunders. Having identified different crowdfunders with different behaviors and project backing strategies, I explored two questions related to the identified clusters. First, I tested if different funding behaviors and strategies led to different individual funding success, which is defined as the percentage of projects that have reached funding goal in the crowdfunder's portfolio. Second, I examined how crowdfunders' membership evolved across two time periods.

Data

The dataset comprises all technology projects listed from January to November 2014 in *Kickstarter*.[3] A total of 6,193 projects were captured during the data collection period. 4,374 US projects were used in this study. 350,023 crowdfunders (or backers)[4] were identified from the collected project data. As *Kickstarter* does not disclose the exact time when a backer backs a project, I 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, I was able to collect a snapshot of all projects' backer information once every 4-7 days.

I split the data into two parts: Period 1 ranges from January to June 2014, whereas Period 2 ranges from July to November 2014, for two reasons. First, it

[3] Starting from December 2014, *Kickstarter* no longer discloses existing backer information on the project page. Hence, data from December 2014 was excluded.
[4] Crowdfunders are referred to as backers in *Kickstarter*. I use these two terms interchangeably.

allows me to test the robustness of the archetypes. Second, it allows me to examine the change of a crowdfunder' membership across two periods. I make use of crowdfunders' historical backing records to determine what behavioral profiles and funding strategies a typical crowdfunder exhibits. A tabulation of the number of projects backed per person (Table 3) shows that the majority of the identified crowdfunders backed only one or two projects within the observation period. As I was inferring crowdfunder profiles from their backing behavior, I excluded backers who only had one or two backing record(s) in the sample so that I did not read too much into a single instance of an individual's behavior. This leaves me with data of 10,188 and 7,433 backers in Period 1 and Period 2, respectively.

Table 3 Distribution of Number of Projects Backed

Period 1		Period 2	
Number of Projects Backed	Number of Backers	Number of Projects Backed	Number of Backers
1	198393	1	128862
2	16379	2	14511
3	4961	3	4444
4	2100	4	1988
5	1091	5	1029
6	627	6	633
7	368	7	366
8	230	8	256
9	178	9	188
10	125	10	128
.	.	.	.
117	1	137	1
244	5	138	1

Variables and Theoretical Considerations

The exploration of crowdfunder heterogeneity is based on the assumption that there exist different groups of individuals with different strategies and behaviors. A notable and widely accepted hypothesis is that there exist at least two groups of individuals in a market: the “influentials” and the “imitators” (Van den Bulte & Joshi, 2007). According to Watts and Dodds (2007), the idea of opinion leaders, or “influentials”, “came to occupy a central place” (pp. 441) in literature including diffusion of innovations, communications research, and marketing. Two streams of theoretical arguments underlie the influentials vs. imitators mixture (Van den Bulte & Joshi, 2007). The first stream is based on sociological arguments such as individuals’ social characters (Riesman, 1950) or social status (Bourdieu, 1984; Phillips & Zuckerman, 2001). For example, low-status individuals choose to imitate high-status individuals or their peers in order to maintain their status (Burt, 1987). The second stream is based on the information and risk reduction argument (Katz, 1957; Moore, 2014; Rogers, 2003). In essence, imitators follow influentials to reduce risk, as influentials might possess superior information (Van den Bulte & Joshi, 2007, Table 1). Van den Bulte and Joshi (2007) summarize two prominent frameworks under the second stream: the opinion leadership literature (Katz, 1957) and the diffusion of innovation literature (Moore, 2014; Rogers, 2003). The opinion leadership literature is based on the hypothesis that ideas flow from a small group of influentials (called opinion leaders) to rest of the population (Katz, 1957). Center to this two-step hypothesis is information flow from the influentials to the rest of the population. The diffusion of innovation literature originally developed by Rogers (2003) and extended and popularized by Moore (2014) describe different types of individuals in the process of product diffusion. “Innovators” and “early adopters” are described as visionary and are able to appreciate innovation. They are willing to explore new possibilities and adopt innovations when the market is still not clear. The other types – “early majority ”,“ late majority” and “laggards” represent individuals in the mainstream market who are more risk averse and will adopt an innovation only when the feasibility has been established and there is substantial user base (prior adopters). The second stream of arguments is more relevant to the crowdfunding context. There is no clear status seeking in crowdfunding platforms. Rather, many studies have highlighted that crowdfunders are concerned about the risk of low-quality projects given the limited information they can access (Ahlers et al., 2015). Therefore, I use the second stream of literature as a reference and as a guide for my exploratory analysis. I do not expect to identify crowdfunders that conform to what have been prescribed by the models, as that might narrow the scope of the exploratory analysis. Furthermore, there are significant differences between crowdfunders and the consumers in those models. Hence, the types of consumers might not be readily applicable to the crowdfunding context.

There is a rich body of research on the characteristics of influentials (or opinion leaders). Various characteristics have been proposed to identify the influentials (e.g. Chan & Misra, 1990). I identified, based on prior research, three types of variables that characterize the behavioral profile of a typical crowdfunder: risk preference, involvement, and interest.

Risk Preference

The opinion leadership suggests influentials and imitators differ in terms of their risk preference. Several studies have shown that opinion leaders are willing to take on the risk of trying new products. Research has found that opinion leaders are more innovative and constantly try new ideas or products (Myers & Robertson, 1972; Summers, 1970). They are also reported to be more venturesome and are willing to take on the risk involved in trying new products (Price & Ridgway, 1983; Taylor, 1977). In the crowdfunding context, I expect that crowdfunders' risk preferences might differ. Some crowdfunders, like the influentials, are more willing to try innovations. They might also have the ability to bear the risk of backing projects that fail to reach the funding goal or eventually fail to deliver its products. Hence, the first set of variables intends to measure the risk preference of the focal crowdfunder in various aspects. These variables include:

(1) **Ave Log Backers.** Prior literature has recognized that herding takes place, in which other backers' backing decisions serve as an important factor shaping backers' behavior. Such herding is mainly

informational, as potential backers who are concerned about potential risks seek to derive additional information about the project by observing others' decisions (Banerjee, 1992; Bikhchandani, Hirshleifer, & Welch, 1998). In lending-based crowdfunding platform, both Herzenstein et al. (2011) and Zhang and Liu (2012) find evidence of herding on *Prosper*. The crowdfunder's risk preference can be inferred from the extent to which his decision is influenced by others, as risk averse crowdfunders are more likely to pay attention to how many crowdfunders have already backed the project. To estimate the extent to which a project backer's decision is influenced by other backers' decisions, I examined the number of backers cumulated at the time when the crowdfunder pledged his or her money to the project. For each project k in in the crowdfunder's portfolio set C, I identified the cumulated number of backers ($NumBacker_k$) at the point he/she made the backing decision. I then calculated the average of the numbers to estimate how much the crowdfunder was influenced by the number of existing backers. To mitigate the impact of extreme values, natural logarithm of the original value was used for calculating the average. Mathematically, for a crowdfunder who had backed N projects in his/her portfolio, the variable $Ave\ Log\ Backers$ was calculated as:

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

(2) **Ave Log Creator Social Capital**. Relying on signals in making decisions is another strategy to reduce uncertainty in funding projects (Colombo et al., 2015). Prior research has shown that the social capital of the project creator serves as a key signal to potential project backers (e.g. Lin et al., 2013). Prior research has shown that other than social contacts established outside the crowdfunding platform – e.g. Facebook friends,[5] a project creator may also develop social capital within the crowdfunding platform by backing other projects (Colombo et al., 2015). Similarly, Lin et al. (2013) also show that having online friends who are themselves active in *Prosper* serves as a more powerful signal of the lender's creditworthiness than having friends inactive in *Prosper*. If a crowdfunder is more concerned about potential risks and uncertainty, he/she is likely to pay attention to signals embedded in the project campaign. Hence consistent with Colombo et al. (2015), I proxied the social capital of the project creator by using the number of projects backed by the creator. *Kickstarter* provides such information on the project page. Similar to *Average Log Backers*, I examined the number of projects the project creator had backed at the time the crowdfunder pledged his/her money to the project. For each project k in in the crowdfunder's portfolio set C, I identified the number of projects backed by the project creator at the

[5] 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. 2013). Not all project creators in *Kickstarter*, however, show the number of *Facebook* contacts that they have (only half of the projects in my sample did).

time the backer pledged his/her money to the project ($Num\ Creator$ Backed$_k$). I then calculated the average of the numbers to estimate how much the crowdfunder was influenced by such information. Natural logarithm was used to mitigate the impact of extreme values before calculating the average. Mathematically, for a crowdfunder who had backed N projects in his/her portfolio, the variable *Average Log Creator Social Capital* was calculated as:

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

(3) **Ave Log Goal**. Higher project goal size has been shown to be negatively associated with project success (Mollick, 2014). The higher the project goal is, the more backers are needed to fund the project. Favoring projects with a higher goal may be another indication of the crowdfunder's risk seeking behavior. I thus calculated the average project goal of all the projects backed by the crowdfunder and named the variable: $Ave\ Log\ Goal$.

(4) **Ave Log Median Reward**. *Kickstarter* projects allow project creators to specify different rewards for different amounts of crowdfunder contributions. For example, crowdfunders who pledge \$10 can receive a T-shirt, whereas those who pledge \$100 can get a prototype. The amount contributed by the crowdfunder can be used to proxy the crowdfunder's risk preference. A relatively risk averse crowdfunder is more likely to

make a small contribution. Since the amount of crowdfunder's contribution is not disclosed, I used the amounts associated with the rewards to calculate the average size of contribution required. For each project k in the crowdfunder's portfolio, I first calculated the median[6] of the amounts ($Median\ Reward_k$) of the contributions associated with different rewards, excluding the smallest and largest number (natural logarithm of the original value was used). The value was then aggregated at the individual level using the average of the medians calculated:

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

Involvement

Second, I included variables that measure a crowdfunder's involvement in the platform by contributing funds and in the projects by contributing comments. The opinion leadership literature suggests that some influentials are more knowledge about products and are more involved with the product class (Chan & Misra, 1990). Venkatraman (1988) argue that enduring involved individuals can have a significant impact on the diffusion process. Compared to others, these involved individuals "tend to seek information on an ongoing basis, have considerable product knowledge and expertise, influence other people's behavior, and buy new products"(Venkatraman, 1988). Feick and Price (1987, pp. 84) further suggest that "the implicit assumption in examining

[6] Using mean gives similar results.

the personal influence of opinion leaders is that they are motivated to talk about the product because of their involvement with it" (Richins & Root-Shaffer, 1988). In crowdfunding, some crowdfunders might stand out from the rest because of their active involvement in funding projects. Furthermore, they might also be more likely to post comments, as these comments "offer suggestions and feedback that proponents use to modify their projects continuously during a campaign" (Colombo et al., 2015, pp. 4).

I thus included two key attributes that indicated the level of involvement the individual in the projects:

(5) **# Tech Projects Backed (Log)** was the number of projects backed by the crowdfunder on *Kickstarter,* within the technology category.

(6) **# Comments (Log)** was the number of comments the crowdfunder had contributed to the technology projects. *Kickstarter* only allows existing backers to post comments. Content of the comments might include inquiries about the delivery of the product or reward, suggestions on the future development of the projects, and feedback about the product delivered, etc.[7]

Interest Concentration

Interest concentration has been an important characteristic of the crowdfunder in studies on crowdfunder heterogeneity (Hahn & Lee, 2013;

[7] I used the natural logarithm of the original value to mitigate the impact of extreme values for all the variables described so far, except for average stage.

Inbar & Barzilay, 2014). Hahn and Lee (2013) argue that interest concentration indicates, “whether an individual backer is a specialist or a generalist” (pp. 6). They further argue that it can also indicate whether the crowdfunder is knowledgeable and experienced in certain areas. Inbar and Barzilay (2014) also distinguish two types of crowdfunders: “Category-Centered Communities” who only back projects within a category and “Platform-Centered Communities” who back projects spanning multiple categories and argue that crowdfunders of these two communities “vary considerably in their participation patterns” (pp. 13).

Similar topic has also been discussed in the opinion leadership literature. There is a debate on whether opinion leaders in one product category can be opinion leaders in another product category (King & Summers, 1970). Merton (1968) describes two types of influentials. The first type, “the monomorphic influentials” are “the ‘experts’ in a limited field, and their influence does not diffuse into other spheres of decision”. The second type, the “polymorphic influentials”, exert “interpersonal influence in a variety of (some- times seemingly unrelated) spheres” (pp. 468). While some researchers find no evidence of opinion leadership overlap (e.g. Silk, 1966), others show that there is significant overlap of opinion leadership across product categories (e.g. King & Summers, 1970; Marcus & Bauer, 1964).

Following the existing literature, the last variable concerns the crowdfunder’s interest concentration. Although all the sample projects come from the technology category, a closer examination of the projects indicates that projects differ largely from one another. To examine the types of projects within the technology category, I conducted topic analysis to identify meaningful topics highlighted in the textual description provided by project creators. Details of the topic analysis are provided in Appendix A. The topic analysis shows that there exist five distinct topics: *Electronics Design*, *Software Application*, *Hardware*, *New Technology*, and *Patronage*. 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 each crowdfunder, I first calculated the average topic loading on each topic of the projects backed by the individual and then used the averaged topic loading to calculate the Herfindahl-Hirschman Index (HHI) for the individual. HHI is commonly used as a measure of concentration. Here, it was calculated as the sum of the squares of the average topic loadings. A high HHI suggests that the crowdfunder is highly focused on one type of projects. Hence, HHI was used to measure to what extent a crowdfunder was interested in one type of projects or different types of projects. Table 4 summarizes all the variables.

Table 4 Variables for Cluster Analysis

No.	Variable	Description
1	Average Log Backers	Average of the number of backers (natural logarithm) cumulated at the time the crowdfunder pledged his/her money to the project.
2	Average Log Creator Social Capital	Average of the number of projects backed by the project creator (natural logarithm) at the time the crowdfunder pledged his or her money.
3	Average Log Goal	Average of the project goal of projects backed by the crowdfunder.
4	Ave Log Median Reward	Average of the medium reward amount (natural logarithm) excluding the biggest and smallest amount of the projects backed by the crowdfunder.
5	# Tech Projects Backed (Log)	The number of technology projects backed by the crowdfunder on *Kickstarter*. Natural logarithm is used.
6	# Comments (Log)	The number of comments contributed by the crowdfunder to the technology projects on *Kickstarter*. Natural logarithm is used.
7	HHI	Herfindahl-Hirschman Index calculated from the average loadings on the five project types across the projects backed by the crowdfunder.

Methodology

I employed 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 one another than to those in other groups (Aldenderfer & Blashfield, 1984). Cluster analysis has been used by researchers to study different phenomena (e.g. Joseph, Boh, Ang, & Slaughter, 2012; Malhotra, Gosain, & Sawy, 2005).

Table 5 and Table 6 provide descriptive statistics and correlations of all the variables for Period 1 and Period 2, respectively. There are two basic types of clustering algorithms: hierarchical and nonhierarchical (Ketchen & Shook, 1996). Both were employed to ensure the robustness of the results. First, I employed hierarchical cluster analysis following Bensaou and Venkatraman

(1995)’s approach: (1) All analyzed variables were standardized; (2) Euclidean distance was used for calculating the distance matrix, and (3) Ward’s minimum variance method was used for cluster agglomeration. The computation of distance matrix for hierarchical clustering is computationally intensive given the sample size. Hence, for both data from Period 1 and Period 2, I drew a sub-sample of 2000 for the analysis, respectively. Following Malhotra et al. (2005) and Aldenderfer and Blashfield (1984), the number of clusters was determined by inspecting the dendrogram and the amalgamation coefficients, which are the numerical values at which various cases are merged. I graphed the amalgamation coefficients against the number of clusters for both periods in Figure 1. The number of clusters is found at the point where the curve begins to flatten, which suggests that the dissimilarity among cluster members have been significantly reduced. This is similar to a scree plot in factor analysis. Samples from both periods suggest that a five-cluster solution best fits the data.

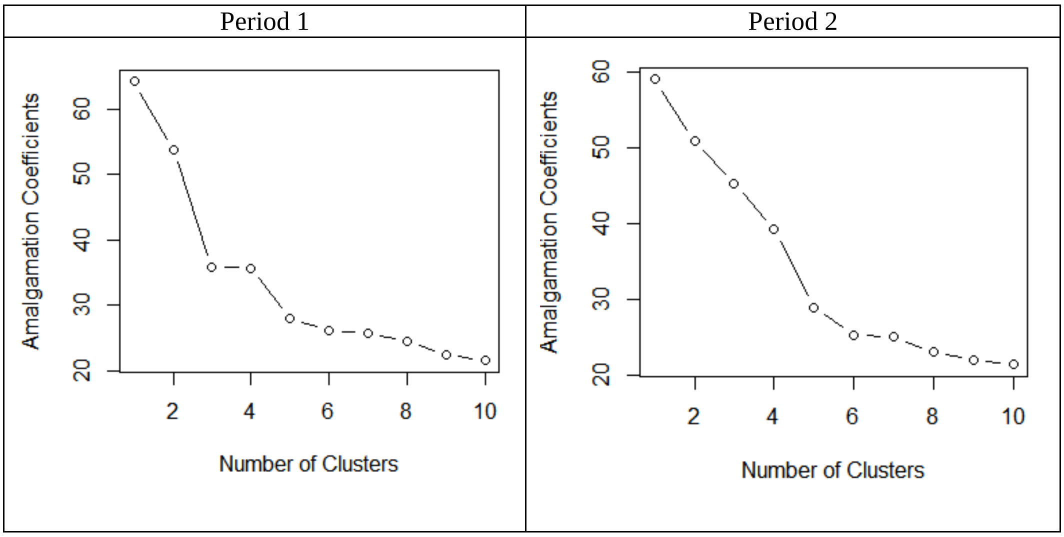


Figure 1 Amalgamation Coefficients against Number of Clusters

To ensure the robustness of the five-cluster solution, the nonhierarchical K-means cluster algorithm was employed to the same samples (Malhotra et al., 2005). To determine the number of clusters, I plotted the within clusters sum of squares against the number of clusters extracted, shown in Figure 2. Similarly, I looked for a bend in the plot, which suggests that the with clusters sum of squares have been significantly reduced (Thorndike, 1953). Again, the bend is found at the five-cluster solution. The Cohen's Kappa between the solution from the hierarchical and the solution from nonhierarchical cluster analysis for is 0.69 and 0.57 for Period 1 and Period 2, respectively, suggesting the robustness of the clustering solution. Given the robustness of the five-cluster solution, the K-means algorithm was further applied to the full data. [8]

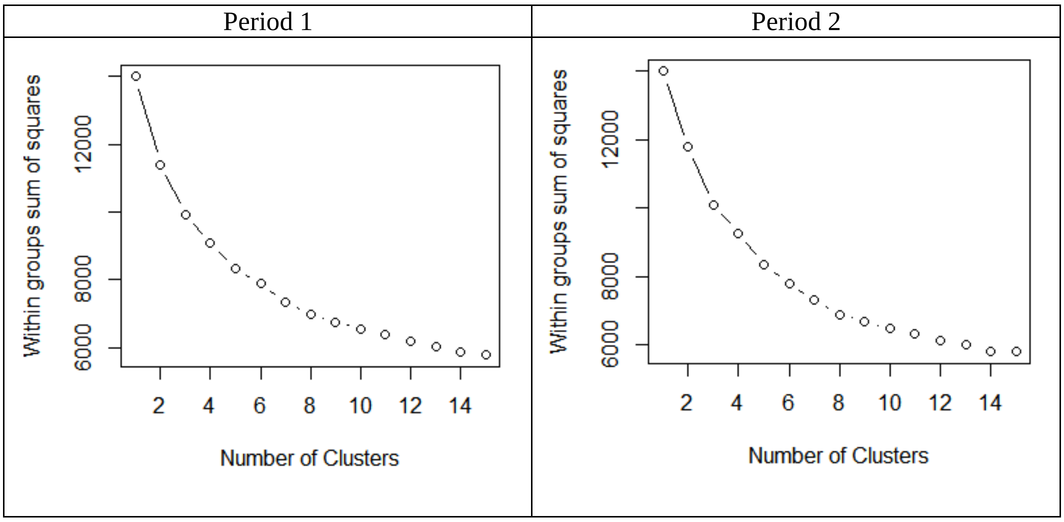


Figure 2 Within Groups Sum of Squares against Number of Clusters

[8] The clustering results remain similar across many runs in both Period 1 and Period 2.

Table 5 Descriptive Statistics and Correlations for Period 1

	Variable	Mean	S.D.	1	2	3	4	5	6	7
1	Average Log Backers	6.84	0.98	1.00						
2	Average Log Creator Social Capital	1.16	0.47	-0.09	1.00					
3	Average Log Goal	10.53	0.79	0.43	-0.25	1.00				
4	Ave Log Median Reward	4.66	0.56	0.08	-0.13	0.63	1.00			
5	# Tech Projects Backed (Log)	2.35	0.81	-0.28	0.01	-0.13	0.03	1.00		
6	# Comments (Log)	0.60	1.04	-0.14	0.03	-0.06	0.02	0.30	1.00	
7	HHI	0.35	0.10	-0.10	0.03	-0.09	-0.12	-0.14	0.00	1.00

Note: Correlations greater than 0.019 are statistically significant at the 0.05 level (two-tailed); Correlations greater than 0.026 are statistically significant at the 0.018 level (two-tailed); Correlations greater than 0.033 are statistically significant at the 0.001 level (two-tailed).

Table 6 Descriptive Statistics and Correlations for Period 2

	Variable	Mean	S.D.	1	2	3	4	5	6	7
1	Average Log Backers	6.34	0.94	1.00						
2	Average Log Creator Social Capital	1.28	0.60	0.26	1.00					
3	Average Log Goal	10.12	0.80	0.11	0.04	1.00				
4	Ave Log Median Reward	4.49	0.56	-0.19	0.12	0.61	1.00			
5	# Tech Projects Backed (Log)	2.61	0.87	-0.23	0.00	0.00	0.12	1.00		
6	# Comments (Log)	0.54	1.02	-0.14	-0.04	0.00	0.04	0.38	1.00	
7	HHI	0.38	0.11	0.12	0.04	-0.01	-0.12	-0.21	-0.05	1.00

Note: Correlations greater than 0.023 are statistically significant at the 0.05 level (two-tailed); Correlations greater than 0.030 are statistically significant at the 0.018 level (two-tailed); Correlations greater than 0.033 are statistically significant at the 0.001 level (two-tailed).

Table 7 Clustering Results

	Period 1					N = 10188
	1	2	3	4	5	Pairwise t-test
Average Log Backers	6.14 (0.77)	6.46 (0.81)	6.53 (0.85)	6.88 (0.79)	7.62 (0.82)	1-2*, 1-3***, 1-4***, 1-5***, 2-3***, 2-4***, 2-5***, 3-4***, 3-5***, 4-5***
Average Log Creator Social Capital	1.10 (0.38)	1.23 (0.42)	1.20 (0.43)	1.43 (0.47)	0.93 (0.43)	1-2, 1-3***, 1-4***, 1-5***, 2-3***, 2-4***, 2-5***, 3-4***, 3-5***, 4-5***
Average Log Goal	10.40 (0.54)	10.39 (0.66)	10.31 (0.66)	9.95 (0.61)	11.32 (0.53)	1-2*, 1-3***, 1-4***, 1-5***, 2-3, 2-4***, 2-5***, 3-4***, 3-5***, 4-5***
Ave Log Median Reward	4.78 (0.54)	4.69 (0.66)	4.47 (0.66)	4.20 (0.61)	5.07 (0.53)	1-2***, 1-3***, 1-4***, 1-5***, 2-3***, 2-4***, 2-5***, 3-4***, 3-5***, 4-5***
# Tech Projects Backed (Log)	3.08 (0.72)	3.08 (0.75)	2.06 (0.60)	2.01 (0.55)	1.98 (0.59)	1-2***, 1-3***, 1-4*, 1-5***, 2-3, 2-4***, 2-5***, 3-4***, 3-5***, 4-5
# Comments (Log)	0.32 (0.51)	2.90 (0.99)	0.42 (0.70)	0.26 (0.51)	0.28 (0.56)	1-2***, 1-3***, 1-4***, 1-5***, 2-3***, 2-4***, 2-5***, 3-4**, 3-5, 4-5
HHI	0.31 (0.06)	0.34 (0.08)	0.53 (0.08)	0.33 (0.06)	0.32 (0.07)	1-2***, 1-3***, 1-4***, 1-5***, 2-3***, 2-4**, 2-5***, 3-4***, 3-5***, 4-5**
% Population	20.5%	11.5%	13.8%	25.7%	28.5%	
	Period 2					N = 7433
Average Log Backers	5.50 (0.74)	5.95 (0.80)	6.36 (0.78)	6.97 (0.74)	6.75 (0.71)	1-2***, 1-3***, 1-4***, 1-5***, 2-3***, 2-4***, 2-5***, 3-4***, 3-5***, 4-5***
Average Log Creator Social Capital	1.00 (0.48)	1.22 (0.51)	1.04 (0.56)	1.37 (0.60)	1.61 (0.55)	1-2***, 1-3*, 1-4***, 1-5***, 2-3***, 2-4***, 2-5***, 3-4***, 3-5***, 4-5***
Average Log Goal	10.00 (0.65)	10.14 (0.71)	10.09 (0.63)	9.37 (0.70)	10.81 (0.45)	1-2, 1-3***, 1-4***, 1-5***, 2-3***, 2-4***, 2-5***, 3-4***, 3-5***, 4-5***
Ave Log Median Reward	4.55 (0.44)	4.57 (0.47)	4.29 (0.41)	3.93 (0.35)	4.92 (0.48)	1-2***, 1-3***, 1-4***, 1-5***, 2-3, 2-4***, 2-5***, 3-4***, 3-5***, 4-5***
# Tech Projects Backed (Log)	3.02 (0.87)	3.56 (0.74)	2.12 (0.65)	2.18 (0.64)	2.43 (0.70)	1-2***, 1-3***, 1-4*, 1-5***, 2-3***, 2-4***, 2-5***, 3-4***, 3-5***, 4-5***
# Comments (Log)	0.28 (0.50)	2.88 (1.04)	0.25 (0.55)	0.21 (0.48)	0.24 (0.49)	1-2***, 1-3, 1-4, 1-5, 2-3***, 2-4***, 2-5***, 3-4**, 3-5, 4-5
HHI	0.32 (0.07)	0.36 (0.10)	0.56 (0.09)	0.36 (0.08)	0.37 (0.08)	1-2***, 1-3***, 1-4***, 1-5***, 2-3***, 2-4*, 2-5***, 3-4***, 3-5***, 4-5*
% Population	24.9%	11.1%	14.5%	21.3%	28.2%	
	Silent Actives	Vocal Actives	Focused Enthusiasts	Trend Followers	Star Seekers	

Note: Pairwise t-test used pooled S.D.; p-value was adjusted using Holm's method.
Significance codes: ***p < 0.001, **p < 0.01, *p < 0.05

Results

The results are consistent across the two periods. Table 7 provides, by cluster, the mean and standard deviation for the seven variables included in the cluster analysis, depicting the composition of the crowdfunder community. Pairwise t-tests were used to compare the means between two clusters. The proportion of the observations in each cluster is shown in the row named "% Population". The clusters were named based on their distinct psychographic and behavioral profiles reflected in the variables that were distinct from the rest of the clusters. I describe each cluster below.

The first cluster is the *Silent Actives*. They comprise 20.5% of the population in Period 1 and 24.9% of the population in Period 2. The most distinct characteristic is that they are active in backing projects, which is reflected in the number of technology projects they have backed *(# Tech Projects Backed* = 3.08 for Period 1; *# Tech Projects Backed* = 3.02 for Period 2). However, they tend not to contribute comments to the projects *(# Comments (log)* = 0.32 for Period 1; *# Comments (log)* = 0.28 for Period 2). Hence, they seem to be involved in the platform by contributing funds but do not get involved in the projects after they have contributed funds. These crowdfunders seem to be the generalists in the market, by backing a wide range of projects actively. They also appear to be more risk seeking in backing projects. They tend to back projects early when the number of crowdfunders is still small (*Average Log Backers* = 6.14 for Period 1; *Average Log Backers* = 5.50 for

Period 2), suggesting that they pay less attention to other crowdfunders' decisions when funding projects. They also tend to pay less attention to the creator's social capital (*Average Log Creator Social Capital* = 1.10 for Period 1; *Average Log Creator Social Capital* = 1.00 for Period 2), which is a signal. In addition, they tend to fund projects with a relatively large goal (*Average Log Goal* = 10.40 for Period 1; *Average Log Goal* = 10.00 for Period 2) and require relative large contributions (*Ave Log Median Reward* = 4.78 for Period 1; *Ave Log Median Reward* = 4.55 for Period 2). Taken together, these active crowdfunders are more risk seeking and favor projects with a relatively large project goal and require relatively large contributions. This risk preference is also reflected in their strategies, as they pay less attention to the information related to the funding success of the project. It seems that these crowdfunders are intrigued by the crowdfunding phenomenon itself and are willing to contribute funds regardless of the risks associated.

The second cluster is named the *Vocal Actives.* They comprise about 11% of the population in both Period 1 and Period 2. Similar to the *Silent Actives*, they are actively involved in the platform by backing projects (*# Tech Projects Backed* = 3.08 for Period 1; *# Tech Projects Backed* = 3.56 for Period 2). Not only so, they are the only group who are also actively posting comments *(# Comments* = 2.90 for Period 1; *# Comments* = 2.88 for Period 2). Compared to the *Silent Actives*, the *Vocal Actives* are concerned about the funding success of the projects and tend to adopt a strategy that values the information related to the funding success of the project. They tend to back projects slightly later

(*Average Log Backers* = 6.46 for Period 1; *Average Log Backers* = 5.95 for Period 2) and pay attention to project signals (*Average Log Creator Social Capital* = 1.23 for Period 1; *Average Log Creator Social Capital* = 1.22 for Period 2).

The *Silent Actives* and the *Vocal Actives* seem to be acting as the "influentials" in the crowdfunding market. These people are willing to back projects at the early stage when there are only a few backers. These early backers play an important role in the funding process (Colombo et al., 2015). First, their contributions in the early funding process help significantly reduce uncertainty regarding the project and generate momentum as subsequent crowdfunders engage in observational learning by deriving information from observing others when having limited information about the project campaign (Banerjee, 1992; Bikhchandani et al., 1992). The contributions of these backers might suggest to potential crowdfunders "many have already scrutinized the project, liked it, and trusted its proponents and their ability to successfully complete the project" (Colombo et al., 2015, pp. 4). Furthermore, the *Vocal Actives* provide additional value to both project creators and potential crowdfunders. As most crowdfunding projects are not fully developed when they are launched on the platform, the *Vocal Actives* can offer suggestions and feedbacks during the campaign for the project creator to refine the project (Colombo et al., 2015), which further reduce the uncertainty about funding success. They can also continue to post comments after the project is funded to monitor the project, thus further addressing the concern about the delivery of the rewards.

The third cluster is named the *Focused Enthusiasts*. They comprise 13.8% of the population in Period 1 and 14.5% of the population in Period 2. They are the only group that typically focus on one or a few types of projects (*HHI* = 0.53 for Period 1; *HHI* = 0.56 for Period 2). They are moderate in other aspects. These crowdfunders might represent the “specialists” in the crowdfunding market who continue to exploit some specific product categories. They might also be more knowledgeable about some specific types of projects and might be able to provide valuable suggestions to the project creators. In addition, their endorsement of the project might serve as a credible signal to potential crowdfunders who are evaluating the project.

The fourth cluster is called the *Trend Followers*. They comprise 25.7% of the population in Period 1 and 21.3% of the population in Period 2. They are more risk averse compared to the *Silent Actives* and the *Vocal Actives*. They tend to back projects that have already accumulated a large number of project backers (*Average Log Backers* = 6.88 for Period 1; *Average Log Backers* = 6.97 for Period 2). They are also more likely to favor projects with credible signals (*# Average Log Creator Social Capital* = 1.43 for Period 1; *# Average Log Creator Social Capital* = 1.37 for Period 2). This suggests that they are highly concerned about the risk on funding success and thus rely on both the number of existing backers and project signals to make funding decisions. In addition, they tend to back projects with a relatively small funding goal and require less contribution. In sum, their funding strategy suggests that the *Trend Followers* are the risk averse crowdfunders in the market.

The last cluster is the *Star Seekers*. They are similar to the *Trend Followers* in that they would only back projects when there are many other backers (*Average Log Backers* = 7.62 for Period 1; *Average Log Backers* = 6.75 for Period 2). The projects backed by them seem to have an extremely large funding goal (*Average Log Goal* = 11.32 for Period 1; *Average Log Goal* = 10.81 for Period 2) and require relative large contributions (*Ave Log Median Reward* = 5.07 for Period 1; *Ave Log Median Reward* = 4.92 for Period 2). Hence, these crowdfunders seem to focus on solely the "superstar" projects that request a substantial amount of fund (Doshi, 2014) and will only back these projects when a large number of crowdfunders have already backed the project.

The last two groups of crowdfunders appear to be the "imitators" in the market. Combined, they occupy about 50% of the total population. Both choose to back the project when a large number crowdfunders have already backed the project. However, there are also significant differences between these two types of crowdfunders. The *Trend Followers* try to avoid projects with a large goal and projects that require large contributions entirely, as these projects might be more difficult to get funded. The *Star Seekers*, on the other hand, choose projects more strategically. They focus on the "superstar" projects on the market but will only back these projects after they have demonstrated that they are “superstars” by attracting a large number of backers.

Table 8 provides a summary of the characteristics of the archetypes.

Table 8 Summary of the Clusters

Cluster	Characteristics
Silent Actives	Actively backing projects Tend NOT to contribute comments Back projects early when the number of backers is still small Pay less attention to the creator’s social capital Prefer projects with a large goal Prefer projects that require large contributions
Vocal Actives	Actively backing projects Tend to contribute comments Compared to the *Silent Actives*, tend to back project slightly later and pay more attention to project signals
Focused Enthusiasts	Focused on one type of project Moderate on other attributes
Trend Followers	Tend to back projects with a large number of backers Pay attention to the creator’s social capital Prefer projects with a SMALL goal Prefer projects that require SMALL contributions
Star Seekers	Tend to back projects with a LARGE goal Tend to back projects with a large number of backers

Discussion

Motivated by the “influentials” vs. “imitators” hypothesis, I start to unpack the crowdfunder heterogeneity by using variables that characterize crowdfunders along three dimensions: risk preference of the crowdfunder, involvement in the crowdfunding platform and projects, and interest concentration. Using an extensive set of variables, I have identified five groups of different crowdfunders, who exhibit different behavioral profiles in funding technology projects in *Kickstarter*. These archetypes seem to conform to the “influentials” vs. “imitators” dichotomy. The *Silent Actives* and the *Vocal*

Actives are the “influentials” in the crowdfunding market. They are more risk seeking, more involved by actively contributing funds and comments, and tend to diversify across different types of projects. The *Trend Followers* and the *Star Seekers* appear to be the “imitators” who are more risk averse and would only back projects when other crowdfunders have done so.

The results also show that the existing “influentials” vs. “imitators” framework does not fully describe heterogeneity in the crowdfunding context. First, I find that there are sub-clusters within the “influentials” and “imitators” type. I find that both the *Silent Actives* and the *Vocal Actives* are likely to be the early backers. This might be due to their active involvement in the crowdfunding activities. They might be more willing to seek information and have considerable knowledge on how to assess crowdfunding projects (Venkatraman, 1988). Hence, they can rely less on other crowdfunders and project signals in making funding decisions. The *Vocal Actives* go a step further. They not only contribute funds actively but also post comments. These comments can help projects creators to refine the project during the funding campaign and after the project is funded. These comments also serve as a monitoring mechanism after the project is funded. Second, I also found two types of crowdfunders – the *Trend Followers* and the *Star Seekers* – who are the “imitators”. These pragmatic crowdfunders care particularly about whether the project can be successfully funded or not, and hence tend to back the project when there have already been a large number of existing backers. However, strategies of these types of crowdfunders also differ substantially. The *Trend*

Followers not only tend to back projects when a significant number of backers have already backed the project but also tend to pay attention to creator's social capital, which is a project quality signal (Colombo et al., 2015). In addition, they try to avoid projects with a bigger project goal or request larger contributions, which are more difficult to get funded. The *Star Seekers* adopt a different approach. They tend to focus on solely on the "superstar" projects with a significantly large goal and have the potential to generate hype among crowdfunders (Doshi, 2014). They will only back the project when they observe the hype. Third, I find a distinct group who tend to focus on a specific project type: the *Focused Enthusiasts.* These backers might be backing projects because they are intrigued by a specific type of technology and are willing to explore it and help to realize it (Moore, 2014).

Different crowdfunders seem to participate in crowdfunding for different goals. The *Focused Enthusiasts* appear to be backing projects because of their interest in a specific type, perhaps for being part of the community (Gerber et al., 2012). The *Vocal Actives* and the *Silent Actives* seem to be backing projects for the joy of participating in crowdfunding. The *Star Seekers* and the *Trend Followers* adopt a strategy that might result in higher individual funding success rate, indicating that they concern more about the funding outcome of the project. In this case, it is likely that they are backing projects for collecting rewards. The sharp contrasting goals suggest that the crowdfunder community might be more complex than what have been described in the literature.

Having identified different archetypes of crowdfunders, I also explore two important questions related to the archetypes: (1) Are there any differences among different crowdfunders in terms of the success rate of the projects backed? (2) How do crowdfunders evolve?

Individual Success

I also examined how the different funding strategies and behaviors are associated with the crowdfunders' funding success (i.e. backing projects that have been successfully funded). For crowdfunders who are concerned about the funding success of the project, understanding what types of strategies have the best funding success rate can provide guidance about what types of strategies they should adopt to achieve better funding success.

The two clusters that conform to the "imitators" (i.e. the *Trend Followers* and the *Star Seekers*) are expected to achieve better funding success. Backing projects that have already attracted a large number of crowdfunders and paying attention to project signals seem to be a deliberate choice of strategy that reflects their risk aversion and relatively lack of experience. In contrast, whether the project will be successfully funded would be less of a concern for *Vocal Actives* and the *Silent Actives*, as these "influentials" are less likely to be concerned about their funding success.

I define the individual success rate as the percentage of the funded projects in the projects backed by the crowdfunder. The average individual success rate of each cluster is shown in Table 9. ANOVA was used to test if significant differences exist among the clusters. Pairwise t-tests were used test the significance of the difference between two clusters. As the pairwise comparisons consider several hypotheses, Holm's method was used to adjust the p-values calculated to control for the multiple comparisons problem (Holm, 1979).

Table 9 Average Individual Success Rate

		1 Silent Actives	2 Vocal Actives	3 Focused Enthusiasts	4 Trend Followers	5 Star Seekers	ANOVA F Value
Period 1	Success Rate	78.09%	81.60%	83.24%	81.74%	86.61%	65.609***
	Pairwise t-test	1-2***, 1-3***, 1-4***, 1-5***, 2-3, 2-4, 2-5***, 3-4***, 3-5*, 4-5***					
Period 2	Success Rate	67.68%	75.55%	79.92%	82.14%	83.45%	172.81***
	Pairwise t-test	1-2***, 1-3***, 1-4***, 1-5***, 2-3***, 2-4***, 2-5***, 3-4*, 3-5***, 4-5					

Note: Pairwise t-test used pooled S.D.; p-value was adjusted using Holm's method;
ANOVA degree of freedom (Df) = 4
Significance codes: ***p < 0.001, **p < 0.01, *p < 0.05

From Table 9, I have several observations. First, as expected, both the *Trend Followers* and the *Star Seekers* achieve higher success rate than the other three types of crowdfunders, confirming that pledging money when a large number of crowdfunders have already pledged their money is an effective strategy for achieving high individual success rate, as projects with a large number of existing crowdfunders are more likely to be funded successfully.

Second, among the crowdfunder archetypes, the *Silent Actives* have the lowest success rate. It is consistent with the speculation that they are more risk seeking and less concerned about the funding success of the project because they pay less attention to the creator social capital and tend to back the project when there are a small number of crowdfunders. It seems that having an interest in many types of projects might lower the success rate, as the crowdfunder may not have the expertise in appreciating and evaluating projects in areas he/she is not familiar with. This is also consistent with the fact that the *Vocal Actives* and the *Focused enthusiasts* have higher success rate than the *Silent Actives.* Focusing on one type of projects, the *Focused enthusiasts* might be more knowledgeable about the projects they have backed compared to the *Silent Actives.* The *Vocal Actives* might also be more knowledgeable because of their active involvement. Furthermore, their comments might also send positive signals to other crowdfunders during the campaign, increasing the probability of the project getting funded.

I further constructed a dataset at the funder-project level to formally investigate the funding success rate of different types of crowdfunders. Consider a case in which Crowdfunder i pledges money to Project j. The dependent variable Y_{ij} is coded as 1 if Project j is eventually funded (i.e. reaches its funding goal), and 0 otherwise. The probability of $Y_{ij} = 1$ is assumed to follow a logistic distribution and is dependent on Crowdfunder i's membership in one of the five types of crowdfunders plus some project attributes. Note that crowdfunder characteristics have been used for generating the clusters. Hence, their effects should be absorbed in the membership dummies. Four dummy variables were created, using the *Focused Enthusiasts* group as the baseline: D_Silent_i, D_Vocal_i, D_Trend_i, D_Star_i. The empirical model is written as:

$$P(Y_{ij}=1) = logit(D\_Silent_i \quad + D\_Vocal_i \quad + D\_Trend_i \\ + D\_Star_i \quad + X_j) \tag{1}$$

In the above model, X_j represents a set of project attributes that have been suggested to affect project funding success:

$$X_j = Log\ Goal_j + Duration_j + Video\ Exist_j + Num\ Created_j \\ + Log\ Num\ Creator\ Backed_j \\ + Log\ Num\ Categories_j + Log\ Num\ Content\ Video_j \\ + Log\ Num\ Content\ Pic_j \tag{2}$$

$Log\ Goal$ is the natural logarithm of the original project goal. $Duration$ is the number of days a project campaign can last. A typical duration is 30 days. $Video\ Exist$ is a dummy variable coded as "1" if the project creators use a video to describe the project or not, and "0" otherwise (Mollick, 2014). $Num\ Created$ [9]is the number of projects the project creators had created prior to creating the focal project (Xu, 2015). $Log\ Num\ Creator\ Backed$ is the natural logarithm of the number of projects backed by the project creator following Colombo et al. (2015). Mollick (2014) argues that preparedness is a signal of project quality that crowdfunders consider (Chen, Yao, & Kotha, 2009). I controlled for creator preparedness by counting the number of different

[9] The largest number is 6. Hence, the original value is used.

rewards ($Log\ Num\ Categories$), assuming that more prepared project creators would create more types of rewards that cater to different crowdfunders. Lastly, I controlled for the amount of information provided in the project description by considering the number of videos ($Log\ Num\ Content\ Video$) and the number of pictures ($Log\ Num\ Content\ Pic$), using natural logarithm of the original number.

I estimated the model for data from both Period 1 and Period 2. Random effects were added at the individual level to control for unobserved individual attributes. Table 10 shows the results for both periods, respectively.

Table 10 Regression Results Cluster Membership and Project Success

DV: Success	Period 1	Period 2
Variable	Coefficient (Standard Error)	Coefficient (Standard Error)
Log Goal	-0.2881*** (0.0125)	-0.1989*** (0.0114)
Duration	-0.0595*** (0.0014)	-0.0329*** (0.0014)
Video Exist	1.1796*** (0.1423)	0.7852*** (0.0847)
Num Created	0.5346*** (0.0162)	0.1753*** (0.0132)
Log Num Creator Backed	0.2389*** (0.0151)	0.3486*** (0.0135)
Log Num Categories	1.5335*** (0.0320)	0.3584*** (0.0401)
Log Num Content Video	0.7081*** (0.0268)	0.3858*** (0.0297)
Log Num Content Pic	0.6070*** (0.0180)	0.3519*** (0.0163)
D_Silent	-0.1954*** (0.0480)	-0.5057*** (0.0486)
D_Vocal	-0.1390** (0.0531)	-0.3171*** (0.0543)
D_Trend	-0.0756 (0.0512)	-0.0034 (0.0562)
D_Star	0.5374*** (0.0531)	0.1750*** (0.0534)
Constant	-1.0345*** (0.1897)	1.2575*** (0.1548)
Log likelihood	-19067	-18539
No. of Observations	49781	41297
No. of Individuals	10188	7433

Note: Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Results from Period 1 and Period 2 are consistent. As expected, the *Star Seekers* are more likely to back successful projects, compared to the rest of the clusters ($D\_Star = 0.5374, p < 0.001$ for Period 1; $D\_Star = 0.1750, p < 0.001$ for Period 2). This again suggests that backing the "superstars" is an effective strategy to achieve higher funding success. The *Trend Followers* and *Focused Enthusiasts* appear to have similarly funding success ($D\_Trend = -0.0756, p > 0.1$ for Period 1; $D\_Trend = -0.0034, p > 0.1$ for Period 2), suggesting that using information (i.e. number of backers and signals) and void risky projects is also effectively strategy to achieve a higher funding success rate, albeit less effective than the *Star Seekers'*. The fact that *Focused Enthusiasts* achieve relatively higher success rate suggests that specializing in one project type is also an effective strategy in achieving higher success rate. This is also consistent with my speculation that these crowdfunders represent the "specialists" in the market, who might be more knowledgeable about some specific types of projects. As these crowdfunders fund projects relatively early, they might also provide valuable information to subsequent crowdfunders. Turning to the *Silent Actives* and the *Vocal Actives*, the coefficient of D_Silent is negative and significant for both periods ($D\_Silent = -0.1954, p < 0.001$ for Period 1; $D\_Silent = -0.5057, p < 0.001$ for Period 2). The coefficient of D_Vocal is also negative and significant for both periods ($D\_Vocal = -0.1309, p < 0.001$ for Period 1; $D\_Vocal = -0.3171, p < 0.001$ for Period 2). Consistent with their risk preferences, the *Vocal Active* and *Silent Actives* are less successful in identifying successfully funded projects. The results are also consistent with my speculation that the *Silent Actives* are the ones who are interested in the crowdfunding phenomenon itself are willing to fund the projects regardless of its probability of being funded. Compared to the *Silent Actives*, the *Vocal Actives* achieve a relatively higher success rate ($z = 1.37,\ p < 0.1$, for Period 1; $z = 4.66,\ p < 0.001$, for Period 2). This might be for the reason that the comments provided by the *Vocal Actives* help the project creators to better refine the project during the campaign. These comments can also provide further information to subsequent crowdfunders, thus increasing the probability of funding success. In addition, the *Vocal Actives*'s strategy to back slightly later than the *Silent Actives* and pay more attention to the project signals might also help them achive a better funding success rate.

In summary, results on the individual funding success rate are highly consistent with the crowdfunders characteristics. First, being more risk aversion, the *Trend Followers* and the *Star Seekers* adopt different strategies to either rely more on the information provided on the campaign page (i.e. existing crowdfunders and project signals) and avoid risky projects that request higher amounts, or focus on "superstar" projects that have ambitious goals and have attracted many existing crowdfunders. Their strategies seem to pay off, as they achieve higher funding success rate than the more risk-seeking individuals such as the *Silent Actives* and the *Vocal Actives*. Two additional strategies or behaviors are also associated with increased individual success rate. First, projects backed by the *Vocal Actives* are more likely to be successful compared to projects backed by the *Silent Actives*, suggesting that the comments provided might be helpful in fundraising. The comments might help the project creators to refine the project during the campaign, or serve as a signal for subsequent crowdfunders. Second, those who tend to focus on one type of projects appear to achieve higher success rate, suggesting that these "specialists" might be more knowledgeable about the project type and hence are able to identify projects that are more likely to be funded.

Evolution

Another interesting question is how crowdfunders evolve over time. Using two periods not only allows me to test the robustness of the archetypes but also allows me to examine the evolution of a crowdfunder's membership longitudinally. I focused on the crowdfunders who appeared in both periods. I identified 2480 crowdfunders who appear in both Period 1 and Period 2. Table 11 shows the evolution paths from Period 1 to Period 2. In Table 11, each row represents a cluster in Period 1. Each cell in the row represents the percentage of crowdfunders in the cluster that evolve into the cluster specified in the column. For example, the number 28% in the first cell in the third row shows that 28% out of the 302 *Focused Enthusiasts* in the first period, evolve into *Silent Actives* in the second period.

In Table 11, the *Vocal Actives* were the most stable type among the five types. 96% of the *Vocal Actives* stayed in the same type over time. The *Silent Actives* were also relatively stable across the two periods. About 61% of the *Silent Actives* identified in the first period stayed in the same type in the second period. Only 22% of them started to back popular projects and became the *Star Seekers*. The *Star Seekers* seem to attract backers from most other types, indicating that the strategy of backing extremely popular projects is widely adopted by crowdfunders. In contrast, the *Focused Enthusiasts* and *Trend Followers* were relatively transient and tended to evolve into other groups. The *Focused Enthusiasts* might later start to pick up interest in other types of projects. A significant number of them became the *Actives* (both silent and vocal) by actively backing projects in the second period. Some of them later became the *Star Seekers* by only going for the popular projects. In general, the *Trend Followers* became less risk averse over time and start to support projects with a higher goal, suggesting that learning might take place. About half of them evolved into the *Silent Actives*, the *Vocal Actives*, and the *Focused Enthusiasts*. A high number of *Trend Followers* became *Silent Actives* in the second period, suggesting that they started to be active in the market. Some of them also later became the *Star Seekers* by only backing highly popular projects.

Table 11 Evolution Paths

	Silent Actives	Vocal Actives	Focused Enthusiasts	Trend Followers	Star Seekers	Total Number of Backers in the Cluster
Silent Actives	61%	5%	4%	7%	22%	828
Vocal Actives	0%	96%	2%	1%	1%	534
Focused Enthusiasts	28%	10%	19%	15%	28%	302
Star Seekers	29%	4%	6%	15%	46%	413
Trend Followers	36%	2%	16%	22%	25%	403
						2480

Note: Each row represents a cluster in the first period. Each cell in the row represents the percentage of the crowdfunder in the cluster who evolve into the type of backers corresponding to the column name.

Theoretical Implications

In this section, I discuss theoretical implications of this study.

My clustering results suggest that the composition of crowdfunders is complex, even within a single platform. The fact that no single group of individuals appears to dominate the *Kickstarter* platform even within a single technology category highlights that the goals and strategies of crowdfunders appear to be rather fragmented. Expanding the conceptualization and operationalization of crowdfunders with different behavioral strategies enriches our understanding of crowdfunders and allows us to explain crowdfunders' behaviors in a more nuanced manner.

I find that the popular "influentials" vs. "imitators" hypothesis also applies to the crowdfunding context. Although these broader types exist in crowdfunding, there are still significant differences within the "influentials" type and the "imitators" type. Therefore, there is a need to develop archetypes and their profiles specific to the crowdfunding context, in order to provide insights for further theory building and practice.

My results also show that crowdfunders within a single platform may not react uniformly to the same project information. Prior research on crowdfunding has shown that crowdfunders tend to herd into popular projects because they believe that other backers might possess superior information and have scrutinized the project (Herzenstein et al., 2011; Zhang & Liu, 2012). As the results show, the *Trend Followers* and the *Star Seekers* seem to care more about the number of existing backers who have backed the project. The *Vocal Actives*, and the *Silent Actives*, on the other hand, are less likely to be influenced by the number of existing crowdfunders. These suggest that potential contradicting findings on whether crowdfunders may exhibit herding behavior can be partly explained by crowdfunder composition. If the crowdfunder community is dominated by the *Trend Followers* and *Star Seekers,* we might observe herding. On the other hand, if the majority of the crowdfunder community are the *Vocal Actives* and *Silent Actives*, researchers might be less likely to observe herding taking place. 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. The evolution of crowdfunders across two periods suggests that future studies should also consider the maturity of the crowdfunder community. As the *Focused Enthusiasts* and the *Trend Followers* are relatively transient and tend to evolve into other types of crowdfunders over time, the crowdfunder community might be dominated by the *Actives*, when new users stop joining the platform.

The existence of several types of crowdfunders suggests that crowdfunding can provide further benefits to project creators in addition to pure financial support. Crowdfunding allows the project creators to obtain exposure to targeted consumers who can provide their opinions at the early stage of product development such as the *Vocal Actives*, or field experts such as the *Focused Enthusiasts*. By pitching projects to these people, project creators can test the market reaction to the product and collect feedback to refine their projects.

My findings also provide a clearer characterization of the early backers. Colombo et al. (2015) summarize three roles of early backers. First, as the "influentials", early backers trigger imitating behavior. Second, early backers can generate word-of-mouth around the project. Third, early backers provide feedback and suggestions to ongoing campaign for continuous modification during the campaign. My findings suggest that not all early backers provide feedback and suggestions. Only a small number of the early backers (i.e. the *Vocal Actives*) provide feedback and comments. Future studies can further explore the importance of these crowdfunders. Moreover, I show that early backers are more likely to be the ones who are actively involved in the crowdfunding activities by backing projects and contributing comments. Future studies can also examine the explanations for this finding.

My results also contribute to the growing crowdfunding literature by providing insights into the mechanisms underlying "the wisdom of the crowd". Critics of crowdfunding suggest that the potential for fraud can be large because of the severe information asymmetry problem between the project creators and crowdfunders and the latter's inability to overcome it (Griffin, 2012). I find that three types of crowdfunders: the *Focused Enthusiasts*, the *Silent Actives*, and the *Vocal Actives*, seem to rely less on others' decisions and use more of their own judgment in evaluating projects and making decisions. These backers may help to mitigate the information asymmetry problem, as they tend to make backing decisions in the early stages of a project campaign, and their decisions may provide information to other less experienced crowdfunders. This appears to be one mechanism played out by the “wisdom of the crowd”. In addition, by posting comments, the *Vocal Actives* provide further help in monitoring the project, further mitigates the problem. Potential crowdfunders can also extract further information from reading the comments posted by the *Vocal Actives* and incorporate the information in their decisions.

Practical Implications

This study also provides practical implications for various parties who may have an interest in crowdfunding platforms. First, to both projects seeking funds and professional investors who may use the success of reward-based crowdfunding projects as an indication of quality, it is important to understand the composition of crowdfunders that are backing projects on the crowdfunding platform. I show that crowdfunders on a single platform are heterogeneous in their behaviors and strategies, each has different values for them. For project creators, seeking funds from the *Focused Enthusiasts*, the *Vocal Actives*, and the *Silent Actives* is important for the project creators at the early funding stage, as these backers tend to back the project early. They also need to pay attention to the composition of the crowdfunder community. If the *Trend Followers* and the *Star Seekers* dominate the crowdfunder community, it is then important for them to develop seeding strategies such as advertising on various media to create a momentum for subsequent funding (Li & Duan, 2014). For the professional investors who may use the success of reward-based crowdfunding projects as an indication of quality, the endorsement of the *Vocal Actives* and the *Focused Enthusiasts* is more valuable than the rest's. They should pay attention to not only the number of backers but also the the identities of the backers.

My results suggest that the value of reward-based crowdfunding platforms goes beyond pure financial support. Project creators can collect valuable feedback and suggestions from the *Vocal Actives* and use them to refine their ideas and projects. They can also expose their projects to the *Focused Enthusiasts*, who are likely to be the specialists in the project type. Getting their endorsement can also boost their confidence in their projects.

My results also provide implications to platform managers. As highlighted by Rochet and Tirole (2003), some buyers can "make the platform more attractive to sellers" on a two-sided platform. My research provides insights into which are the most important backer groups to project creators and to platform managers. The existence of the *Vocal Actives* and *Silent Actives* is likely to make the platform more desirable, as a whole. These people actively back projects and serve as opinion leaders that others can follow after, which benefits the crowd as a whole. The comments contributed by *Vocal Actives* are also valuable at the early stage of product development, especially for project creators using the platform as a testing ground for their products. For specific types of projects, my results show that they have their own specific crowdfunders, the *Focused Enthusiasts,* who are also the most valuable backers for such projects, as they specialize in backing such specific types of projects. It is then important for platform managers to engage and perhaps nurture some groups of crowdfunders such as the *Vocal Actives*, the *Silent Actives*, as well as the *Focused Enthusiasts*, to increase the attractiveness of the platform to project creators. The *Vocal Actives* deserve special attention. This group of crowdfunders is relative stable. It is also less likely for other types of crowdfunders to evolve and become the *Vocal Actives*. Hence, it is important for the managers to attract the *Vocal Actives* from outside the platform and retain their activeness within the platform after they join the platform.

The heterogeneity of the crowdfunders and their differing strategies imply that crowdfunding platform managers may wish to consider providing more information about crowdfunders to increase transparency to users of their platform. First, information about the existing backers seems to be an important source of information to potential backers. Hence, it may be important to disclose backer information to all the potential backers, as some backers' decisions are strongly influenced by the project's existing backers. Second, it is also important to disclose details about crowdfunders for potential backers to judge the quality of the information the crowdfunder might possess. Interestingly, *Kickstarter* no longer shows the backer page, which shows all the projects backed by the crowdfunder. It remains to be seen how that would affect the decisions of crowdfunders over time.

Lastly, for crowdfunders who are concerned about project funding success, my study offers several strategies. First, following others is an effective strategy to achieve higher funding success, as evident in the case of the *Trend Followers* and the *Focused Enthusiasts*. Second, they can also try to avoid projects with a large goal, unless these projects have attracted a large number of crowdfunders. Third, they should also pay attention to the identities of the existing crowdfunders. My results show that the *Vocal Actives* have achieved a better funding success compared to the *Silent Actives*. Hence, it might be wiser to follow *Vocal Actives* instead of following all other crowdfunders.

Conclusion

The growing popularity and significant impact of crowdfunding call for a closer examination of this complex phenomenon. In this chapter, I take the first step by identifying different types of crowdfunders. My results show that crowdfunders are highly heterogeneous, with different strategies and behaviors. Researchers may have to be cautious when theorizing and modeling the behaviors of crowdfunders.

CHAPTER 4 CROWDFUNDER EXPERIENCE AND THE RELIANCE ON INFORMATION PROVIDED ON THE PROJECT PAGE

Introduction

I have shown in Chapter 3 that crowdfunders are heterogeneous and their characteristics have important implications for theory building and practice. In this chapter, I conducted a follow-on study to examine how the heterogeneity of crowdfunders influences the way crowdfunder rely on various types of information provided on the campaign page in making funding decisions by focusing on one of the most visible dimensions of crowdfunder heterogeneity: crowdfunder experience.

This study is motivated by the information asymmetry problem in crowdfunding. Crowdfunding is largely based on the idea of disintermediation, in which fundraisers are directly connected to funders without traditional institutions such as banks and venture capital or private equity companies. Along with the disintermediation is the removal of the information advantages of these intermediates and additional mechanisms such as screening and monitoring that prevent moral hazards. As a result, crowdfunders are often faced with a high level of uncertainty about project quality (Ahlers et al., 2015). The asynchronous interaction between funders and project creators and limited screening mechanisms due to the openness of the platforms further exacerbate the problem. However, the clear success of some crowdfunding platforms suggests that crowdfunders are able to overcome the information problem to some extent.

So far, prior research has started to address this question from the perspectives of either the project creator or the crowdfunder. From the project creator's perspective, prior research has focused on signaling theory (Akerlof, 1970; Spence, 1973) and seeks to identify several project attributes that serve as effective signals used by project creators to communicate project quality in order to reduce crowdfunders' uncertainty and thus increase their fundraising success. Prior research has shown that crowdfunders are able to evaluate projects by interpreting signals sent by the project creators in different types of crowdfunding platforms. In the case of lending-based crowdfunding, Lin et al. (2013) find that friendship networks on *Prosper* serve as signals of borrowers' credit quality, thus increasing the probability that lenders will be successfully funded. Similarly, Giudici et al. (2013) demonstrate how project creators' social capital influences the probability of success on 11 Italian crowdfunding platforms. Ahlers et al. (2015) find that retaining equity and providing more detailed information about risks are effective signals that influence the probability of funding success in the context of equity-based crowdfunding.

From the crowdfunder's perspective, much of the attention has been given to how crowdfunders rely on previous crowdfunders' decisions in making decisions. Observational learning theory underlies much of this work: its premise is that individuals' decisions are affected by their observation of others' past decisions because they believe that others have private information that is unknown to them (Bikhchandani et al., 1992). Prior studies have clearly identified that herding takes place on crowdfunding platforms. For example, Zhang and Liu (2012) find evidence of rational herding in *Prosper*, where crowdfunders use lending decisions by others to infer borrowers' creditworthiness. Similarly, Herzenstein et al. (2011) find evidence of "strategic herding", where bidders tend to bid on auctions with more bids, but only to the point where the auction is funded. Agrawal, Catalini, and Goldfarb (2015a) show how syndication, in which "lead investors" bring deals to other investors, facilitates fundraising in equity-based crowdfunding.

In this study, I extend the existing literature in several ways. First, current studies that focus on how crowdfunders rely on previous crowdfunders' decisions do not consider the heterogeneity of crowdfunders. However, the nature of crowdfunding is that it attracts a much wider and more heterogeneous audience than traditional fundraising channels such banks or venture capital companies. Different crowdfunders might have different emphases on different sets of project information depending on their individual characteristics. Research in other domains has indicated the importance of studying heterogeneity in terms of individual differences, especially for reconciling inconsistent findings (e.g. Bettman & Park, 1980; Dhar & Zhu, 2006; Park & Kim, 2008). For example, Park and Kim (2008) show that different types of electronic word-of-mouth have different effects on consumers, depending on the level of expertise. Dhar and Zhu (2006) suggest that investor literacy mitigates disposition effect, a tendency to recognize gains (sell purchased stocks appreciated in value) than to recognize losses (sell purchased stocks depreciated in value). In the crowdfunding domain, there is still little research on how individual characteristics affect how crowdfunders evaluate crowdfunding projects and make funding decisions. In this study, I synthesize prior literature from both project creator's perspective (using signaling theory) and crowdfunder's perspective (using observation learning theory) and investigate how crowdfunder heterogeneity might affect crowdfunders' reliance on the information provided on the project campaign page to overcome the information asymmetry problem and make funding decisions.

Second, prior literature on how crowdfunders make funding decisions tends to focus on one type of information (e.g. number of previous crowdfunders) and thus does not consider different types of information and their relative influence on different crowdfunders. For example, in examining herding behavior in lending-based crowdfunding, both Herzenstein et al. (2011) and Lee and Lee (2012) focuses on how the number of bids attracts subsequent bids. Research in others domains such as electronic word-of -mouth has started to examine effects of different types of information on consumer choices. For example, in studying how consumers rely on previous customer reviews in making decisions, Huang and Chen (2006) compares recommendations from other consumers versus recommendations from an expert and show that recommendations from other consumers are more effective than recommendations from an expert. Even the same set of information can also be interpreted differently by different crowdfunders. For example, when using consumer reviews in making decisions, consumers can either read the review texts or rely on summary statistics (Chevalier & Mayzlin, 2006). In this study, I examine and compare multiple types of information at the same time and their relative influence on crowdfunders' decisions. By considering crowdfunder heterogeneity, I show that different crowdfunders have different emphases on different types of information, which highlights the importance of studying crowdfunder heterogeneity and individual differences in the crowdfunding domain.

To explore the effects of crowdfunder heterogeneity, I focus on crowdfunder experience, one of the most important and visible dimensions of crowdfunder heterogeneity. Literature has shown that the experience of a decision maker is a critical variable influencing his/her decisions in various contexts including personnel decision (Taylor 1975), investment (Jacob et al. 1999; Mikhail et al. 1997; Nicolosi et al. 2009; Swain and Haka 2000), auditing (Bonner 1990; Ho 1994; Libby and Frederick 1990). Experience has also been found to influence crowdfunders strategies. In the context of lending-based crowdfunding, Simonsohn and Ariely (2008) have found that experienced bidders are less likely to choose bids with low starting prices. In summary, I ask the following research question: (1) How do crowdfunders use information provided in project campaign page to overcome the information asymmetry problem and make project funding decisions? and (2) how does a crowdfunder's experience influence his/her reliance on different types of information provided?

To answer these questions, I draw upon the Elaboration Likelihood Model (ELM). The ELM posits that there exist two routes via which an individual process the information: the central route and the peripheral route. A less experienced crowdfunder is more likely to process information via the peripheral route and rely on visible cues (e.g. number of crowdfunders) in making project funding decisions because he/she is less able to engage in effortful information processing. In contrast, an experienced crowdfunder is more likely to process information via the central route, which is more effortful. Hence, he/her is more likely to be influenced by the actual content of the information.

In the following part of this chapter, I will first review the relevant literature and propose my hypotheses. I will then describe the empirical study that provides support for my hypotheses. Lastly, I discuss implications for both research and practice.

Literature and Hypotheses

The Information Asymmetry Problem

Crowdfunders have limited information and are faced with high levels of uncertainty about the projects available for funding. The first type of uncertainty concerns funding success. Even though most crowdfunding platforms adopt an “all-or-nothing” funding mechanism in which a project that fails to reach its funding goal before the deadline will return all previously pledged funds to the funders, providing funds to projects that fail to reach funding goal entails opportunity cost of time and effort. The second type of uncertainty concerns the ultimate success of the project and the delivery of the reward to the funders. According to Mollick (2014), approximately 75% of *Kickstarter* projects face delivery delays. Moreover, most projects on crowdfunding platforms are works in progress, and the true product quality is uncertain (Belleflamme et al., 2014).[10]

Such information problem is intensively acute on crowdfunding platforms for several reasons. First, a lack of screening mechanisms on most crowdfunding platforms means that the supply of poor projects can be large relative to that of good projects. For example, on the lending-based platform – *Prosper.com*, only a FICO credit score and a credit report from *Experian* are required before posting an online listing (Lin et al. 2013). On the reward-based platform, *Kickstarter* specifically states that they do not care if the project will succeed or if the creator has the ability to complete his/her project. Second, given the asynchronous and public nature of interactions with project creators, crowdfunders also have limited information gathering and monitoring mechanisms at their disposal, which stands in contrast to the traditional offline face-to-face financial transactions in the form of either direct investment or

[10] In this study, I do not distinguish between these two types of uncertainties. Instead, I focus on the decisions a crowdfunder make in choosing projects, assuming that the crowdfunder would consider both uncertainties in making decisions.

investment in financial intermediates. Third, the ubiquitous crowdfunding platform means that everyone can have the access to crowdfunding, many of whom do not possess the financial sophistication of angel investors or venture capitalists (Ahlers et al., 2015).

The information asymmetry problem and uncertainty about the “quality” of the projects imply that fraud and low-quality projects can be large if potential crowdfunders were not able to identify projects with good quality. The worst result would be a crowdfunding market of “lemons”, where good quality projects withdraw from the market (Akerlof, 1970). The clear success of several crowdfunding markets suggests the opposite, that crowdfunders were able to overcome the information asymmetry problem to some extent.

Prior research has started to look into how crowdfunders overcome the information problem from either the project creator’s perspective or the crowdfunder’s perspective. From the project creator’s perspective, prior research has focused on signaling theory (Akerlof, 1970; Spence, 1973) and seeks to identify several project attributes that serve as effective signals used by project creators to communicate project quality in order to reduce crowdfunders’ uncertainty and thus increase their fundraising success. According to Spence (1973), an attribute can be used as a signal to communicate quality, if (1) the attribute can be altered by the communicating party and (2) the marginal cost of obtaining the signal is lower for the party holding the higher quality products compared to those with lower quality products (Higgins, Stephan, & Thursby, 2011). He applied the theory to the case of job-market, where employees that were more productive invested in education as a signal of their quality. Employers recognized this signal, as they were willing to pay more for employees who show their education signal. Prior studies have shown that several project attributes and project creator attributes serve as effective signals that are interpreted by crowdfunders in evaluating projects. For example, Ahlers et al. (2015) find that retaining equity and providing more detailed information about risks are effective signals that impact the probability of funding success in equity-based crowdfunding. It has also been shown that project creators' social capital is an effective signal for project quality in both lending-based and reward-based crowdfunding (Colombo et al., 2015; Giudici et al., 2013; Lin et al., 2013; Zvilichovsky et al., 2015). Lin et al. (2013) find that friendship networks on *Prosper* serve as signals of borrowers' credit quality, thus increasing the probability of funding success. Similarly, Giudici et al. (2013) demonstrate how project creators' *Facebook* contacts influence the probability of success on 11 Italian crowdfunding platforms. Both Zvilichovsky et al. (2015) and Colombo et al. (2015) find that the social capital developed within the platform is a credible signal associated with fundraising success.

From the crowdfunder' perspective, much attention has been given to how crowdfunders rely on previous crowdfunders' decisions in making funding decisions. Observational learning theory underlies much of this work: its premise is that individuals' decisions are affected by their observation of others' past decisions because they believe that those others have private information that is unknown to them (Bikhchandani et al., 1998). For example, Zhang and Liu (2012) find evidence of rational herding in *Prosper*, where crowdfunders use lending decisions by others to infer borrowers' creditworthiness. Similarly, Herzenstein et al. (2011) find evidence of "strategic herding", where bidders tend to bid on auctions with more bids, but only to the point where the auction is funded. Agrawal et al. (2015a) show how syndication, in which "lead investors" bring deals to other investors, facilitates fundraising in equity-based crowdfunding.

Crowdfunder Heterogeneity and the Elaboration Likelihood Model

Both sets of literature that focus on reducing uncertainty about crowdfunding projects assume that all crowdfunders are homogenously influenced by a set of project information. The literature so far has focused mainly on establishing whether the information is used by crowdfunders when evaluating crowdfunding projects. These studies do not consider the heterogeneity of crowdfunders. As highlighted in Chapter 3, crowdfunders in the same platform are highly heterogeneous and exhibit different project funding strategies and behaviors. This suggests that crowdfunder heterogeneity is an important factor to consider in examining how crowdfunders make use of the information provided in making project funding decisions. To exploring crowdfunder heterogeneity, I focus on a crowdfunder's experience, one of the most important and visible dimensions of crowdfunder heterogeneity. Literature has shown that the experience of a decision maker is a critical variable influencing his/her decisions in various contexts including personnel decision (Taylor 1975), investment (Dhar & Zhu, 2006; Jacob, Lys, & Neale, 1999; Mikhail, Walther, & Willis, 1997; Nicolosi, Peng, & Zhu, 2009; Swain & Haka, 2000), auditing (Bonner 1990; Ho 1994; Libby and Frederick 1990), and shopping (Park & Kim, 2008; Zhu & Zhang, 2010). Research in the fields related to crowdfunding, such as investment and online market also highlights the importance of studying individual experience. For example, Franke et al. (2008) study venture capitalists' evaluations of venture proposals and find that novice VCs and expert VCs focuses on different aspects of start-up team characteristics. They find that novice VCs tend to focus on the qualifications of individual team members, while experienced VCs focus more on team cohesion. In studying trading records, Dhar and Zhu (2006) document that wealthier individuals and individuals employed in professional occupations exhibit a lower disposition effect, a tendency to realize gains than to realize losses. Park and Kim (2008) show that different types of electronic word-of-mouth have different effects on consumers, depending on the level of expertise. So far, understanding of the effects of crowdfunder experience on their decision making is limited.

To explain how a crowdfunder's experience affects his/her reliance on the information provided on the campaign page in making funding decisions, I draw on the Elaboration Likelihood Model (ELM) as my theoretical lens (Petty & Cacioppo, 1986a). The ELM distinguishes between two routes in which information is processed: the central route and the peripheral route. When taking the central route, individuals engage in detailed information processing by carefully scrutinizing available information, inferring the relevance, and forming a critical judgment. When taking the peripheral route, individuals rely on cues and simple heuristics in making decisions. The difference between the two routes lies in the depth of information processing (i.e. elaboration), which is influenced by the individual's motivation and ability. When an individual is motivated and has the ability to process (or to elaborate) the information, the elaboration likelihood is high, and he/she is more likely to carefully scrutinize the information and be thoughtful about the information available. In this case, individuals are more likely to be influenced via the central route. In contrast, if an individual is less motivated or does not have the ability, he/she is likely to be influenced via the peripheral route (Petty & Cacioppo, 1986b). The ELM posits that the two routes process different information (Bhattacherjee & Sanford, 2006). The central route processes message-related arguments (e.g. argument quality), whereas the peripheral route processes cues (e.g. source credibility) (Bhattacherjee & Sanford, 2006; Tam & Ho, 2005). Hence, variables that demand extensive information processing are posited to influence decisions via the central route, whereas variables that require less information processing are posited to influence decisions via the peripheral route. The ELM model is depicted in Figure 3. [11]

[11] The decision in my model is referred as attitude change in the referent literature. I use decision here for the sake of clarity and subsequence discussion.

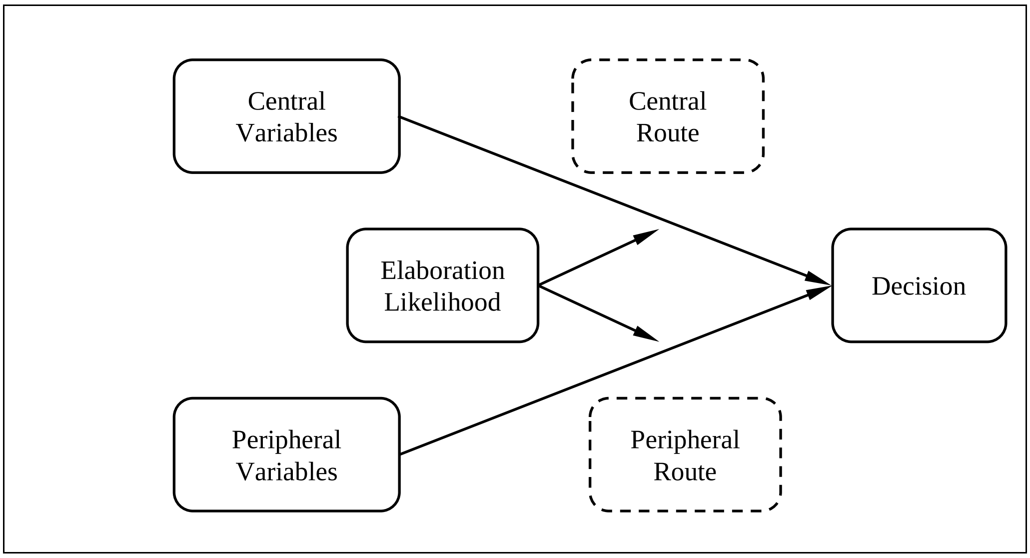


Figure 3 Elaboration Likelihood Model

The ELM suggests that, although individuals' decisions are influenced via both central route and peripheral route, their relative importance varies among individuals depending on their motivation and ability. According to the theory (Petty & Cacioppo, 1986a, Postulate 6), there exists a trade-off between the two routes (Petty & Wegener, 1999). As one moves along the elaboration continuum toward deeper information processing, the relative importance of the central route on the final decision is enhanced, increasing the relative impact of the variables evaluated via the central route. Similarly, as one moves toward the lower end of the elaboration continuum, the relative importance of the variables evaluated via the peripheral route increases.

The ELM has been applied by IS researchers in studying different IT artifacts and phenomenon. Bhattacherjee and Sanford (2006) adopt ELM in examining how external influence (i.e. argument quality and source credibility) and individual attributes (job relevance and user expertise) shape their technology acceptance and how the effects are persistent over time. In a similar vein, Sussman and Siegal (2003) study how knowledge workers adopt information in e-mails. They also find that argument quality interacts with expertise and involvement to affect perceived usefulness. Angst and Agarwal (2009) integrate concern for information privacy (CFIP) with ELM to examine how individuals' attitudes change regarding whether to opt-in to an electronic health record (EHR) system. They found that CFIP interacts with argument framing and issue involvement in influencing attitude toward EHR adoption.

In many studies, the ability to process information is operationalized as prior experience or expertise (Bhattacherjee & Sanford, 2006). Applied to the context of crowdfunding, I argue that experience increases an individual's ability to process information, thus increasing the elaboration likelihood. In this case, the individual is more likely to be influenced by information evaluated via the central route and less likely to be influenced by information evaluated via the peripheral route.

ELM provides a useful framework for examining how experience affects a crowdfunder's reliance on the information provided to overcome the information asymmetry problem. Specifically, a relatively experienced crowdfunder is more likely to engage in active cognitive activity in processing information. Therefore, he/she is more likely to rely on the content of the information (e.g. argument quality) In contrast, a relative inexperienced crowdfunder is less likely to possess the ability to extensively process the information and hence is more likely to rely on non-content cues in making decisions (Park & Lee, 2009).

Prior search has examined how crowdfunders overcome the information problem from both the project creator's perspective and the crowdfunder's perspective. First, a potential crowdfunder can rely on "signals" that embedded in the project description provided by the project creator in making funding decisions (Ahlers et al., 2015; Lin et al., 2013). Second, a potential crowdfunder can rely on the social information by observing other crowdfunders' decisions and comments (Herzenstein et al., 2011; Zhang & Liu, 2012). For either set of information, theory and empirical evidence have alluded to the possibility that experience may play a role in moderating their effects on crowdfunders' decisions. For example, in theorizing how board prestige signals a new firm's organizational legitimacy to investors, Certo (2003) suggests that prestigious investors are more able to differentiate between prestigious and non-prestigious board structures and hence the signaling effect will be stronger for prestigious investors. On the other hand, Higgins et al. (2011) suggest that signals such as star scientists become less important when other information become available. These findings can be potentially reconciled using the proposed model. Prestigious investors have the ability understand and assess signals such as complex board structures. Hence, the importance of the signal may increases. When lacking experience, investors have to rely on signals that are more visible and easy to interpret, such as star scientists affiliation. In the next part, I will propose a set of hypotheses that synthesize past search and use the ELM model to explain how crowdfunder experience might moderate the effects of the project information on crowdfunders' decisions.

In terms of social information, studies on the effects of electronic word-of-mouth have also examined the moderating role of experience. For example, Cheung, Xiao, and Liu (2014) find that consumer expertise negatively moderates the relationship between peer consumer review and consumer purchase decision, as consumers with high expertise are more confident in their own judgment and tend to rely on their own knowledge to make decisions rather than using heuristics cues (Park & Kim, 2008).

In the following part, I draw upon existing studies from both the project creator's perspective and crowdfunder's perspective and propose a set of hypotheses on how crowdfunder experience might affect their reliance on the information provided on the campaign page in making decisions. Figure 4 depicts the conceptual framework and hypotheses.

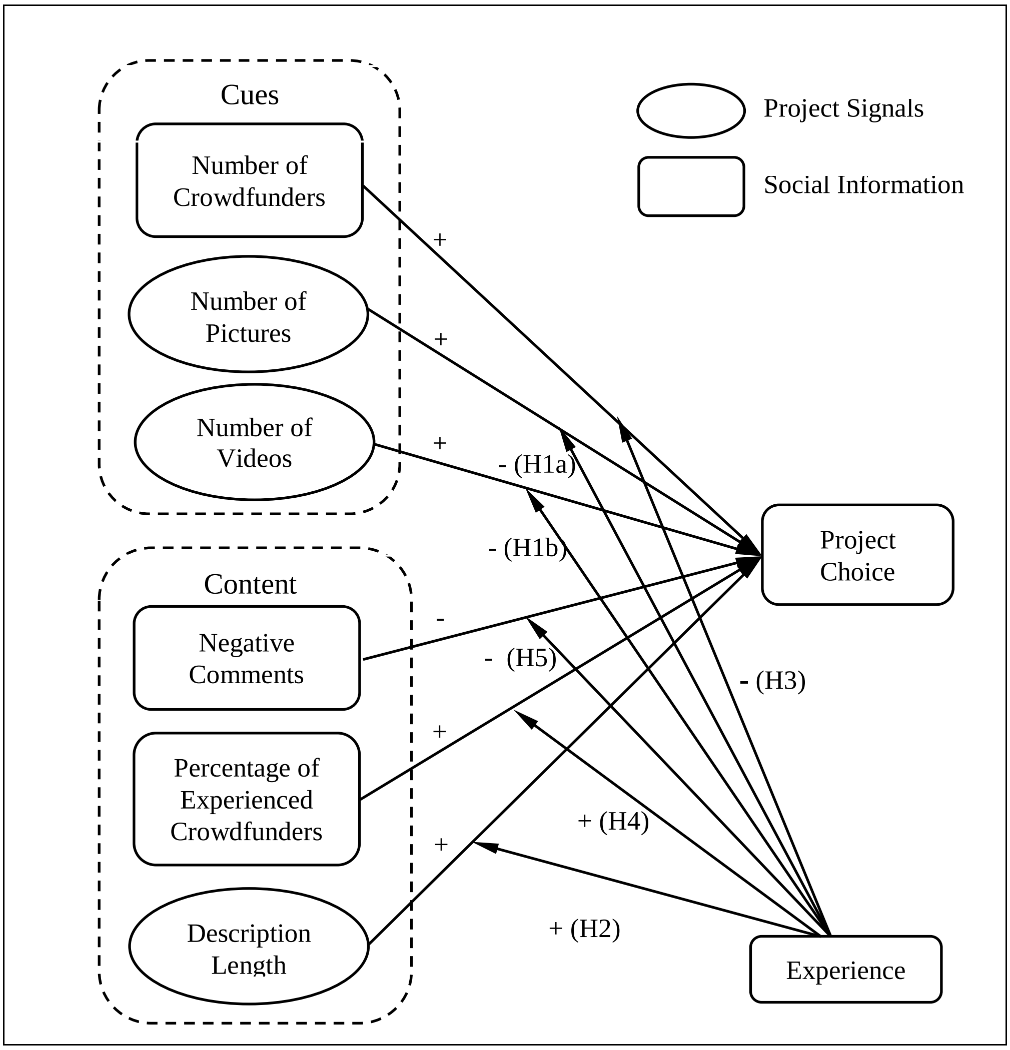


Figure 4 Conceptual Framework

Crowdfunder Experience and Signaling

Several project attributes can be used by project creators as signals to help to overcome the information asymmetry problem. For example, Ahlers et al. (2015) find that retaining equity and providing more detailed information about risks are effective signals that impact the funding success. In reward-based crowdfunding, project creators can provide a rich set of information to signal the project’s quality. For example, the project creator can explain its project’s prospects, its technology, and the founding team using texts, pictures, and videos. Although the overall success of the many platforms suggests that signals do play a role in helping potential crowdfunders overcome the information asymmetry problem on average, decoding the information might not be an easy task for all the crowdfunders. Furthermore, literature has highlighted the role of the receiver in the signaling mechanism (Connelly, Certo, Ireland, & Reutzel, 2011). For the signal to take effect, it has to be assessed, analyzed, and interpreted by the receiver. The signal might not be effective if the receiver is not able to interpret it or is not paying attention to it (Rynes, Bretz, & Gerhart, 1991). In crowdfunding, the amount of information revealed might serve as a signal of project quality, as the more information the project creator is willing to disclose, the more confident the project creator is in the project. This is evident in Michels (2012)'s study of loan listings in *Prosper.com* – a lending-based crowdfunding platform. He finds that the effects of voluntary, unverifiable disclosures reduce the cost of debt. The effects are stronger when verifiable information alone is not sufficient to differentiate credible borrowers from borrowers with poor credit. For a potential crowdfunder, a simple heuristic would be the amount of information disclosed by the project by mentally counting the number of pictures and videos provided on the project page, as videos and pictures are more visible compared to the texts, and counting them requires relatively less cognitive effort (Pieters & Wedel, 2004). However, these cues may be of very poor information value if one does not look at the actual content of the information. Hence, for experienced crowdfunders, these cues would be less important:

H1a: Experienced crowdfunders are less likely than inexperienced crowdfunders to back projects that have more pictures embedded in the project description.

H1b: Experienced crowdfunders are less likely than inexperienced crowdfunders to back projects that have more videos embedded in the project description.

By contract, the actual content of the project description may provide useful information to potential crowdfunders. Research has shown that venture capitalists do look for information embedded in business plans when making funding decisions. For example, Chen et al. (2009) argue that "entrepreneurial passion" demonstrated in business plans affect venture capitalists' decisions.

The content of the project description might also convey complex signals information about the project quality. In studying the impact of electronic word-of-mouth, Chevalier and Mayzlin (2006) find evidence that consumers do read review text rather than rely on summary statistics. Processing and analyzing the content of the information demand a significant amount of cognitive effort. Thus, the experienced crowdfunders are more likely to read the content of project description and be influenced by the complex signals embedded in it. The effects of these signals are likely to be correlated with the length of the description. In studying the effects of review length on the effects of electronic word-of-mouth on sales, Chevalier and Mayzlin (2006) suggest that the length of the review "is correlated with the enthusiasm of the review in ways that are not captured by the star measures" (pp. 350). Following them, I expect the length of the project content will be stronger for the experienced crowdfunders:

H2: Experienced crowdfunders are more likely than inexperienced crowdfunders to back projects that have a longer project description.

Crowdfunder Experience and the Reliance on Social Information

The second set of information a potential crowdfunder can observe is the social information provided on the project page, including both the decisions made by other crowdfunders and the comments posted by them (Cheung et al., 2014).

Research has found that existing crowdfunders have a significant impact on subsequent crowdfunders' decisions (Herzenstein et al., 2011; Li & Duan, 2014; Zhang & Liu, 2012). Crowdfunders are found to favor projects that have attracted a sufficient number of funders. Such herding phenomenon is mainly informational, as potential crowdfunders derive additional information by observing others' decisions when facing information asymmetry problem (Banerjee, 1992; Bikhchandani et al., 1992).[12] For example, Zhang and Liu (2012) find that rational herding takes place on *Prosper.com*, a lending-based crowdfunding platform. They show that negative project attributes (e.g. poor credit grades, high debt-to-income ratios) amplify herding momentum, as crowdfunders believe that others should have additional private information about a project to justify the herd. Similarly, Herzenstein et al. (2011) find "strategic herding" on *Prosper* where a listing with more bids is more attractive to crowdfunders, but only to the point where the listing has reached its funding goal.

[12] There are several underlying mechanisms for the observed herding behavior, including sanctions on deviants, positive payoff externalities, conformity preference, and communication. Bikhchandani et al. (1992) provide an excellent summary. Bikhchandani, S., Hirshleifer, D., & Welch, I. 1992. A Theory of Fads, Fashion, Custom, and Cultural Change as Informational Cascades. ***Journal of Political Economy***, 100(5): 992-1026.

The number of existing crowdfunders is usually directly provided by the crowdfunding platform as a summary statistic and hence can be directly observed by potential crowdfunders and used as a cue in making decisions. However, the number of existing crowdfunders might be of poor informational quality. Although mimicking others' past decisions can be rational, at times, for individuals with poor private information (Herzenstein et al., 2011; Zhang & Liu, 2012), it suffers from potential informational cascades, which leads to wrong decisions and poor information aggregation when subsequent individuals discard their private information. Studies have suggested that experienced individuals are less likely to herd, whereas the observational learning effect is stronger for less experienced individuals (e.g., Cai, Chen, & Fang, 2009). In fact, Simonsohn and Ariely (2008) have found that experienced bidders are less likely to herd into *eBay* auctions with lower starting prices, as it is a mistake that experienced bidders have learned to avoid. Similarly, Clement and Tse (2005) find that experienced analysts are more likely to issue "bold" forecasts (which turn out to be more accurate) rather than forecasts that are consistent with the rest of the analyst herd. Hence, I hypothesize:

H3: Experienced crowdfunders are less likely than inexperienced crowdfunders to back projects that have already accumulated a large number of crowdfunders.

In addition to the number of existing crowdfunders, crowdfunding platforms also disclose crowdfunders' identity. In this regard, the endorsement of some crowdfunders might provide more valuable information than the number of crowdfunders. Several studies have shown that a small group of individuals (e.g. opinion leaders, or fashion leaders) are more influential than others. Recent studies on opinion leadership also suggest that opinion leaders act as key intermediates in forming public opinions (Godes & Mayzlin, 2009; Watts & Dodds, 2007). In the crowdfunding context, Kim and Viswanathan (2014) show that experts including app developer and experienced backers are likely to influence *the crowd* and that *the crowd* is able to identify experts in the market and follow their decisions accordingly. Experienced crowdfunders might possess more valuable information than the ordinary crowd. Hence, following the "experts" might be a wiser strategy for a potential crowdfunder who rely on others' decisions. Identifying the experts in the existing crowdfunder list require the potential crowdfunder to closely scrutinize the crowdfunder list, identify who are the experts, and judge on the private beliefs they hold. According to ELM, this requires a higher level of elaboration and is likely to take place for those who are capable of processing the information extensively and suffer less from cognitive overload. Hence, I expect that the experienced crowdfunders are more likely to back projects that have been backed by "experts" in the market.

H4: Experienced crowdfunders are more likely than inexperienced crowdfunders to back projects that have already accumulated a high percentage of experienced crowdfunders.

Similar to other online platforms, crowdfunding platforms also display comments contributed by existing crowdfunders in addition to the number of existing backers and the identity of existing backers (Chen, Wang, & Xie, 2011; Godes et al., 2005).These comments from the existing backers serve several purposes. First, it serves as a channel for the project creators to collect suggestions to improve the project during and after the project campaign. Second, it severs as a communication channel for existing backers to follow up with the project creator after they fund the project. Third, it provides additional information to potential crowdfunders in assessing the project quality and making funding decisions. So far, the effects of comments in the crowdfunding context have not been explored. In other online contexts, online feedback or word-of-mouth has been shown to influence consumer decision and product sales (Chevalier & Mayzlin, 2006; Duan, Gu, & Whinston, 2008; Liu, 2006; Senecal & Nantel, 2004). For example, Chevalier and Mayzlin (2006) compared book sales on two websites and show that an improvement in book reviews leads to an increase in sales relative to the other site. Liu (2006) and Duan et al. (2008) both show that the number of reviews is associated with movie sales.

Different from the online review system found in many other electronic word-of-mouth platforms, the comment system provided by crowdfunding platforms do not have summary statistics such as star rating. Hence, if potential crowdfunders' decisions do incorporate information derived from the comments, such information is likely to be derived from the actual content of the comments. In addition, there are differences between positive and negative comments. I expect that negative comments are more influential than positive comments. This is because most crowdfunding platforms allow only existing backers (those who have already pledge their money) to post comments. These people are more likely to feel positive about the project before providing funds to the project. In fact, many positive comments are only expressions of excitement, encouragement, and congratulation such as “good Job”, “well done!”, “can’t wait to see the product” etc. Such information is less likely to provide additional information to a potential crowdfunder, especially when one can already observe other crowdfunders’ decisions. On the other hand, negative comments are more informative, as they can indicate problems from continued project monitoring and information search about the project by the existing crowdfunders. These negative comments are more likely to influence potential crowdfunders’ decisions. Literature has shown that negative reviews attract more attention and provide more diagnostic information (Ito, Larsen, Smith, & Cacioppo, 1998; Rozin & Royzman, 2001). Such negative bias has been found in many studies of online consumer comments (Chen et al., 2011; Chevalier & Mayzlin, 2006; Sen & Lerman, 2007). For example, Chevalier and Mayzlin (2006) find that the impact of one-star reviews is greater than the impact of one-star reviews. Chen et al. (2011) find that negative word-of-mouth is more influential than positive word-of-mouth in a natural experiment. Furthermore, negative reviews are also found to be more useful by consumers (Kuan, Hui, Prasarnphanich, & Lai, 2015).

Reading the content of the comments involves extensive information processing. Therefore, crowdfunders who are more able to elaborate the information is more likely to be influenced by the content of the comments. My argument is similar to Lee, Park, and Han (2008) 's. Applying the ELM, they argue that high involvement consumers are more likely to scrutinize the relevant information and hence is more likely to be influenced by high quality negative reviews, compared to the low involvement consumers, who are more likely to be influenced by the proportion of negative comments. Hence, I expect that experienced crowdfunders have the ability to scrutinize the content of the reviews posted by existing backers and think about most of the information given in them:

H5: Experienced crowdfunders are more likely than inexperienced crowdfunders to avoid projects that have received negative comments.

Methodology

Model

I used a choice model to test the hypotheses. I begin to build the model by assuming a random utility function. For a backer i, faced with choice set C_i of J_i choices, the utility of choice $j \in C_i$ to backer *i* is supposed to be:

$$
\begin{aligned}
U_{ij} = \; & \beta_{1,i} Log\ Num\ Content\ Pic_j \\
& + \beta_{2,i} Log\ Num\ Cotent\ Video_j \\
& + \beta_{3,i} Log\ Cotent\ Length_j \\
& + \beta_{4,i} Log\ Num\ Backer_j \\
& + \beta_{5,i} Per\ Expert_j \\
& + \beta_{6,i} Neg\ Comment_j \\
& + \sum_{k=1}^{K} \beta_k Control_{k,\mathrm{j}} + \varepsilon_{\boldsymbol{ij}} \qquad (3)
\end{aligned}
$$

In the above specification, I assume that a backer's taste is homogeneous with respect to the K control variables, but different with respect to the six project attributes of interest – the number of content pictures ($Log\ Num\ Content\ Pic$), the number of content videos ($Log\ Num\ Content\ Video$), the length of the content ($Log\ Content\ Length$), the number of existing crowdfunders ($Log\ Num\ Backer$), the percentage of experienced crowdfunders ($Per\ Expert$), and the measure of negative comments ($Neg\ Comment$). I further assume that for the six project attributes, the associated coefficients are dependent on the backer experience plus a constant:

$$\beta_{l,i} = \alpha_l exp_i + \theta_l, l \in \{1,2, \dots ,6\} \qquad (4)$$

Plugging the four equations into Equation (1), the utility U_{ij} becomes:

$$
\begin{aligned}
U_{ij} = \quad & \alpha_1(exp_i Log\ Num\ Content\ Pic_j) \\
& + \alpha_2(exp_i Log\ Num\ Cotent\ Video_j) \\
& + \alpha_3(exp_i Log\ Cotent\ Length_j) \\
& + \alpha_4(exp_i Log\ Num\ Backer_j) \\
& + \alpha_5(exp_i Per\ Expert_j) \\
& + \alpha_6(exp_i Neg\ Comment_j) \\
& + \theta_1 Log\ Num\ Content\ Pic_j \\
& + \theta_2 Log\ Num\ Cotent\ Video_j \\
& + \theta_3 Log\ Cotent\ Length_j \\
& + \theta_4 Log\ Num\ Backer_j \\
& + \theta_5 Per\ Expert_j \\
& + \theta_6 Neg\ Comment_j \\
& + \sum_{k=1}^{K} \beta_k Control_{k,\mathrm{j}} + \varepsilon_{\boldsymbol{ij}} \\
= \quad & V_{ij} + \varepsilon_{\boldsymbol{ij}} \qquad (5)
\end{aligned}
$$

Here, V_{ij} represents the deterministic portion of the utility, whereas ε_{ij} represents the random error that is unknown to the researcher.

A utility maximizing individual will choose the option that gives the highest utility. Hence, the probability of choice j being chosen by backer i is the probability that choice j gives the highest utility:

$$P\left(Y_{ij} = 1\right) = Prob\left(U_{ij} > U_{ik}, \forall \mathrm{k} \neq \mathrm{j}\right)$$

$$= Prob\left(V_{ij} + \varepsilon_{ij} > V_{ik} + \varepsilon_{ik}, \forall \mathrm{k} \neq \mathrm{j}\right)$$

$$= Prob\left(\varepsilon_{ik} < V_{ij} - V_{ik} + \varepsilon_{ij}, \forall \mathrm{k} \neq \mathrm{j}\right) \tag{6}$$

If we further assume that $\boldsymbol{\varepsilon_{ij}}$ are independently, identically distributed with type I extreme value, whose cumulative distribution function can be written as:

$$F\left(\boldsymbol{\varepsilon_{ij}}\right) = e^{-e^{-\varepsilon_{ij}}} \tag{7}$$

McFadden (1973) has shown that

$$P\left(Y_{ij} = 1\right) = \frac{exp(V_{ij})}{\sum_{k=1}^{J_i} exp(V_{ik})} \tag{8}$$

Equation (8) is effectively a conditional logistic model with interactions (Train, 2009). The coefficients can be estimated using maximum likelihood (ML). Note that a variable that is invariant in the choice set cannot be included in the model, as it “shifts the origin of the ‘representative utility’ function leaving all the selection probability unchanged” (McFadden, 1973, footnote 6). Train (2009) also notes that “the only parameters that can be estimated (that is, are identified) are those that capture differences across alternatives” (pp. 20). Mathematically, Greene (2012) suggests that “terms that do not vary across alternatives—that is, those specific to the individual—fall out of the probability" (pp. 762). To illustrate this, consider:

$$V'_{ij} = \ V_{ij} + \ \theta * attri_i \tag{9}$$

Where $attri_i$ represents an individual attribute that does not vary across choices. θ is the associated coefficient. Equation (8) can be written as:

$$\begin{aligned} P(Y_{ij} = 1) &= \frac{\exp(\,V'_{ij})}{\sum_{k=1}^{J_i} \exp(\,V'_{ik})} = \frac{exp(\,V_{ij} + \ \theta \times attri_i)}{\sum_{k=1}^{J_i} exp(\,V_{ik} + \ \theta \times attri_i)} \\ &= \ \frac{exp(\,V_{ij})\exp(\,\theta \times attri_i)}{\sum_{k=1}^{J_i} exp(\,V_{ik})\exp(\,\theta \times attri_i)} \\ &= \ P(Y_{ij} = 1) = \frac{exp(\,V_{ij})}{\sum_{k=1}^{J_i} exp(\,V_{ik})} \end{aligned} \tag{10}$$

The individual attribute is dropped from both the denominator and nominator. Hence, Equation (10) is identical to Equation (8). A detailed discussion can be found in Greene (2012, pp. 762).

Data

My dataset comprises technology (including both software and hardware) projects collected from *Kickstarter* from April 1, 2013, to December 31, 2014. Since the website was significantly changed from January 1, 2014, I focused on this period when the website was relative stable.

During the observation period, there were 13 project categories.[13] I focused on the projects listed under the "technology" category because these projects often offer pre-orders of a product prototype and a clear delivery date for the stated rewards (Mollick, 2014). Hence, the technology category includes many projects with significant potential to become a technology venture firm after a successful fundraising effort (e.g. Oculus Rift). Moreover, prior research has shown that technology projects attract the majority of funds from outside the creator's home region (Kim & Viswanathan, 2014). Given the promise of crowdfunding to overcome geographical constraints, I chose to focus only on projects in the technology category. The findings may also inform research on technology entrepreneurship.

When arriving at the website, a crowdfunder is presented with projects listed under four entries: "Most Funded", "Successfully Funded", "Popular", and "Staff Picks". I collected all the projects listed under these four entries. As *Kickstarter* did not disclose the time when a crowdfunder pledges his/her money, I constantly updated the backer information[14] and used these multiple snapshots to work out an estimation of the time when a backer backs a project. Given the sheer volume of data, I was able to collect a snapshot once every 4-7 days. In total, 753 projects were captured. To facilitate the comparison, I focused on projects that were denominated in US dollar. 625 US projects were

[13] They were Art, Comics, Dance, Design, Fashion, Film & Video, Food, Games, Music, Photography, Publishing, Technology, and Theater.

[14] *Kickstarter* refers the crowdfunders who have already pledged their funds as "backers". *Kickstarter* did not disclose backer information for projects with less than 10 backers. For these projects, I could not obtain when the crowdfunders backed the project.

used in my data analysis. For these projects, 220,361 backing decisions made by 151,816 crowdfunders were identified. I further split the backing decisions into two parts: decisions made from April 2013 to August 2013 was used for determining who were the experienced crowdfunders and decisions made from September 2013 to December 2013 was used for hypothesis testing. In sum, the empirical analysis was based on 87,396 decisions made by 70,612 crowdfunders during September 1, 2013, to December 31, 2013. Modeling all the backing decisions were beyond my computer's computational power. I thus randomly sampled 9,000 decisions for hypothesis testing. The results remained stable across different samples.

Constructing Choice Set

For each project-backing instance, I constructed a set of projects as alternatives for the crowdfunder. I considered all the projects that were open for funding at the time when the decision was made. A similar approach is used in Gompers, Mukharlyamov, and Xuan (2016). In studying how a founding venture capitalist chose partners, the authors constructed a set of plausible potential partners that were available for the venture capitalist to choose.

At any point in time, there were about 180 projects open for funding. To deal with the excessive choice set and reduce the computational burden, I followed the procedure described by McFadden (1978) by randomly sampling 39 choices together with the project chosen as the choice set. Changing the sampling number does not affect the results. For each crowdfunder i and the choice j, I constructed the following variables.

Crowdfunder Experience

I counted the number of technology projects backed as the crowdfunder's experience. To calculate the number, I leveraged the data I collected after the website change from January 2014. After the website change, projects were shown in a list and all the projects were revealed, including projects of which with less than 10 backers. For those crowdfunders I did not have the exact time when he/she backed the project,[15] I used the end date of the project campaign as a proxy of the time when he/she backed the project. This gave me a conservative estimate of the backer experience. For each backing decision made, I counted how many technology projects the crowdfunder had backed prior to this project as the crowdfunder's experience. I further corroborated the calculated number with the number of projects backed shown on the crowdfunder profile page I collected for 330,766 crowdfunders. For these 330,766 crowdfunders, the correlation coefficient between the estimated number of technology projects backed and the time-matched listed number of technology project backed on the profile page was 0.99. Simple linear regression using the listed number of projects as the dependent variable and the estimated number of projects backed as independent variable showed that the estimated coefficient was 0.98 (R-squared = 0.99), indicating that these two

[15] The backer information is revealed when there are more than 10 backers or the funding period is closed.

numbers were nearly identical. I thus relied on the estimated number of technology projects backed as the proxy for crowdfunder experience in the subsequent analysis.[16] I used the natural logarithm of the original variable and named it: $Log\ Exp$.

Cues

Number of Content Pictures and Number of Content Videos. The number of content pictures is the count of the pictures embedded in the project description. Natural logarithm of the original value is used. The variable is named: $Log\ Num\ Content\ Pic$. Similarly, the number of content videos is the count of the videos embedded in the project description (using natural logarithm of the original value). The variable is named: $Log\ Num\ Content\ Video$.

Number of Existing Crowdfunders. The number of existing crowdfunders is shown on the project page with the "Backers" tab and can be directly observed by a potential backer.[17] I used the number of existing crowdfunders cumulated for each project choice when the crowdfunder made the project backing decision. I took the natural logarithm of the original value and named this variable $Log\ Num\ Backer$.

[16] The projects collected before 2014 were a subset of all the projects available. To ensure these projects represent a random sample of the project population at that time, I compared this sample to the sample I collected after the website change when all the projects launched before 2014 became observable. I found no differences between the two samples in all the project attributes.
[17] The website has undergone several changes. Currently the number of existing crowdfunders cannot be directly observed from the project page. To find out the number, one has to first click on the "Community" tab, and find the number in the associated community page.

Content of the Information

Project Description Length. The length of project description is measured as the word count of the project description. Natural logarithm of the original variable is used. The variable is named: $Log\ Content\ Length$.

Number of Existing Experienced Crowdfunders. In order to determine who were the experienced crowdfunders, I split the data into two parts: data from April 2013 to August 2013 was used for determining who were the experienced crowdfunders and data from September 2013 to December 2013 was used for hypothesis testing. Table 12 shows the quantiles of backer experience. As shown in Table 12, about 10% of the crowdfunders had backed more than three projects as of August 2013. I thus considered these crowdfunders as the experienced crowdfunders in the dataset. For all the existing crowdfunders cumulated for each project choice, I calculated the percentage of experienced crowdfunders and named the variable *Per Expert*.

Table 12 Quantiles of Crowdfunder Experience

Quantile	Experience	Quantile	Experience
10%	1	94%	4
70%	1	95%	4
80%	2	96%	5
90%	3	97%	6
91%	3	98%	7
92%	3	99%	11
93%	4	100%	267

Negative Comments. I used a text analysis software called *Linguistic Inquiry and Word Count* (LIWC) to analyze the comments posted by existing crowdfunders. LIWC was developed by Pennebaker, Boyd, Jordan, and Blackburn (2015) for studying various emotional, cognitive, and structural components in text samples. It has become a popular tool for business researchers and been applied in various published studies (Goes, Lin, & Au Yeung, 2014; Hong, Huang, Burtch, & Li, 2016; Li, 2008; Yin, Bond, & Zhang, 2014). Central to LIWC is its proprietary dictionary comprised of about 6,400 words, word stems, and select emoticons, each being classified into one or more word categories (e.g. Anxiety and Anger).When running the software, each word in the input text is compared to the dictionary. If there is a match in the dictionary, the appropriate word category scale for the word is incremented. Finally, a final score for each word category is generated, representing the percentage of the words in the input text matching the category. Following Yin et al. (2014), I focused on two negative emotions embedded in the comments: anxiety and anger. The *Anxiety* word category includes 116 words such as "worried", "fearful" etc. The *Anger* word category includes 230 words such as "hate", "kill", "annoyed" etc. (Pennebaker et al., 2015). Each comment was processed by LIWC. The negative score was calculated as the percentage of anxiety words and anger words. For each project choice, the measure of negative comments is the average of the negative scores of all the comments posted prior to the time when the crowdfunder made the project backing decision. The variable is named as $Neg\ Comment$.

Control Variables

Drawing upon previous studies on *Kickstarter*, I also included several control variables in my models. First, I controlled for several project static measures that have been found to affect project funding success (Mollick, 2014).

$Hardorsoft$ is a dummy variable coded as "1" if the project belongs to the "Hardware" subcategory and coded as "0" if it belongs to the "Software" subcategory. $Duration$ is the number of days a project campaign can last. Typically, the duration of a project is 30 days. $Video\ Exist$ is a dummy variable coded as "1" if the project creators use a video to describe the project or not, and "0" otherwise. Project creators can upload either an image or a video to describe their idea. Most of the projects use a video. I also controlled for the project's goal size by using the natural logarithm of the original project goal ($Log\ Goal$).

Second, I also included several variables to control for project creators' characteristics. $Num\ Created$ is the number of projects the project creators had created prior to creating the focal project. Xu (2015) has shown that learning takes place for serial project creators and it improves funding outcomes. I controlled for the number of projects backed by the project creator ($Log\ Num\ Creator\ Backed$) following Colombo et al. (2015), who suggest that the number of projects backed by the project creator is a proxy for the social capital that the project creator develops within the platform. I controlled for creator's activeness by using the number of updates ($Log\ Num\ Update$). The number of project updates shows how often the creators update the project information. Mollick (2014) argues that preparedness is a signal of project quality that crowdfunders consider (Chen et al., 2009). I controlled for creator preparedness by counting the number of different rewards ($Log\ Num\ Categories$), assuming that more prepared project creators would create more types of rewards that cater to different crowdfunders.

Lastly, I controlled for several variables related to campaign dynamics. $Recommended$ is a dummy variable indicating if the campaign was featured in the projects recommended by *Kickstarter*. $Successful$ is a dummy variable indicating if the choice has met its funding goal by the time the backer made his/her backing decision. In *Kickstarter*, a successfully funded project can still receive funds as long as it has not reached the funding deadline. Herzenstein et al. (2011) have found that bidders are more likely to bid on an auction with more bids only to the extent at which it has received full funding. To control for the so-called "strategic herding", I included this variable in my models. $Stage$ is the percentage of the funding period that had elapsed since the project was launched. For all the logarithms, I added one to the original value before taking logarithm to overcome the non-negativity constraint. Table 13 describes the variables. Table 14 reports description statistics and correlation coefficients between variables.

Table 13 Study 2 Variable Description

No.	Variable	Description
1	Hardorsoft	A dummy variable coded as 1 if the project is a "Hardware" project, and coded as 0 if the project is a "Software" project.
2	Duration	The duration of the project. It shows how long the project is open for funding.
3	Video Exist	A dummy variable indicating if the project page contains a video.
4	Log Goal	The amount of the money the project aims to raise. Natural logarithm is used.
5	Num Created	Number of projects created by the project creator. A proxy for the project creator's experience.
6	Log Num Creator Backed	Number of projects backed by the project creator. A proxy for the project creator's social capital within the platform (Colombo et al., 2014). Natural logarithm is used.
7	Log Num Updates	Number of updates posted by the project creator. A proxy for creator activity. Natural logarithm is used.
8	Log Num Categories	Number of reward categories of the project. It measures how many kinds of rewards are offered by the project to potential backers. Natural logarithm is used.
9	Recommended	A dummy variable indicating if the project is featured in the "Recommended" Section.
10	Successful	A dummy variable indicating if the project has met its funding goal.
11	Stage	Percentage of time elapsed since the project is launched.
12	Log Num Content Pic	Natural logarithm of the number of pictures embedded in the project description.
13	Log Num Content Video	Natural logarithm of the number of videos embedded in the project description.
14	Log Content Length	Natural logarithm of the number of words in the project description.
15	Log Num Backer	Natural logarithm of the number of existing crowdfunders for the project at the time when the crowdfunder made the choice.
16	Per Expert	Percentage of experienced crowdfunders among the existing crowdfunders for the project at the time when the crowdfunder made the choice.
17	Neg Comment	Average negative score of the comments posted at the time when the crowdfunder made the choice.
18	Log Exp	Natural logarithm of the number of projects backed by the crowdfunder prior to making the focal decision.

As shown in Table 14, all the correlation coefficients are below 0.6. To test multicollinearity, I calculated variance inflation factor (VIF) for all the variables in my models including the interaction terms. All the VIFs were below 3, indicating that multicollinearity was not a serious concern. The conditional logistic models were estimated using CLOGIT command in Stata 12. To account for repeated observations of the same crowdfunder in the sample, I specified that the standard errors allow for intragroup correlation. All the interaction terms were centered before entering the model.

Table 14 Descriptive Statistics and Correlations

	Variable	Mean	S.D.	1	2	3	4	5	6	7
1	Hardorsoft	0.79	0.41	1.00						
2	Duration	36.15	9.83	0.05	1.00					
3	Video Exist	0.93	0.26	0.20	-0.01	1.00				
4	Log Goal	10.14	1.56	0.12	0.05	0.21	1.00			
5	Num Created	1.31	0.77	0.09	0.09	-0.13	-0.31	1.00		
6	Log Num Creator Backed	1.01	0.97	0.20	0.09	0.12	0.02	0.13	1.00	
7	Log Num Updates	0.90	0.76	0.22	0.05	0.21	0.06	0.08	0.32	1.00
8	Log Num Categories	2.24	0.44	0.08	0.08	0.21	0.24	-0.10	0.20	0.28
9	Recommended	0.12	0.32	0.08	0.06	0.10	0.07	-0.04	0.14	0.25
10	Successful	0.04	0.20	-0.03	0.03	-0.06	-0.01	-0.01	-0.02	-0.02
11	Stage	0.55	0.27	0.01	-0.09	0.08	-0.04	-0.01	0.00	0.39
12	Log Num Content Pic	2.30	0.95	0.43	0.21	0.32	0.31	-0.02	0.22	0.28
13	Log Num Content Video	0.45	0.60	0.17	0.11	0.16	0.15	-0.05	0.15	0.26
14	Log Content Length	7.17	0.62	0.28	0.02	0.34	0.30	-0.09	0.20	0.27
15	Log Num Backer	3.94	1.83	0.29	0.05	0.21	0.21	0.02	0.37	0.55
16	Per Expert	0.27	0.25	0.40	0.02	0.19	-0.08	0.25	0.19	0.25
17	Neg Comment	0.07	0.23	-0.01	-0.05	0.09	-0.02	-0.02	0.13	0.15

	Variable	8	9	10	11	12	13	14	15	16	17
9	Recommended	0.22	1.00								
10	Successful	-0.03	-0.01	1.00							
11	Stage	-0.04	0.05	-0.01	1.00						
12	Log Num Content Pic	0.43	0.13	-0.02	-0.06	1.00					
13	Log Num Content Video	0.28	0.17	-0.07	0.01	0.35	1.00				
14	Log Content Length	0.33	0.09	-0.04	0.02	0.52	0.35	1.00			
15	Log Num Backer	0.39	0.36	-0.01	0.17	0.37	0.22	0.25	1.00		
16	Per Expert	0.04	0.07	-0.21	0.12	0.21	0.13	0.16	0.36	1.00	
17	Neg Comment	0.04	0.01	-0.07	0.13	0.01	0.05	0.10	0.16	0.08	1.00

Note: Correlations more than 0.005 are statistically significant at the 0.001 level (two-tailed);
Num of Obs. = 360,000

Table 15 Regression Results

Coeffcient	Model 1		Model 2		Model 3		Model 4	
	Coef. (SE)	Marginal Effects (SE)	Coef. (SE)	Marginal Effects (SE)	Coef. (SE)	Marginal Effects (SE)	Coef. (SE)	Marginal Effects (SE)
Hardorsoft	-0.1202*	-0.0162*	-0.1184*	-0.0155*	-0.0461	-0.0019	-0.0383	-0.0015
	(0.0589)	(0.0079)	(0.0589)	(0.0078)	(0.0602)	(0.0024)	(0.0605)	(0.0024)
Duration	-0.0382***	-0.0052***	-0.0383***	-0.0050***	-0.039***	-0.0016***	-0.0389***	-0.0016***
	(0.0016)	(0.0003)	(0.0016)	(0.0003)	(0.0016)	(0.0002)	(0.0016)	(0.0002)
Video Exist	0.1908.	0.0258.	0.1896.	0.0249.	0.0834	0.0034	0.0779	0.0031
	(0.0985)	(0.0132)	(0.0987)	(0.0127)	(0.0989)	(0.0041)	(0.0987)	(0.0041)
Log Goal	-0.1201***	-0.0162***	-0.1197***	-0.0157***	-0.1142***	-0.0046***	-0.1138***	-0.0046***
	(0.0121)	(0.0017)	(0.0122)	(0.0018)	(0.012)	(0.0007)	(0.0121)	(0.0007)
Num Created	-0.1008***	-0.0136***	-0.0995***	-0.0131***	-0.1317***	-0.0054***	-0.1332***	-0.0053***
	(0.0203)	(0.0028)	(0.0203)	(0.0027)	(0.0201)	(0.0008)	(0.0202)	(0.0008)
Log Num Creator Backed	-0.0321**	-0.0043**	-0.0338**	-0.0044**	-0.0356**	-0.0014**	-0.0375**	-0.0015**
	(0.0123)	(0.0017)	(0.0123)	(0.0016)	(0.0124)	(0.0005)	(0.0124)	(0.0005)
Log Num Updates	-0.0098	-0.0013	-0.0135	-0.0018	-0.0178	-0.0007	-0.0178	-0.0007
	(0.0262)	(0.0035)	(0.0263)	(0.0034)	(0.0265)	(0.0011)	(0.0265)	(0.0011)
Log Num Categories	-0.1737***	-0.0235***	-0.1787***	-0.0234***	-0.1621***	-0.0066***	-0.1716***	-0.0069***
	(0.0403)	(0.0055)	(0.0403)	(0.0055)	(0.0403)	(0.0017)	(0.0404)	(0.0017)
Recommended	0.1385***	0.0187***	0.1404***	0.0184***	0.1309***	0.0053***	0.1295***	0.0052***
	(0.0292)	(0.0040)	(0.0293)	(0.0039)	(0.0296)	(0.0014)	(0.0297)	(0.0014)
Successful	0.4115	0.0556	0.3793	0.0497	0.4814	0.0196	0.4691	0.0188
	(0.9992)	(0.1350)	(0.9964)	(0.1306)	(1.0153)	(0.0419)	(1.0156)	(0.0413)
Stage	-2.2706***	-0.3067***	-2.2699***	-0.2977***	-2.2476***	-0.0913***	-2.2524***	-0.0901***
	(0.0618)	(0.0101)	(0.0617)	(0.0107)	(0.0622)	(0.0112)	(0.0623)	(0.0112)
Log Num Content Pic	0.0947***	0.0128***	0.0979***	0.0128***	0.0883***	0.0036***	0.0885***	0.0035***
	(0.0248)	(0.0034)	(0.0247)	(0.0033)	(0.0251)	(0.0010)	(0.0251)	(0.0010)
Log Num Content Video	0.0961***	0.0130***	0.0995***	0.0131***	0.0897***	0.0036***	0.0957***	0.0038***
	(0.0223)	(0.0031)	(0.0223)	(0.0030)	(0.0224)	(0.0010)	(0.0227)	(0.0010)
Log Content Length	-0.0914**	-0.0123**	-0.0919**	-0.0121**	-0.0678*	-0.0028*	-0.0694*	-0.0028*
	(0.0326)	(0.0045)	(0.0326)	(0.0042)	(0.0327)	(0.0011)	(0.0328)	(0.0011)
Log Num Backer	1.1443***	0.1546***	1.1439***	0.1500***	1.1522***	0.0468***	1.1517***	0.0461***
	(0.0117)	(0.0025)	(0.0117)	(0.0033)	(0.0117)	(0.0060)	(0.0117)	(0.0060)
Per Expert	1.8905***	0.2554***	1.8881***	0.2476***	1.6831***	0.0684***	1.6914***	0.0677***
	(0.0998)	(0.0121)	(0.0999)	(0.0116)	(0.0983)	(0.0094)	(0.0984)	(0.0094)
Neg Comment	-0.1548	-0.0209	-0.1581	-0.0207	-0.1221	-0.0050	-0.1305	-0.0052
	(0.1024)	(0.0139)	(0.1021)	(0.0135)	(0.1052)	(0.0043)	(0.1054)	(0.0043)
Log Num Content Pic			-0.0504**	-0.0066**			-0.0123	-0.0005
× Log Exp			(0.017)	(0.0022)			(0.0174)	(0.0007)
Log Num Content Video			-0.0843***	-0.0111***			-0.0530**	-0.0021**
× Log Exp			(0.0183)	(0.0024)			(0.0178)	(0.0008)
Log Content Length			0.0708**	0.0093**			0.0666**	0.0027*
× Log Exp			(0.0253)	(0.0033)			(0.0252)	(0.0011)
Log Num Backer					-0.0559***	-0.0023***	-0.0511***	-0.0020***
× Log Exp					(0.0102)	(0.0005)	(0.0104)	(0.0005)
Per Expert					1.2431***	0.0505***	1.2657***	0.0506***
× Log Exp					(0.0795)	(0.0073)	(0.0804)	(0.0074)
Neg Comment					-0.3111***	-0.0126**	-0.2988***	-0.0120**
× Log Exp					(0.0872)	(0.0039)	(0.0899)	(0.0040)
AIC	39087.73		39050.86		38422.69		38415.1	

Notes: Coefficient and standard deviation (in parentheses) presented.

Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Number of Observations: 360,000; Number of Cases: 9,000;

Results

Main Results

The results are reported in Table 15. Like many other non-linear models, the interpretation of the coefficients is not as straightforward as that in linear models. The marginal effects are dependent on the estimated coefficients and the specific data point (Ai & Norton, 2003). To make the interpretation more informative, I used a hypothetical case to calculate and plot probabilities at different data points using Equation (8). Consider a case where all alternatives are identical with all attributes set at the sample mean. In this case, the probability of any choice being chosen is 2.5% for all the 40 choices. Holding the remaining 39 choices constant, I then vary the attributes of the first choice and examine how the probability of it being chosen changes with the attributes.

Model 1 includes all the control variables together all the main effects. Crowdfunders seem to be less likely to choose projects with a longer duration ($\beta_{Duration} = -0.0382, p < 0.001$) and a larger project size ($\beta_{Log\ Goal} = -0.1201, p < 0.001$), as longer project duration and larger project size both decrease the probability of a project being chosen. Projects created by experienced project creators are less likely to be chosen ($\beta_{Num\ Created} = -0.1008, p < 0.001$). In general crowdfunders are less likely to choose projects created by project creators who have backed a high number of projects

($\beta_{Log\ Num\ Creator\ Backed} = -0.0321, p < 0.01$), contrary to the existing findings that creator social capital is an effective signal (Colombo et al., 2015; Giudici et al., 2013). The number of reward categories decreases the probability of a project being chosen ($\beta_{Log\ Num\ Categories} = -0.1737, p < 0.001$). Being featured in the "Recommended" section also increases the probability of a project being chosen ($\beta_{Recommended} = 0.1385, p < 0.001$). Lastly, crowdfunders are more likely to back projects at the early funding stage ($\beta_{Stage} = -2.2706, p < 0.001$).

Turning to the main effects of project signals, the coefficient of $Log\ Num\ Content\ Pic$ is positive and significant ($\theta_1 = 0.0947, p < 0.001$), suggesting that in general crowdfunders are more likely to back projects with more pictures embedded in the project description. The coefficient of $Log\ Num\ Content\ Video$ is also positive and significant ($\theta_2 = 0.0961, p < 0.001$). In general, projects with more videos embedded in the description are also more attractive to potential crowdfunders. Interestingly, the coefficient of $Log\ Content\ Length$ is negative and significant ($\theta_3 = -0.0914, p < 0.01$), suggesting that in general crowdfunders are less likely to back projects with a longer project description.

Turning to the main effects of variables representing social information, the coefficient of $Log\ Num\ Backer$ is positive and significant ($\theta_4 = 1.1443, p < 0.001$), suggesting that crowdfunders tend to back projects with a large number of existing backers. Similarly, the coefficient of $Per\ Expert$ is also positive and significant ($\theta_5 = 1.8905, p < 0.001$), suggesting that crowdfunders also tend to back projects with a high percentage of experienced backers. With respect to comments, the coefficient of $Neg\ Comment$ is negative but not significant ($\theta_6 = -0.1548, p > 0.1$), suggesting that in general, crowdfunders do not pay attention to the negative sentiment embedded in the comments posted by existing backers. My subsequent analysis shows that only the experienced crowdfunders are more likely to be influenced by the negative comments.

Model 2 includes interactions with respect to the project signals. Model 3 includes interactions with respect to the social information. Model 4 includes all the interactions. The estimated results are highly consistent across different model specifications. Hence, the following analysis is based on results in the full model (Model 4).

Turning to the project signals, *H1a* suggests that experienced crowdfunders are less likely than inexperienced crowdfunders to back projects that have more pictures embedded in the project description. The coefficient of the interaction term $Log\ Num\ Content\ Pic \times Log\ Exp$ is negative but not significant ($\alpha_1 = -0123, p > 0.1$). Hence, I did not find support for *H1a*. *H1b* posits that experienced crowdfunders are less likely than inexperienced crowdfunders to back projects that have more videos embedded in the project description. The coefficient of the interaction term $Log\ Num\ Content\ Video \times Log\ Exp$ is negative and significant ($\alpha_2 = -0.0530, p < 0.01$), providing support for *H1b*. My calculation shows that for a crowdfunder with zero prior experience, if $Log\ Num\ Content\ Video$ increases from one standard deviation below the mean (-0.15) to one standard deviation above the mean (1.05), or from 1 video to 3 videos for the choice, the probability of it being chosen would increase from 2.36% to 2.64%, an increase by 11.9%. For a crowdfunder who has backed 7 projects ($Log\ Exp = 2$), the same increase of $Log\ Num\ Content\ Video$ would slightly decrease the probability of the project being chosen from 2.52% to 2.48%, an decrease by 1.6%. The interaction is shown in Figure 5.1. *H2* posits that experienced crowdfunders are more likely than inexperienced crowdfunders to back projects that have a longer project description. The coefficient of the interaction term $Log\ Content\ Length \times Log\ Exp$ is positive and significant ($\alpha_3 = 0.0666, p < 0.01$), providing support for *H2*. For a crowdfunder with zero prior experience, if $Log\ Content\ Length$ increases from one standard deviation below the mean (6.55) to one standard deviation above the mean (7.79), or the length of the project description of a choice changes from 700 words to 2400 words, the probability of it being chosen would decrease from 2.61% to 2.40%, or an decrease by 8%. The effects, however, is the opposite for the experienced crowdfunders. For a crowdfunder who has backed 7 projects, the same change would actually increase from 2.41% to 2.60%. or an increase by 7.9%. The interaction is shown in Figure 5.2. It is clear that a longer project description has different meanings for inexperienced and experienced crowdfunders. Inexperienced crowdfunders seem to shy away from projects with longer description. It might be because that they do not have the ability to process the information embedded in the project description and might suffer from information overload (Jones, Ravid, & Rafaeli, 2004; Park & Lee, 2009). On the other hand, experienced crowdfunders have the ability to analyze the project description and scrutinize for valuable information embedded in the text hence favor projects with a longer description.

Turning to the social information, *H3* suggests that experienced crowdfunders are less likely than inexperienced crowdfunders to back projects that have already accumulated a large number of crowdfunders. The coefficient of the interaction term $Log\ Num\ Backer \times Log\ Exp$ is negative and significant, providing support for *H3* ($\alpha_4 = -0.0511, p < 0.001$). For a crowdfunder with zero prior experience, if $Log\ Num\ Backer$ increases from one standard deviation below the mean (2.11) to one standard deviation above the mean (5.77), or the number of backers increases from 8 to 320, the probability of the project being chosen by the crowdfunder would increase from 0.31% to 17.42%. This suggests that the number of existing crowdfunders is an important factor affecting crowdfunders' decisions. For experienced crowdfunders, the effect is less strong. For a crowdfunder who has backed 7 projects ($Log\ Exp = 2$), the same increase would only increase the probability of the project being chosen by the crowdfunder from 0.37% to 14.89%. The interaction is plotted in Figure 5.3. *H4* suggests that experienced crowdfunders are more likely than inexperienced crowdfunders to back projects that have already accumulated a high percentage of experienced crowdfunders. *H4* is supported. The coefficient of the interaction term $Per\ Expert \times Log\ Exp$ is positive and significant ($\alpha_5 = 1.2657, p < 0.001$). For a crowdfunder with zero prior experience, if $Per\ Expert$ increases from 2% to 52%, the probability of the project being chosen by the crowdfunder would increase from 1.65% to 37.7%, whereas for a crowdfunder who has backed 7 projects ($Log\ Exp = 2$) the same increase would increase the probability of the project being chosen from 0.88% to 68.3%. The interaction plot is shown in Figure 5.4. Lastly, *H5* hypothesizes that experienced crowdfunders are more likely than inexperienced crowdfunders to void projects that have received negative comments. The main effect of $Neg\ Comment$ is negative, although it is not significant ($\theta_6 = -0.1305, p > 0.1$). This is consistent with my expectation that crowdfunders would avoid projects that have received negative comments. The interaction term $Neg\ Comment \times Log\ Exp$ is negative and significant ($\alpha_6 = -0.2988, p < 0.001$), supporting *H5*. Hence, only the experienced crowdfunders would pay attention to the neative comments. For a crowdfunder with zero prior experience, if $Neg\ Comment$ increases from 0 to 0.3, the probability of the project being chosen by the crowdfunder would slightly decrease from 2.52% to 2.43%. By contrast, for a crowdfunder who has backed 7 projects ($Log\ Exp = 2$), the same increase would decrease the probability of the project being chosen from 2.63% to 2.12%. The interaction plot is shown in Figure 5.5.

Figure 5.1 Number of Videos against Probability of Being Chosen (H1b)

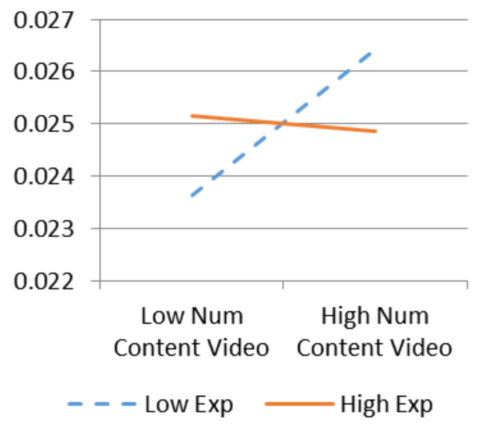


Figure 5.2 Content Length against probability of being Chosen (H2)

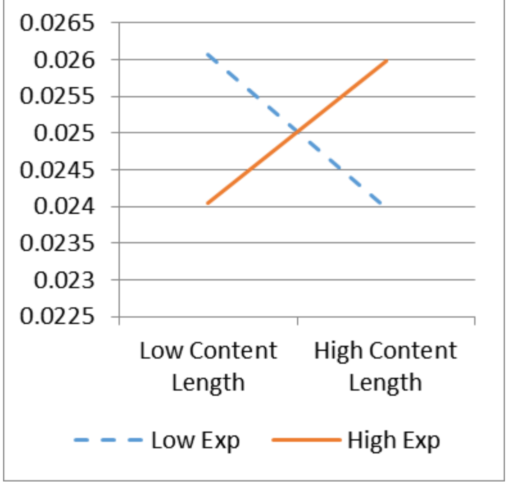


Figure 5.3 Number of Backers against Probability of Being Chosen (H3)

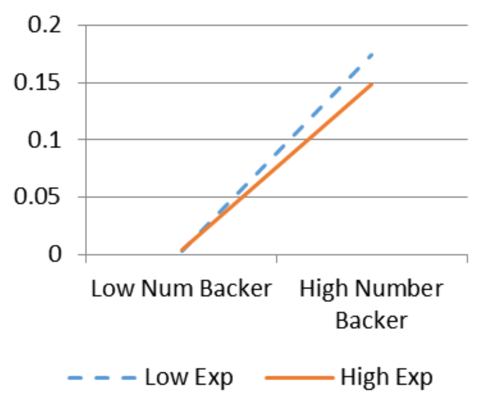
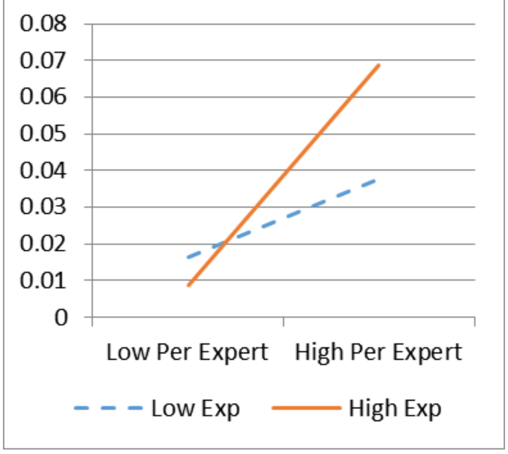


Figure 5.4 Percentage of Experts against Probability of being Chosen (H4)



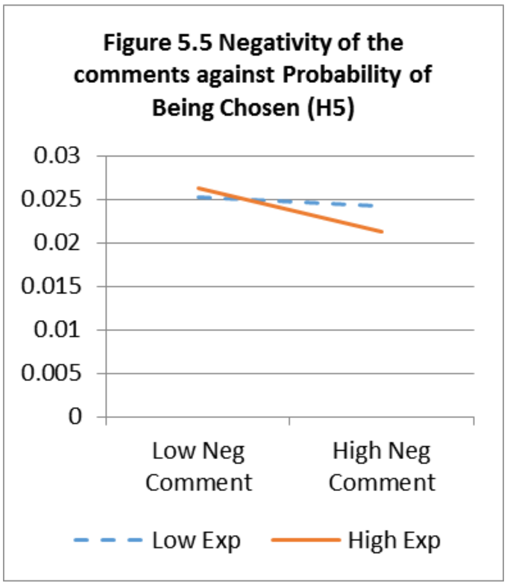


Figure 5 Interaction Plots

Robustness Tests

I also conducted several robustness tests. First, I re-estimated the population-averaged effects using generalized estimating equation (GEE). The estimated effects were similar to my main results. The estimated results are shown in Table 16. In addition to the population-averaged effects, I also estimated the results using random effects models. The results are also similar to the main results. The estimated results are shown in Table 17. Second, I tested if changing the cut-off number for experienced crowdfunders would change the results. In the main analysis, I treated the top 10% crowdfunders in terms of the number of projects backed as the experienced crowdfunders. I re-estimated the models using 5% as the cut-off value for experienced crowdfunders. The results are included in Table 18. Third, I also tested if changing the way the choice set was constructed would change the results. To test this, I considered projects listed on the same page with the chosen project as the choice set. The results are presented in Table 19. All the robustness tests show that results remain qualitatively similar to my main results.

Table 16 Robustness Check 1: GEE Population Averaged Models

Coefficient	Model 1	Model 2	Model 3	Model 4
	GEE Population Averaged	GEE Population Averaged	GEE Population Averaged	GEE Population Averaged
Constant	-5.4270***	-6.0091***	-0.7818**	-0.7947**
	(0.2378)	(0.1974)	(0.2357)	(0.2357)
Hardorsoft	-0.0023	-0.0046	0.0438	0.0530
	(0.0549)	(0.0549)	(0.0556)	(0.0557)
Duration	-0.0364***	-0.0364***	-0.0377***	-0.0375***
	(0.0016)	(0.0016)	(0.0016)	(0.0016)
Video Exist	-0.0211	-0.0073	-0.1160	-0.1125
	(0.0972)	(0.0974)	(0.0974)	(0.0975)
Log Goal	-0.0996***	-0.0997***	-0.0946***	-0.0962***
	(0.0122)	(0.0122)	(0.0122)	(0.0122)
Num Created	-0.0661**	-0.0643**	-0.0978***	-0.0990***
	(0.0218)	(0.0218)	(0.0218)	(0.0219)
Log Num Creator Backed	-0.0246*	-0.0264*	-0.0280*	-0.0292*
	(0.0124)	(0.0124)	(0.0125)	(0.0125)
Log Num Updates	0.0144	0.0110	0.0094	0.0089
	(0.0258)	(0.0258)	(0.0259)	(0.0260)
Log Num Categories	-0.2486***	-0.2515***	-0.2340***	-0.2426***
	(0.0368)	(0.0368)	(0.0370)	(0.0371)
Recommended	0.2969***	0.2961***	0.2813***	0.2796***
	(0.0279)	(0.0280)	(0.0282)	(0.0282)
Successful	0.1711**	0.1703**	0.0720	0.0778
	(0.0575)	(0.0577)	(0.0583)	(0.0584)
Stage	-2.4548***	-2.4563***	-2.4402***	-2.4444***
	(0.0632)	(0.0632)	(0.0635)	(0.0635)
Log Num Content Pic	0.0816***	0.0815***	0.0752**	0.0739**
	(0.0230)	(0.0230)	(0.0232)	(0.0232)
Log Num Content Video	0.1715***	0.1708***	0.1652***	0.1688***
	(0.0226)	(0.0226)	(0.0227)	(0.0227)
Log Content Length	-0.1176***	-0.1130***	-0.1059**	-0.1007**
	(0.0312)	(0.0312)	(0.0312)	(0.0312)
Log Num Backer	1.1275***	1.1279***	1.1405***	1.1409***
	(0.0097)	(0.0097)	(0.0098)	(0.0098)
Per Expert	1.1523***	1.1543***	1.0559***	1.0625***
	(0.0824)	(0.0824)	(0.0832)	(0.0833)
Neg Comment	-0.4062***	-0.4045***	-0.4091***	-0.4182***
	(0.0842)	(0.0841)	(0.0857)	(0.0857)

Log Num Content Pic	-0.0108		0.0274
× Log Exp	(0.0154)		(0.0168)
Log Num Content Video	-0.1068***		-0.0786***
× Log Exp	(0.0185)		(0.0181)
Log Content Length	0.0949***		0.0725**
× Log Exp	(0.0245)		(0.0244)
Log Num Backer		-0.0364***	-0.0384***
× Log Exp		(0.0038)	(0.0044)
Per Expert		1.1744***	1.1681***
× Log Exp		(0.0463)	(0.0467)
Neg Comment		-0.5132***	-0.5486***
× Log Exp		(0.0763)	(0.0786)

Notes: Coefficient and standard deviation (in parentheses) presented.
Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Number of Observations: 360,000; Number of Cases: 9,000;
Data grouped by case.

Table 17 Robustness Check 2: Random Effects Models

Coefficient	Model 1	Model 2	Model 3	Model 4
	Random Effects	Random Effects	Random Effects	Random Effects
Constant	-5.5178***	-6.2048***	-0.7222**	-0.7266**
	(0.2412)	(0.2010)	(0.2372)	(0.2372)
Hardorsoft	-0.0420	-0.0429	0.0079	0.0164
	(0.0554)	(0.0554)	(0.0560)	(0.0562)
Duration	-0.0371***	-0.0371***	-0.0382***	-0.0380***
	(0.0016)	(0.0016)	(0.0016)	(0.0016)
Video Exist	0.0002	0.0108	-0.0988	-0.0976
	(0.0983)	(0.0985)	(0.0984)	(0.0985)
Log Goal	-0.0966***	-0.0968***	-0.0912***	-0.0926***
	(0.0122)	(0.0122)	(0.0122)	(0.0122)
Num Created	-0.0790***	-0.0774***	-0.1115***	-0.1128***
	(0.0219)	(0.0219)	(0.0218)	(0.0220)
Log Num Creator Backed	-0.0208.	-0.0226.	-0.0248*	-0.0261*
	(0.0125)	(0.0125)	(0.0125)	(0.0125)
Log Num Updates	0.0198	0.0161	0.0135	0.0132
	(0.0259)	(0.0260)	(0.0261)	(0.0261)
Log Num Categories	-0.2481***	-0.2514***	-0.2329***	-0.2423***
	(0.0372)	(0.0372)	(0.0373)	(0.0374)
Recommended	0.2722***	0.2723***	0.2571***	0.2558***
	(0.0283)	(0.0283)	(0.0285)	(0.0285)
Successful	0.2895***	0.2870***	0.1785**	0.1840**
	(0.0642)	(0.0643)	(0.0647)	(0.0649)
Stage	-2.4891***	-2.4907***	-2.4673***	-2.4724***
	(0.0642)	(0.0642)	(0.0644)	(0.0644)
Log Num Content Pic	0.0764**	0.0764**	0.0697**	0.0685**
	(0.0232)	(0.0232)	(0.0234)	(0.0233)
Log Num Content Video	0.1638***	0.1644***	0.1581***	0.1621***
	(0.0227)	(0.0227)	(0.0228)	(0.0228)
Log Content Length	-0.1307***	-0.1274***	-0.1182***	-0.1138***
	(0.0315)	(0.0315)	(0.0315)	(0.0315)
Log Num Backer	1.1544***	1.1546***	1.1652***	1.1655***
	(0.0106)	(0.0106)	(0.0107)	(0.0107)
Per Expert	1.3635***	1.3642***	1.2557***	1.2622***
	(0.0862)	(0.0861)	(0.0867)	(0.0868)
Neg Comment	-0.4508***	-0.4484***	-0.4374***	-0.4464***
	(0.0872)	(0.0871)	(0.0883)	(0.0883)
Log Num Content Pic × Log Exp		-0.0247		0.0192
		(0.0156)		(0.0168)

Log Num Content Video × Log Exp		-0.1027*** (0.0186)		-0.0757*** (0.0182)
Log Content Length × Log Exp		0.0911*** (0.0247)		0.0729** (0.0244)
Log Num Backer × Log Exp			-0.0388*** (0.0039)	-0.0397*** (0.0045)
Per Expert × Log Exp			1.2011*** (0.0483)	1.1966*** (0.0487)
Neg Comment × Log Exp			-0.4627*** (0.0780)	-0.4942*** (0.0804)
	56182.54	56143.56	55540.31	55522.94

Notes: Coefficient and standard deviation (in parentheses) presented.
Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Number of Observations: 360,000; Number of Cases: 9,000;
Data grouped by case.

Table 18 Robustness Check 3: Using Top 5% as the Experienced Crowdfunders

Coefficient	Model 1	Model 2	Model 3	Model 4
	Coef. (SE)	Coef. (SE)	Coef. (SE)	Coef. (SE)
Hardorsoft	-0.2497***	-0.2507***	-0.2088***	-0.2033***
	(0.0535)	(0.0534)	(0.0548)	(0.0549)
Duration	-0.0356***	-0.0355***	-0.0363***	-0.0363***
	(0.0015)	(0.0015)	(0.0015)	(0.0015)
Video Exist	0.2880**	0.2855**	0.2586**	0.2465*
	(0.0961)	(0.0959)	(0.0966)	(0.0963)
Log Goal	-0.0777***	-0.0772***	-0.0741***	-0.0740***
	(0.0142)	(0.0142)	(0.0141)	(0.0141)
Num Created	-0.1769***	-0.1755***	-0.1804***	-0.1807***
	(0.0229)	(0.0229)	(0.0225)	(0.0226)
Log Num Creator Backed	-0.0604***	-0.0615***	-0.0589***	-0.0601***
	(0.0129)	(0.0129)	(0.0130)	(0.0130)
Log Num Updates	0.0567*	0.0527*	0.0408	0.0421
	(0.0257)	(0.0258)	(0.0259)	(0.0260)
Log Num Categories	-0.0506	-0.0544	-0.0500	-0.0568
	(0.0367)	(0.0366)	(0.0365)	(0.0366)
Recommended	0.2195***	0.2200***	0.2199***	0.2191***
	(0.0295)	(0.0296)	(0.0298)	(0.0299)
Successful	0.1728	0.1720	0.1620	0.1500
	(0.8233)	(0.8275)	(0.8646)	(0.8664)
Stage	-2.5383***	-2.5349***	-2.4885***	-2.4956***
	(0.0644)	(0.0643)	(0.0645)	(0.0647)
Log Num Content Pic	0.0000***	0.0000***	0.0000***	0.0000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Log Num Content Video	0.0603**	0.0641**	0.0475*	0.0496*
	(0.0211)	(0.0212)	(0.0213)	(0.0215)
Log Content Length	-0.1766***	-0.1758***	-0.1551***	-0.1588***
	(0.0317)	(0.0317)	(0.0320)	(0.0320)
Log Num Backer	1.1032***	1.1027***	1.1105***	1.1101***
	(0.0113)	(0.0113)	(0.0113)	(0.0113)
Per Expert	1.9858***	1.9817***	1.9283***	1.9388***
	(0.0778)	(0.0777)	(0.0767)	(0.0767)
Neg Comment	0.1152	0.1165	0.1350	0.1309
	(0.0885)	(0.0882)	(0.0902)	(0.0904)
Log Num Content Pic		0.0000**		0.0000
× Log Exp		(0.0000)		(0.0000)
Log Num Content Video		-0.0840***		-0.0297.
× Log Exp		(0.0167)		(0.0164)

Log Content Length		0.0679**		0.0574**
× Log Exp		(0.0223)		(0.0219)
Log Num Backer			-0.0832***	-0.0874***
× Log Exp			(0.0092)	(0.0101)
Per Expert			0.8796***	0.8758***
× Log Exp			(0.0624)	(0.0624)
Neg Comment			-0.2554**	-0.2529**
× Log Exp			(0.0827)	(0.0847)
AIC	38955.81	38924.76	38413.77	38409.06

Notes. Coefficient and standard deviation (in parentheses) presented.
Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Number of Observations: 360,000
Number of Cases: 9,000

Table 19 Robustness Check 4: Using Projects on the Same Page as the Choice Set

Coefficient	Model 1	Model 2	Model 3	Model 4
	Coef. (SE)	Coef. (SE)	Coef. (SE)	Coef. (SE)
Hardorsoft	-0.1056*	-0.1009*	-0.0671	-0.0552
	(0.0493)	(0.0493)	(0.0502)	(0.0505)
Duration	-0.0285***	-0.0286***	-0.0293***	-0.0292***
	(0.0016)	(0.0016)	(0.0016)	(0.0016)
Video Exist	0.4432***	0.4432***	0.3493**	0.3337**
	(0.1075)	(0.1081)	(0.1086)	(0.1073)
Log Goal	-0.0434**	-0.0445**	-0.0464**	-0.0445**
	(0.0163)	(0.0164)	(0.0162)	(0.0163)
Num Created	-0.1377***	-0.1377***	-0.1643***	-0.1636***
	(0.0202)	(0.0202)	(0.0206)	(0.0205)
Log Num Creator Backed	-0.1261***	-0.1276***	-0.1242***	-0.1246***
	(0.0147)	(0.0147)	(0.0148)	(0.0148)
Log Num Updates	0.1651***	0.1619***	0.1465***	0.1511***
	(0.0300)	(0.0301)	(0.0301)	(0.0302)
Log Num Categories	-0.0791*	-0.0888*	-0.0724*	-0.0848*
	(0.0359)	(0.0358)	(0.0358)	(0.0361)
Recommended	-0.0030	-0.0037	-0.0140	-0.0130
	(0.0291)	(0.0292)	(0.0297)	(0.0297)
Successful	-17.3032***	-17.295***	-17.3275***	-17.3197***
	(0.0614)	(0.0616)	(0.0618)	(0.0626)
Stage	-2.5902***	-2.5903***	-2.5606***	-2.5728***
	(0.0669)	(0.0668)	(0.0672)	(0.0675)
Log Num Content Pic	-0.0000***	-0.0000***	-0.0000***	-0.0000***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Log Num Content Video	0.0542*	0.0628**	0.0464*	0.0493*
	(0.0234)	(0.0235)	(0.0235)	(0.0237)
Log Content Length	-0.2433***	-0.2430***	-0.2154***	-0.2250***
	(0.0337)	(0.0338)	(0.0339)	(0.0341)
Log Num Backer	1.1031***	1.1027***	1.1150***	1.1144***
	(0.0147)	(0.0147)	(0.0147)	(0.0148)
Per Expert	2.3195***	2.3058***	2.1111***	2.1457***
	(0.0990)	(0.0989)	(0.1005)	(0.1008)
Neg Comment	0.0842	0.0842	0.0766	0.0702
	(0.0916)	(0.0916)	(0.0925)	(0.0933)
Log Num Content Pic		0.0000		0.0000***
× Log Exp		(0.0000)		(0.0000)
Log Num Content Video		-0.0989***		-0.0492**
× Log Exp		(0.0178)		(0.0177)

Log Content Length		0.0943***		0.1068***
× Log Exp		(0.0225)		(0.0222)
Log Num Backer			-0.0927***	-0.1002***
× Log Exp			(0.0120)	(0.0128)
Per Expert			1.0163***	1.0356***
× Log Exp			(0.0956)	(0.0972)
Neg Comment			-0.2265**	-0.2253**
× Log Exp			(0.0757)	(0.0775)
AIC	29813.65	29781.37	29290.62	29254.8

Notes. Coefficient and standard deviation (in parentheses) presented.
Significance codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
Number of Observations: 135,000
Number of Cases: 9,000

Discussion

In this chapter, I investigate how crowdfunder experience might affect a crowdfunder's reliance on the information provided on the project campaign page to overcome the information asymmetry problem and make decisions. Drawing upon the Elaboration Likelihood Model (ELM), I hypothesize that crowdfunders' ability to extensively process information increases with their experience. As a result, experienced crowdfunders are more likely to process information via the central route and rely more on the content of the information. In contrast, inexperienced crowdfunders are more likely to process information via the peripheral route and rely more on the cues. Drawing upon existing studies on how crowdfunders might overcome the information asymmetry problem, I propose a set of hypotheses with regard to two types information provided on the project campaign page: project signals and social information. All of my five hypotheses were supported by data collected from *Kickstarter*.

First, I find evidence showing that crowdfunders tend to choose projects with more pictures and videos in the project description, although the effects of pictures are less strong. This suggests that crowdfunders do consider these simple cues as signals of project quality in making decisions. Moreover, the effects of these simple cues are stronger for the relative inexperienced crowdfunders because these crowdfunders do not have the ability to process the information extensively. When crowdfunders gain experience, their ability to elaborate the information increases. As a result, they will pay more attention to the content of the information. My results show a stark contrast between the experienced crowdfunders and the inexperienced crowdfunders. Inexperienced crowdfunders are less likely to back projects with a longer description, showing that they might not have the ability to process the information embedded in the description and might suffer from information overload (Jones et al., 2004). Experienced crowdfunders, on the other hand, tend to back projects with a longer description. This might be because the length of the description is a proxy of some important information embedded in the description (Chevalier & Mayzlin, 2006).

Second, I find that the number of existing crowdfunders who have already pledged their money to the project influences both experienced and inexperienced crowdfunders, consistent with several studies that have found that herding takes place in lending-based crowdfunding (Herzenstein et al., 2011; Zhang & Liu, 2012). Two mechanisms have been proposed to account for the observed herding phenomena in crowdfunding: network externalities and informational cascades.[18] Network externalities take place when the payoff of making a decision increases with the number of people who make the same decision (Katz & Shapiro, 1985, 1986). Adopting the network externalities perspective, Li and Duan (2014) argue that crowdfunders are more likely to back a project that has already attracted a critical mass of funding. In the

[18] Bikhchandani et al. (1992) summarize four mechanisms for uniform social behaviour: (1) sanctions on deviants, (2) positive payoff externalities, (3) conformity preference, and (4) communication (pp. 993).

context of lending-based crowdfunding, both Herzenstein et al. (2011) and Zhang and Liu (2012) adopt the information cascades perspective, arguing that herding is informational and individuals follow others' decisions because they believe that others might have superior information about the quality of the project. My argument and findings are in line with the latter perspective, that herding is informational. Facing the information asymmetry problem, crowdfunders rely on other crowdfunders to derived additional information about the quality of the project. I also find that experienced crowdfunders are less likely to herd, which is also consistent with the observational learning perspective (Venezia, Nashikkar, & Shapira, 2011). Experienced crowdfunders tend to rely more on their own experiences and are more confident in their own judgment and are less reliance on others when making decisions (Cheung et al., 2014; Park & Kim, 2008). Furthermore, the experienced crowdfunders tend to herd strategically by attributing the privileged information held by other experienced crowdfunders instead of relying on the summary statistics provided on the page (Quiamzade & L'Huillier, 2009). This is explained by the ELM, as these experienced crowdfunders have the ability to analyze the detailed backer information provided on the backer page.

Third, I find that in addition to the decisions made by existing crowdfunders, the comments contributed by existing crowdfunders also provide additional information to potential crowdfunders (Chen et al., 2011; Cheung et al., 2014). Consistent with existing findings, I find that negative comments influence crowdfunders decisions. I also find such effect is stronger for experienced crowdfunders, consistent with the prediction of the Elaboration Likelihood Model.

Lastly, I find significant individual differences among crowdfunders in using the information provided on the campaign page to make funding decisions. Such differences are predicted by the Elaboration Likelihood Model. Although both project signals and social information are important for a crowdfunder, I find that the importance might vary for different crowdfunders. As crowdfunders gain experience, they pay more attention to the content of the information rather than rely on simple cues. In the following part, I discuss the implications of this study for research and practice.

Implications for Research

My research has several implications for research. First, this study highlights the importance of incorporating crowdfunder heterogeneity in theorizing on crowdfunder behavior. Prior studies that study crowdfunder behavior tend to focus on the project level analysis, with the assumption that crowdfunders are homogeneous and rely on the same information in making funding decisions (Herzenstein et al., 2011; Zhang & Liu, 2012). My findings suggest that contextual factors, such as crowdfunder experience, might moderate the effects of the constructs of interest. In fact, this study shows that the number of videos and the length of the project description might have opposite effects on inexperienced crowdfunders and experienced crowdfunders. Hence, differences in findings might be partly attributed to methodological shortcoming: that researchers conduct project level analysis and do not control for individual differences either because researchers are not aware of the effects of individual differences or because the data do not provide such information. For example, if the dataset is obtained from a relatively established site where most crowdfunders have joined the site for a long time and are relatively experienced, researchers are less likely to find that crowdfunders favor projects with more videos in the description. Future research can also explore other factors, such the breadth of crowdfunder interest (Hahn & Lee, 2013; Inbar & Barzilay, 2014) and consumer domain knowledge (Mollick & Nanda, 2015), and how they might affect crowdfunder decision making.

Second, my research also contributes to the crowdfunding literature on the effects of crowdfunder experience. Although the effects of experience on decision tasks have been studied in the accounting and finance literature (Clement, 1999; Clement & Tse, 2005; Ho, 1994; Jacob et al., 1999; Libby & Frederick, 1990; Nicolosi et al., 2009), there is still limited understanding about how crowdfunder experience might affect decision making. In fact, differences between inexperienced and experienced individuals are more important in the context of crowdfunding, where a project' funding success is determined by both experienced and inexperienced crowdfunders. This is different from many accounting and investing tasks, where the experienced individuals usually make the important decisions. Future research could follow the crowdfunder community longitudinally and examine how the composition of experienced and inexperienced crowdfunders evolve, and how that affects project funding outcomes and the platform's overall funding activities.

Third, my research also contributes to the online word-of-mouth literature. So far, literature on the effects of electronic word-of-mouth has mainly focused on consumer products such as movies (Duan et al., 2008) and books (Chevalier & Mayzlin, 2006) through mechanisms of increasing awareness (Berger, Sorensen, & Rasmussen, 2010) and persuasion (Dellarocas, Zhang, & Awad, 2007). This study offers a different perspective, that comments posted by existing crowdfunders during the campaign can help provide further diagnostic information for potential crowdfunders in facing the information asymmetry problem. Furthermore, this study also points out one of the contingencies: that the effects of these comments are partially dependent on the crowdfunder's ability to analyze the comments (Jones et al., 2004; Park & Lee, 2009). In fact, inexperience crowdfunders do not pay attention to these comments. Future research could further explore other factors that may affect crowdfunders' reliance on the comments, such as their motivation to receive rewards.

Lastly, the differences between inexperienced and experienced crowdfunders suggest that learning might be taking place in crowdfunding. Several studies have begun to examine learning from the project creator's perspective (Xu, 2015; Yang & Hahn, 2015). Xu (2015) finds that project creators update their beliefs based on the feedback from their previous projects. Yang and Hahn (2015) document that direct learning from serial project founding experiences and indirect learning from backing projects both provide positive feedback to the project creator. My findings suggest that learning might also take place for the crowdfunders (Freedman & Jin, 2011). Future research could conduct longitudinal studies on the learning of the crowdfunders. This study also suggests that crowdfunders might also participate in crowdfunding activities to learn. They might be using crowdfunding platforms as a place to get exposure to creative ideas and they might also be funding projects to practice their investing strategies. Research can explore what crowdfunders learn from participating in crowdfunding activities and how these experiences affect their subsequent strategies and other activities in the organization (e.g. creativity or VC investment).

Implications for Practice

This study also has several implications for practice. First, for project creators, my research suggests that they should consider different strategies depending on the composition of the crowdfunder community. If the majority of the crowdfunders are inexperienced, seeding strategies might be important, as these crowdfunders focus more on the summary statistics such as the number of existing crowdfunders and the number of comments. Getting a critical mass by momentum building at the early funding stage is important for funding success (Li & Duan, 2014). Off-line social networks such as friends and family might be helpful (Agrawal et al., 2015b). The project creators could consider inviting friends and family to provide seed funds for their projects. On the other hand, if the crowdfunder community is relatively experienced, it is more important to attract the experienced crowdfunders at the early stage of the funding process. The project creator might consider seeking endorsement from experienced crowdfunders. In this case, offline social networks might also help. Project creators should also realize that inexperienced crowdfunders might not have the ability to process the rich information provided in the text description. Hence, using more videos and pictures would be an effective strategy to attract these inexperienced crowdfunders. For experienced crowdfunders, they should provide detailed description of the project. They should also carefully manage the comments and address the concerns of existing backers quickly, as experienced crowdfunders would pay attention to these types of information.

Second, managers can develop different strategies depending on the crowdfunder composition. For a platform where the crowdfunders are relatively new to this new phenomenon, the managers should try to make summary statistics (e.g. number of backers) more visible to subsequent crowdfunders. They should also advise project creators to use a succinct textual description but embed more pictures and videos to illustrate their ideas. On the other hand, if the crowdfunding platform is reaching a mature stage where most of the crowdfunders are relatively experienced, managers should try to provide rich information for potential crowdfunders to make decisions, as these crowdfunders are more likely to pay attention to the details in the information. For example, they can provide a summary of projects backed by the crowdfunder in order for potential crowdfunders to judge on the expertise of the crowdfunder.[19] They may introduce a badge system to show who the most active crowdfunders are and who contribute the most.

Third, regarding comments, platform managers should realize that not all the crowdfunders have the cognitive ability to process the comments. Much like online word-of-mouth, backers are allowed to post comments freely. Potential crowdfunders might suffer from the overload of a large number of short comments and may not be able to derive useful information from these comments. Managers could introduce sorting mechanisms to identify the most valuable comments. Managers can also consider providing comment helpfulness ratings as in *Quora* and *Amazon* (Ghose & Ipeirotis, 2011). All those would also help the relatively inexperienced crowdfunders make decisions.

Limitations

My research has several limitations. First, I am constrained by the empirical quantitative approach. Although my results are robust and fit the proposed ELM framework well, I could not rule out all the possible alternative mechanisms. Further lab experiments and survey research are encouraged. My second limitation is that my research is based on a single crowdfunding site. Hence, I was not able to triangulate my findings with findings from other sites. Third, although many crowdfunding sites enjoy a certain level of resemblance in their platform design, I was not able to test if different layouts of the

[19] *Kickstarter* used to provide such information, but the crowdfunder profile page is no longer available.

information would affect crowdfunders' decisions. Longitudinal studies of the same platform and cross-platform comparisons can help to substantiate the findings.

CHAPTER 5 CONCLUSION

Crowdfunding is becoming an important fundraising source for creative projects. It allows fundraisers to tap on a broader audience to pool financial resources in support of initiatives. The current literature tends to assume that crowdfunders are a homogeneous group adopting a certain strategy or exhibiting a certain behavior. Having that assumption, most of the studies tend to conduct analysis at the project level. However, the nature of crowdfunding suggests that the participants might be more diverse, as crowdfunding platforms tend to have limited entry barriers to participants so that everyone with Internet access can participate in crowdfunding campaigns. Hence, it is likely that crowdfunders might exhibit different behaviors and adopt different strategies.

Following prior studies on crowdfunder heterogeneity (Hahn & Lee, 2013; Inbar & Barzilay, 2014), I start to explore the heterogeneity of crowdfunders in this dissertation. Inspired by the "influentials" vs. "imitators" hypothesis and drawing upon the opinion leadership literature, I employed an inductive exploratory research to explore the archetypes of crowdfunders along three dimensions: risk preferences, involvement, and interest concentration. My results revealed five distinct types of crowdfunders: the *Silent Actives,* the *Vocal Actives*, the *Focused Enthusiasts*, the *Trend Followers* and the *Star Seekers*, each adopting a certain strategy and exhibiting a certain behavior. These results confirm that the "influentials" vs "imitators" hypothesis applies to the crowdfunding context to some extent but cannot explain all the differences among different crowdfunders. Having identified different types of crowdfunders, I further examined two important questions related to the archetypes. First, I examine how the different funding strategies and behaviors are associated with the crowdfunders' funding success (i.e. backing projects that have successfully funded). I find that a crowdfunder's funding success is consistent with his/her strategy. The *Vocal Actives* and the *Silent Actives*, being more risk seeking, achieve lower success rate compared to the *Trend Followers* and the *Star Seekers*. Second, I investigate the evolution of different types of crowdfunders over time. My results show that the *Vocal Actives* and the *Silent Actives* are relative stable across time but the rest three types tend to evolve into other types.

Having identified different types of crowdfunders, in the second research project, I focused on one of the most visible and important dimensions of crowdfunder heterogeneity – crowdfunder experience and examined how it affect crowdfunders' reliance on the information provided on the project campaign page to overcome the information asymmetry problem. Drawing upon the Elaboration Likelihood Model (ELM), I argue that the experience of a crowdfunder increases his/her ability to elaborate the information provided on the project campaign page. Experienced crowdfunders are more likely to process the information via the central route and rely more on the actual content of the project information. Inexperienced crowdfunders are more likely to process information via the peripheral route and rely more on simple cues. Drawing upon existing literature, I propose a set of hypotheses related to how crowdfunders overcome the information asymmetry problem via mechanisms: the signaling mechanism (Spence, 1973) and the observational learning mechanism (Banerjee, 1992; Bikhchandani et al., 1992). My hypotheses are supported by data collected from *Kickstarter*. With respect to the signaling mechanism, I find that inexperienced crowdfunders are more likely to pay attention to the number of videos embedded in the project description, as the number of videos is relatively visible and require less cognitive processing. By contrast, I find that experienced crowdfunders favor projects with a long text description because they are more likely to elaboration the information provided in the project description. With respect to the observational learning mechanism, I find that both experienced and inexperienced crowdfunders are more likely to back projects with a large number of existing backers but the effect is stronger for the inexperienced crowdfunders because they are more likely to rely on cues provided on the project page such as summary statistics when making decisions. I also find that the effects of cues are less strong for the experienced crowdfunders. As they have the ability to analyze the content of the backer information and comments, they are more likely to be influenced by the decisions made by the “experts” and are more likely to avoid projects that receive negative comments.

Overall, my research highlights the importance of recognizing crowdfunder heterogeneity in both theory building and practice.

APPENDIX A TOPIC ANALYSIS

Topic analysis seeks to find a set of topics that can represent documents within a collection. Most topic models, such as probabilistic Latent Semantic Indexing (pLSI) (Hofmann, 1999), and Latent Dirichlet Allocation (LDA) (Blei, Ng, & Jordan, 2003), assume that a document is generated by a two-step probabilistic procedure (Steyvers & Griffiths, 2007): (1) draw a topic according to a topic distribution and (2) draw a word according to a word distribution within the topic. This kind of models is termed generative models because they specify how a document is generated according to some latent variables (Steyvers & Griffiths, 2007). By fitting the topic model, topic analysis generates a predefined number of topics with its respective distribution that is supposed to generate the observed data. Each topic is described by keywords. Each document in the collection is then assigned a probability associated weight to each of the topics.

I chose Latent Dirichlet Allocation as the algorithm for topic analysis, rather than pLSI because pLSI has been shown to be a special form of LDA, and LDA can help to overcome several shortcomings of pLSI (Blei et al., 2003; Girolami & Kabán, 2003). LDA has been successfully applied to several academic studies. For example, in studying the blog reading behavior of employees, Singh, Sahoo, and Mukhopadhyay (2014) used LDA to classify blog posts into 10 work related or non-work related topics. Similarly, Wu

(2013) used LDA to classify all communication documents into 100 topics for constructing each individual's information diversity.

I used MALLET (Machine Learning for Language Toolkit) for LDA modeling. To ensure that the topics derived are not simply "hot topics" characterizing project reflecting the latest fad, I used a wider collection of data by adding another set of projects collected over an additional 9-month period. In total, I used 7,661 project descriptions collected from April 2013 to December 2014, including both completed projects (both successful and failed) and ongoing projects. Stop words were first removed as they occur much more frequently than other words and can obstruct the analysis. As LDA requires a predefined number of topics, I explored the data by employing LDA with 2 to 10 topics. I inspected the topic keywords of each solution to identify meaningful topics with clear boundaries. Based on the interpretations of all the solutions, I chose the 5-topic structure, as that provided the clearest and most interpretable topic structure. The key words of the first run are reported in Table A1. The 4 and 6-topic structure solution is represented in Table A2 to show the comparison. Further, to ensure the robustness of the classification, I re-ran LDA with 5 topics, and those for the second run are also reported in Table A2. The inter-rater agreement (*Kappa*) between the two runs with 5-topic structure after alignment was 70%, showing robustness.[20] I thus use the results from the first run for the subsequent analysis.

[20] For calculating the inter-rater agreement, documents were assigned to a topic according to the highest topic loading. Documents without a dominant loading (all the topic loadings are below 0.5) are assigned to a "mixed" topic.

Table A1 Topic Keywords

Topic 1	board design project parts make arduino software hardware power kit control time boards printer production open source components build kickstarter people project team make world ll kickstarter time community music students learn technology ve play work create video experience
Topic 2	app data software time project development users user make mobile android web application information system apps create work features access
Topic 3	product design production device battery phone make manufacturing power time light kickstarter devices quality prototype technology usb products iphone camera
Topic 4	water project system power energy design time product solar make production technology years cost high prototype space made air small
Topic 5	people project make time team world work students community website kickstarter goal create accountability technology experience support challenges learn years money

Table A2 Keywords of Topic Analysis with 4-6 Topics

4-topic results	
Topic 1	device design control software hardware board production devices project make power usb arduino system product sensor time bluetooth data kickstarter
Topic 2	app time make project people create work users development software website user mobile web kickstarter video support accountability free information
Topic 3	design product production make power time project parts kickstarter battery made manufacturing prototype light quality work system water high energy
Topic 4	project students team technology world space people school research years science community make work goal system build support time data
5-topic second run	
Topic 1	board project design parts make software arduino hardware power control kit open time boards printer source production build components kickstarter
Topic 2	app time project make people data software users development user web work create information mobile application website free features system
Topic 3	project people team make students world technology community time work experience support school goal kickstarter create years game learning learn
Topic 4	project water design power product time system energy production make solar years made light high prototype kickstarter cost technology work
Topic 5	product device design production phone devices battery make time manufacturing power smart prototype kickstarter quality control technology usb iphone camera
6-topic result	
Topic 1	product device design production phone battery power devices manufacturing smart light technology time prototype usb quality make iphone products bluetooth
Topic 2	board software hardware project arduino control design power open boards sensor system source usb make kit parts controller components time
Topic 3	app time project people make users data user information development web software website mobile work application accountability create business free

Topic 4	students team project technology space school people research world science community work support years goal year learning time university build
Topic 5	design make project parts time water production product power system made printer energy kickstarter prototype cost build high work machine
Topic 6	video make app project music time game create kickstarter people play work experience world games software it's great support love

Table A3 Sample Text for Each Topic

No.	Sample Text	Loading
	Topic 1: Electronics Design Projects	
1.1	Unleash the full power of an Arduino in 10 different kinds of ATtiny chips.The Chipper Shield allows anyone with an Arduino or AVR programmer to easily program ATtiny chips. ATtiny chips are the core behind many projects that only need a few pins and cost a fraction of an Arduino ($1-4). With access to PWM and Analog pins ATtiny chips can take on any project in 8, 14 and 20 pin form factors.	1.00
1.2	freeSoC offers 60 general purpose I/O pins, 8 special I/O pins, and a direct USB connection to the PSoC 5 microcontroller on board. It has an Arduino compatible pinout, as well as five 10-pin expansion headers, each breaking out 8 GPIO, power, and ground.	1.00
1.3	This card provides separate Ground, 3.3V and Signal connections for each of the Raspberry Pi GPIO pins. This card also has a PTC fuse on the 3.3V power line to protect your Raspberry Pi from short circuits. This card works with either the older Raspberry Pi or the new Raspberry Pi Model B+ cards.	0.99
	Topic 2: Software & App Projects	
2.1	...This gives us a motivation to work on this project and build this Open Source Mobile Sync and Backup Platform, we call "MobileSyncer". This will be Open Source, All backers will receive full source code of this project. There is No Hidden Agenda. We want everyone to be comfortable and have confidence, As User Knows, what he is using.	1.00
2.2	Simple, Free, Government-level Security for your Email accounts.Welcome to Mailelf - the private & encrypted email system you control. Stop anyone (even governments) from reading your personal messages. Mailelf won’t make you sign-up, pay-up, or join a new service! Designed to get the most secure email system into the hands of every Internet user on the planet.	1.00
2.3	MAGE, or Mobile Application Generation Environment, is an easy-to-use product that allows anyone to create a mobile application without any programming simply by loading MAGE in their browser. MAGE is perfect for experienced application creators and beginners alike. Load the creation panel; select a template or work from scratch; load your website or drag and drop content and images; select features and build.	1.00
	Topic 3: Hardware	
3.1	… So we developed the Flybridge PowerDock, addressing not only cable management, by neatly storing your cable in behind the unit, but also creating a housing that slips over your power supply, making an all in one wall charging dock	1.00

3.2	featuring...Condense Backup BatteryCondense is the first mobile battery that works to help eliminate wire clutter, and keep all your devices fully charged while on the go.We built Condense to be as versatile as possible, without sacrificing battery capacity or other features such as "plug and play" abilities.Condense also features a lightning plug adapter that protects your iPhone's charging insert from damage that a traditional dock can potentially cause. The adapter also protects the lightning plug from dust, foreign materials, and also makes docking your phone a breeze.	1.00
3.3	What is QHARTZ?- The next generation of innovation in wireless portable charging. Something new, multi-functional, and stylish for easy use.Charges any device, smartphone, tablet, and/or camera at any time and any place. Most importantly it is WIRELESS and can be 100% cord free. QUARTZ- is elegant, thin, innovative and super easy to use. With a built in intelligent sensor, all you have to do is double tap the device to activate it's power source. It has a fine bezel finish with anodized aluminum.	1.00
	Topic 4: New Technology Initiatives	
4.1	Join us on a high tech adventure that will recycle an abundant waste product to produce electricity and heat for sale while reducing greenhouse gas emissions and improving the world in which we live! Leading this project is Dr. Igor Matveev PhD a former Soviet Union defense scientist. Dr. Matveev now lives and works in America pushing the envelope in the new field of Plasma Assisted Combustion (PAC)...	0.99
4.2	This project is a first step to developing perennial crops that are planted once and then harvested for multiple years. I believe perennial crops will address many of modern agriculture's problems. Perennial crops will allow farmers in both the developing and developed worlds to grow more food on less land with less water and with fewer chemicals...	0.95
4.3	We can grow organic vegetables “extremely local” and "extremely vertically" year round using 90% less water than traditional farming methods using carbon neutral energy sources. We can grow these fresh vegetables in old industrial buildings (insteadof growing in a greenhouse) and maximize per square foot growing space insome instances 12:1 (12 plants per square foot) compared to traditional farming methods and 10:1 compared to standard greenhouses or hydroponic applications. This is the idea behind the Vertical Growing Station or "VGS"...	0.96
	Topic 5: Patronage Projects	
5.1	Books platform uses the same concept of buying selling and renting the books but with some little modification. In this platform we will help student’s rent and sell their books to other students by connecting them with each other with this platform. We are not serving as a retailer and we will not buy sell and rent any books, we will just help students by providing this platform. Students will chose the books and their prices, and for that we will also provide the price compare feature so that a student can chose the best price for books.	1.00
5.2	Why We Need DonationsModernCSC will allow high school students to enter the competition free of charge, so we need the help of the community to make this competition possible. Your donations will pay for event envelopes, flash drives to submit projects, prizes for the winning competitors, and posters and flyers to advertise the competition.	1.00
5.3	DFW Rocks Social Media Goes National!The DFW Rocks Social Media Day – 3rd Annual Conference is a gathering of business owners, social media enthusiasts, web designers and techies. This conference is for any person that wants to learn more or improve their online skills!	1.00

In order to make sense of the meaning of each topic, I looked at the actual textual description of projects with high loadings on each topic. Texts from sample project descriptions are presented in Table A3. Each topic describes a type of project in the technology category. The first type of projects is about electronics design. Keywords associated with this topic include “board”, “design”, “arduino”, “hardware”, “kit”, and “control”. Examples include projects creating accessories that can connect to electronics platforms such Raspberry Pi and Arduino. The second type of projects is software and mobile Apps. Keywords include “app”, “software”, “mobile”, and “android” etc., which are all associated with software. The third type of projects refers to design and production projects, which I rename as hardware projects. This type of projects is mostly about a recently designed creative product that is ready for production. Creators of this kind of projects are usually using *Kickstarter* to raise money for mass production of their design. Keywords for this category include “product”, “design”, “production”, and “device” etc. The fourth type of projects is about new technology initiatives such as green energy, genetic modified plants, space program etc. Keywords associated with this topic include “water”, “system”, “energy”, “power”, and “solar” etc. Examples include initiatives to recycle waste and produce electricity, to create a genetically modified crop, and to generate a vertical growing station for vegetables. The last project type describes projects requesting for patronage to support a technological or scientific initiative, for example, supporting a team in a competition. Examples include projects raising money to help students to rent and sell books. Keywords for this topic include “people”, “team”, “community”, and “students”, which are mostly patronage-oriented.

REFERENCES

Afuah, A., & Tucci, C. L. 2012. Crowdsourcing as a Solution to Distant Search. ***Academy of Management Review***, 37(3): 355-375.

Agrawal, A., Catalini, C., & Goldfarb, A. 2015a. Are Syndicates the Killer App of Equity Crowdfunding? Available at SSRN: http://ssrn.com/abstract=2569988.

Agrawal, A., Catalini, C., & Goldfarb, A. 2015b. Crowdfunding: Geography, Social Networks, and the Timing of Investment Decisions. ***Journal of Economics & Management Strategy***, 24(2): 253-274.

Ahlers, G., Cumming, D. J., Guenther, C., & Schweizer, D. 2015. Signaling in Equity Crowdfunding. ***Entrepreneurship Theory and Practice***, 39(4): 955–980.

Ai, C., & Norton, E. C. 2003. Interaction Terms in Logit and Probit Models. ***Economics Letters***, 80(1): 123-129.

Akerlof, G. A. 1970. The Market for "lemons": Quality Uncertainty and the Market Mechanism. ***Quarterly Journal of Economics***, 84(3): 488-500.

Aldenderfer, M. S., & Blashfield, R. K. 1984. ***Cluster Analysis***. Beverly Hills: Sage Publication.

Allison, T. H., Davis, B. C., Short, J. C., & Webb, J. W. 2015. Crowdfunding in a Prosocial Microlending Environment: Examining the Role of Intrinsic versus Extrinsic Cues. ***Entrepreneurship Theory and Practice***, 39(1): 53-73.

Angst, C. M., & Agarwal, R. 2009. Adoption of Electronic Health Records in the Presence of Privacy Concerns: The Elaboration Likelihood Model and Individual Persuasion. ***MIS Quarterly***, 33(2): 339-370.

Banerjee, A. V. 1992. A Simple Model of Herd Behavior. ***Quarterly Journal of Economics***, 107(3): 797-817.

Bapna, R., Goes, P., Gupta, A., & Jin, Y. 2004. User Heterogeneity and Its Impact on Electronic Auction Market Design: An Empirical Exploration. ***MIS Quarterly***, 28(1): 21-43.

Baum, J. A., & Silverman, B. S. 2004. Picking Winners or Building Them? Alliance, Intellectual, and Human Capital as Selection Criteria in Venture Financing and Performance of Biotechnology Startups. ***Journal of Business Venturing***, 19(3): 411-436.

Belleflamme, P., Lambert, T., & Schwienbacher, A. 2014. Crowdfunding: Tapping the Right Crowd. ***Journal of Business Venturing***, 29(5): 585-609.

Belleflamme, P., Omrani, N., & Peitz, M. 2015. The Economics of Crowdfunding Platforms. Available at SSRN: http://ssrn.com/abstract=2585611.

Bensaou, M., & Venkatraman, N. 1995. Configurations of Interorganizational Relationships: A Comparison between US and Japanese Automakers. ***Management Science***, 41(9): 1471-1492.

Berger, J., Sorensen, A. T., & Rasmussen, S. J. 2010. Positive Effects of Negative Publicity: When Negative Reviews Increase Sales. ***Marketing Science***, 29(5): 815-827.

Bettman, J. R., & Park, C. W. 1980. Effects of Prior Knowledge and Experience and Phase of the Choice Process on Consumer Decision Processes: A Protocol Analysis. ***Journal of Consumer Research***, 7(3): 234-248.

Bhattacherjee, A., & Sanford, C. 2006. Influence Processes for Information Technology Acceptance: An Elaboration Likelihood Model. ***MIS Quarterly***, 30(4): 805-825.

Bikhchandani, S., Hirshleifer, D., & Welch, I. 1992. A Theory of Fads, Fashion, Custom, and Cultural Change as Informational Cascades. ***Journal of Political Economy***, 100(5): 992-1026.

Bikhchandani, S., Hirshleifer, D., & Welch, I. 1998. Learning from the Behavior of Others: Conformity, Fads, and Informational Cascades. ***Journal of Economic Perspectives***, 12(3): 151-170.

Blei, D. M., Ng, A. Y., & Jordan, M. I. 2003. Latent Dirichlet Allocation. ***Journal of Machine Learning Research***, 3: 993-1022.

Bourdieu, P. 1984. ***Distinction: A Social Critique of the Judgement of Taste***. Cambridge, MA: Harvard University Press.

Bruton, G., Khavul, S., Siegel, D., & Wright, M. 2015. New Financial Alternatives in Seeding Entrepreneurship: Microfinance, Crowdfunding, and Peer-to-Peer Innovations. ***Entrepreneurship Theory and Practice***, 39(1): 9-26.

Burt, R. S. 1987. Social Contagion and Innovation: Cohesion versus Structural Equivalence. ***American Journal of Sociology***, 92(6): 1287-1335.

Burtch, G., Ghose, A., & Wattal, S. 2013. An Empirical Examination of the Antecedents and Consequences of Contribution Patterns in Crowd-Funded Markets. ***Information Systems Research***, 24(3): 499 - 519.

Burtch, G., Ghose, A., & Wattal, S. 2014. Cultural Differences and Geography as Determinants of Online Prosocial Lending. ***MIS Quarterly***, 38(3): 773-794.

Burtch, G., Ghose, A., & Wattal, S. 2015. The Hidden Cost of Accommodating Crowdfunder Privacy Preferences: A Randomized Field Experiment. ***Management Science***, 61(5): 949-962.

Burtch, G., Ghose, A., & Wattal, S. 2016. Secret Admirers: An Empirical Examination of Information Hiding and Contribution Dynamics in Online Crowdfunding. ***Information Systems Research***, 27(3): 478 - 496.

Cai, H., Chen, Y., & Fang, H. 2009. Observational Learning: Evidence from a Randomized Natural Field Experiment. ***American Economic Review***, 99(3): 864-882.

Certo, S. T. 2003. Influencing Initial Public Offering Investors with Prestige: Signaling with Board Structures. ***Academy of Management Review***, 28(3): 432-446.

Chan, K. K., & Misra, S. 1990. Characteristics of the Opinion Leader: A New Dimension. ***Journal of Advertising***, 19(3): 53-60.

Chen, X.-P., Yao, X., & Kotha, S. 2009. Entrepreneur Passion and Preparedness in Business Plan Presentations: A Persuasion Analysis of Venture Capitalists' Funding Decisions. ***Academy of Management Journal***, 52(1): 199-214.

Chen, Y., Wang, Q., & Xie, J. 2011. Online Social Interactions: A Natural Experiment on Word Of Mouth versus Observational Learning. ***Journal of Marketing Research***, 48(2): 238-254.

Cheung, C. M., Xiao, B. S., & Liu, I. L. 2014. Do Actions Speak Louder than Voices? The Signaling Role of Social Information Cues in Influencing Consumer Purchase Decisions. ***Decision Support Systems***, 65: 50-58.

Chevalier, J. A., & Mayzlin, D. 2006. The Effect of Word of Mouth on Sales: Online Book Reviews. ***Journal of Marketing Research***, 43(3): 345-354.

Cholakova, M., & Clarysse, B. 2015. Does the Possibility to Make Equity Investments in Crowdfunding Projects Crowd Out Reward - Based Investments? ***Entrepreneurship Theory and Practice***, 39(1): 145-172.

Clark-Murphy, M., & Soutar, G. 2005. Individual Investor Preferences: A Segmentation Analysis. ***Journal of Behavioral Finance***, 6(1): 6-14.

Clement, M. B. 1999. Analyst Forecast Accuracy: Do Ability, Resources, and Portfolio Complexity Matter? ***Journal of Accounting and Economics***, 27(3): 285-303.

Clement, M. B., & Tse, S. Y. 2005. Financial Analyst Characteristics and Herding Behavior in Forecasting. ***Journal of Finance***, 60(1): 307-341.

Collins, L., & Pierrakis, Y. 2012. The Venture Crowd: Crowdfunding Equity Investment into Business, Vol. 2016: NESTA.

Colombo, M. G., Franzoni, C., & Rossi - Lamastra, C. 2015. Internal Social Capital and the Attraction of Early Contributions in Crowdfunding. ***Entrepreneurship Theory and Practice***, 39(1): 75-100.

Connelly, B. L., Certo, S. T., Ireland, R. D., & Reutzel, C. R. 2011. Signaling Theory: A Review and Assessment. ***Journal of Management***, 37(1): 39-67.

Currim, I. S. 1981. Using Segmentation Approaches for Better Prediction and Understanding from Consumer Mode Choice Models. ***Journal of Marketing Research***, 18(3): 301-309.

Dellarocas, C., Zhang, X. M., & Awad, N. F. 2007. Exploring the Value of Online Product Reviews in Forecasting Sales: The Case of Motion Pictures. ***Journal of Interactive Marketing***, 21(4): 23-45.

Dhar, R., & Zhu, N. 2006. Up Close and Personal: Investor Sophistication and the Disposition Effect. ***Management Science***, 52(5): 726-740.

Doshi, A. 2014. The Impact of High Performance Outliers on Two-Sided Platforms: Evidence from Crowdfunding. Available at SSRN: http://ssrn.com/abstract=2422111.

Duan, W., Gu, B., & Whinston, A. B. 2008. Do Online Reviews Matter? — An Empirical Investigation of Panel Data. ***Decision Support Systems***, 45(4): 1007-1016.

Feick, L. F., & Price, L. L. 1987. The Market Maven: A Diffuser of Marketplace Information. ***Journal of Marketing***, 51(1): 83-97.

Fiedler, K. D., Grover, V., & Teng, J. T. 1996. An Empirically Derived Taxonomy of Information Technology Structure and Its Relationship to Organizational Structure. ***Journal of Management Information Systems***, 13(1): 9-34.

Franke, N., Gruber, M., Harhoff, D., & Henkel, J. 2008. Venture Capitalists' Evaluations of Start-Up Teams: Trade-Offs, Knock-Out Criteria, and the Impact of VC Experience. ***Entrepreneurship Theory and Practice***, 32(3): 459-483.

Freear, J., Sohl, J. E., & Wetzel, W. E. 1994. Angels and Non-Angels: Are There Differences? ***Journal of Business Venturing***, 9(2): 109-123.

Freedman, S. M., & Jin, G. Z. 2011. Learning by Doing with Asymmetric Information: evidence from Prosper. com: National Bureau of Economic Research.

Galak, J., Small, D., & Stephen, A. T. 2011. Microfinance Decision Making: A Field Study of Prosocial Lending. ***Journal of Marketing Research***, 48: 130-137.

Gao, Q., & Lin, M. 2015. Lemon or Cherry? The Value of Texts. Available at SSRN: http://ssrn.com/abstract=2446114.

Gerber, E. M., Hui, J. S., & Kuo, P.-Y. 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.

Ghose, A., & Ipeirotis, P. G. 2011. Estimating the Helpfulness and Economic Impact of Product Reviews: Mining Text and Reviewer Characteristics. ***IEEE Transactions on Knowledge and Data Engineering***, 23(10): 1498-1512.

Girolami, M., & Kabán, A. 2003. ***On an Equivalence between PLSI and LDA***. Paper presented at the Proceedings of the 26th Annual International ACM SIGIR Conference on Research and Development in Information Retrieval.

Giudici, G., Guerini, M., & Lamastra, C. R. 2013. Why Crowdfunding Projects Can Succeed: The Role of Proponents' Individual and Territorial Social Capital. Available at SSRN: http://ssrn.com/abstract=2255944.

Godes, D., & Mayzlin, D. 2009. Firm-Created Word-of-Mouth Communication: Evidence from a Field Test. ***Marketing Science***, 28(4): 721-739.

Godes, D., Mayzlin, D., Chen, Y., Das, S., Dellarocas, C., Pfeiffer, B., Libai, B., Sen, S., Shi, M., & Verlegh, P. 2005. The Firm's Management of Social Interactions. ***Marketing Letters***, 16(3-4): 415-428.

Goes, P. B., Lin, M., & Au Yeung, C.-m. 2014. “Popularity Effect” in User-Generated Content: Evidence from Online Product Reviews. ***Information Systems Research***, 25(2): 222-238.

Gompers, P. A., Mukharlyamov, V., & Xuan, Y. 2016. The Cost of Friendship. ***Journal of Financial Economics***, 119(3).

Greenberg, M. D., Gerber, E. M., Greenberg, J., & Mollick, E. 2016. Activist Choice Homophily and the Crowdfunding of Female Founders. ***Administrative Science Quarterly***, Forthcoming.

Greene, W. H. 2012. ***Econometric Analysis*** (7 ed.). Prentice Hall, One Lake Street, Upper Saddle River, NJ 07458: Pearson Education, Inc.

Griffin, Z. 2012. Crowdfunding: Fleecing the American Masses: Case Western Reserve Journal of Law, Technology & the Internet, Forthcoming. Available at SSRN: http://ssrn.com/abstract=2030001.

Hahn, J., & Lee, G. 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.

Hakenes, H., & Schlegel, F. 2014. Exploiting the Financial Wisdom of the Crowd. Crowdfunding as a Tool to Aggregate Vague Information. Available at http://ssrn.com/abstract=2475025.

Herzenstein, M., Dholakia, U. M., & Andrews, R. L. 2011. Strategic Herding Behavior in Peer-to-Peer Loan Auctions. ***Journal of Interactive Marketing***, 25(1): 27-36.

Higgins, M. J., Stephan, P. E., & Thursby, J. G. 2011. Conveying Quality and Value in Emerging Industries: Star Scientists and the Role of Signals in Biotechnology. ***Research Policy***, 40(4): 605-617.

Hildebrand, T., Puri, M., & Rocholl, J. 2016. Adverse Incentives in Crowdfunding. ***Management Science***, Forthcoming.

Ho, J. L. 1994. The Effect of Experience on Consensus of Going-Concern Judgments. ***Behavioral Research in Accounting***, 6: 160-177.

Hofmann, T. 1999. ***Probabilistic Latent Semantic Indexing***. Paper presented at the Proceedings of the 22nd Annual International ACM SIGIR Conference on Research and Development in Information Retrieval.

Holm, S. 1979. A Simple Sequentially Rejective Multiple Test Procedure. ***Scandinavian Journal of Statistics***, 6(2): 65-70.

Hong, Y., Huang, N., Burtch, G., & Li, C. 2016. Culture, Conformity, and Emotional Suppression in Online Reviews. ***Journal of the Association for Information Systems***, 17(11).

Howe, J. 2006. The Rise of Crowdsourcing. ***Wired magazine***, 14(6): 1-4.

Hu, M., Li, X., & Shi, M. 2015. Product and Pricing Decisions in Crowdfunding. ***Marketing Science***, 34(3): 331-345.

Huang, J. H., & Chen, Y. F. 2006. Herding in Online Product Choice. ***Psychology and Marketing***, 23(5): 413-428.

Inbar, Y., & Barzilay, O. 2014. Community Impact on Crowdfunding Performance. Available at SSRN: http://ssrn.com/abstract=2524910.

Ito, T. A., Larsen, J. T., Smith, N. K., & Cacioppo, J. T. 1998. Negative Information Weighs More Heavily on the Brain: The Negativity Bias in Evaluative Categorizations. 75: 887-900.

Jacob, J., Lys, T. Z., & Neale, M. A. 1999. Expertise in Forecasting Performance of Security Analysts. ***Journal of Accounting and Economics***, 28(1): 51-82.

Jones, Q., Ravid, G., & Rafaeli, S. 2004. Information Overload and the Message Dynamics of Online Interaction Spaces: A Theoretical Model and Empirical Exploration. ***Information Systems Research***, 15(2): 194-210.

Joseph, D., Boh, W. F., Ang, S., & Slaughter, S. 2012. The Career Paths Less (or More) Traveled: A Sequence Analysis of IT Career Histories, Mobility Patterns, and Career Success. ***MIS Quarterly***, 36(2): 427-452.

Katz, E. 1957. The Two-Step Flow of Communication: An Up-to-Date Report on an Hypothesis. ***Public Opinion Quarterly***, 21: 61-78.

Katz, M. L., & Shapiro, C. 1985. Network Externalities, Competition, and Compatibility. ***American Economic Review***, 75(3): 424-440.

Katz, M. L., & Shapiro, C. 1986. Technology Adoption in the Presence of Network Externalities. ***Journal of Political Economy***, 94(4): 822-841.

Ketchen, D. J., & Shook, C. L. 1996. The Application of Cluster Analysis in Strategic Management Research: An Analysis and Critique. ***Strategic Management Journal***, 17(6): 441-458.

Kim, K., & Hann, I.-H. 2015. Does Crowdfunding Democratize Access to Finance? A Geographical Analysis of Technology Projects. Available at SSRN: http://ssrn.com/abstract=2334590.

Kim, K., & Viswanathan, S. 2014. The Experts in the Crowd: The Role of Reputable Investors in a Crowdfunding Market. Available at SSRN: http://ssrn.com/abstract=2258243.

King, C. W., & Summers, J. O. 1970. Overlap of Opinion Leadership across Consumer Product Categories. ***Journal of Marketing Research***, 7(1): 43-50.

Kirsch, D., Goldfarb, B., & Gera, A. 2009. Form or Substance: The Role of Business Plans in Venture Capital Decision Making. ***Strategic Management Journal***, 30(5): 487-515.

Koning, R., & Model, J. 2013. Social Influence Mechanisms in Crowdfunding Cascades: When Nothing is Better than Something. Available at SSRN: http://ssrn.com/abstract=2308161.

Kuan, K. K. Y., Hui, K.-L., Prasarnphanich, P., & Lai, H.-Y. 2015. What Makes a Review Voted? An Empirical Investigation of Review Voting in Online Review Systems. ***Journal of the Association for Information Systems***, 16(1): 48-71.

Kuppuswamy, V., & Bayus, B. L. 2015. Crowdfunding Creative Ideas: the Dynamics of Projects Backers in Kickstarter. Available at SSRN: http://ssrn.com/abstract=2234765.

Lee, E., & Lee, B. 2012. Herding Hehavior in Online P2P Lending: An Empirical Investigation. ***Electronic Commerce Research and Applications***, 11(5): 495-503.

Lee, J., Park, D. H., & Han, I. 2008. The Effect of Negative Online Consumer Reviews on Product Attitude: An Information Processing View. ***Electronic Commerce Research and Applications***, 7(3): 341-352.

Lehner, O. 2012. ***A Literature Review and Research Agenda for Crowdfunding of Social Ventures***. Paper presented at the Research Colloquium on Social Entrepreneurship, 16th-19th July, University of Oxford, Skoll Center of SAID Business School UK.

Li, F. 2008. Annual Report Readability, Current Earnings, and Earnings Persistence. ***Journal of Accounting and Economics***, 45(2): 221-247.

Li, Z., & Duan, J. A. 2014. Dynamic Strategies for Successful Online Crowdfunding. Available at SSRN: http://ssrn.com/abstract=2506352.

Libby, R., & Frederick, D. M. 1990. Experience and the Ability to Explain Audit Findings. ***Journal of Accounting Research***, 28(2): 348-367.

Lin, M., Prabhala, N. R., & Viswanathan, S. 2013. Judging Borrowers by the Company They Keep: Friendship Networks and Information Asymmetry in Online Peer-to-Peer Lending. ***Management Science***, 59(1): 17-35.

Lin, M., & Viswanathan, S. 2015. Home Bias in Online Investments: An Empirical Study of an Online Crowd Funding Market. ***Management Science*** 62(5): 1393 - 1414.

Liu, Y. 2006. Word of Mouth for Movies: Its Dynamics and Impact on Box Office Revenue. ***Journal of Marketing***, 70(3): 74-89.

Malhotra, A., Gosain, S., & Sawy, O. A. E. 2005. Absorptive Capacity Configurations in Supply Chains: Gearing for Partner-Enabled Market Knowledge Creation. ***MIS Quarterly***, 29(1): 145-187.

Marcus, A. S., & Bauer, R. A. 1964. Yes: There are Generalized Opinion Leaders. ***The Public Opinion Quarterly***, 28(4): 628-632.

Marom, D., Robb, A., & Sade, O. 2015. Gender Dynamics in Crowdfunding (Kickstarter): Evidence on Entrepreneurs, Investors, Deals and Taste-Based Discrimination. Available at SSRN: https://ssrn.com/abstract=2442954.

Marom, D., & Sade, O. 2013. Are the Life and Death of an Early Stage Venture Indeed in the Power of the Tongue? Lessons from Online Crowdfunding Pitches. Available at SSRN: http://ssrn.com/abstract=2255707.

Massolution. 2015. The Crowdfunding Industry Report, Vol. 2015.

McFadden, D. 1973. Conditional Logit Analysis of Qualitative Choice Behavior, ***Frontiers In Econometrics***: 105-142. New York: Academic Press.

McFadden, D. 1978. Modelling the Choice of Residential Location, ***Spatial Interaction Theory and Planning Models***: 75-96. Amsterdam: North Holland.
Merton, R. K. 1968. ***Social Theory and Social Structure***: Simon and Schuster.
Michels, J. 2012. Do Unverifiable Disclosures Matter? Evidence from Peer-To-Peer Lending. ***The Accounting Review***, 87(4): 1385-1413.
Mikhail, M. B., Walther, B. R., & Willis, R. H. 1997. Do Security Analysts Improve Their Performance with Experience? ***Journal of Accounting Research***, 35: 131-157.
Mollick, E. 2014. The Dynamics of Crowdfunding: An Exploratory Study. ***Journal of Business Venturing***, 29(1): 1-16.
Mollick, E., & Kuppuswamy, V. 2014. When Firms are Potemkin Villages: Entrepreneurs and Formal Organizations. Available at SSRN: https://ssrn.com/abstract=2377020.
Mollick, E. R., & Nanda, R. 2015. Wisdom or Madness? Comparing Crowds with Expert Evaluation in Funding the Arts. ***Management Science*** 62(6): 1533 - 1553.
Moore, G. A. 2014. ***Crossing the Chasm: Marketing and Selling High-Tech Products to Mainstream Customers*** (3 ed.). New York: Harper-Collins.
Myers, J. H., & Robertson, T. S. 1972. Dimensions of Opinion Leadership. ***Journal of Marketing Research***, 9(1): 41-46.
Nickerson, R. C., Varshney, U., & Muntermann, J. 2013. A Method for Taxonomy Development and Its Application in Information Systems. ***European Journal of Information Systems***, 22(3): 336-359.
Nicolosi, G., Peng, L., & Zhu, N. 2009. Do Individual Investors Learn from Their Trading Experience? ***Journal of Financial Markets***, 12(2): 317-336.
Ordanini, A., Miceli, L., Pizzetti, M., & Parasuraman, A. 2011. Crowd-Funding: Transforming Customers into Investors through Innovative Service Platforms. ***Journal of Service Management***, 22(4): 443-470.
Park, D.-H., & Kim, S. 2008. The Effects of Consumer Knowledge on Message Processing of Electronic Word-of-Mouth via Online Consumer Reviews. ***Electronic Commerce Research and Applications***, 7(4): 399-410.
Park, D.-H., & Lee, J. 2009. eWOM Overload and Its Effect on Consumer Behavioral Intention Depending on Consumer Involvement. ***Electronic Commerce Research and Applications***, 7(4): 386-398.
Pennebaker, J. W., Boyd, R. L., Jordan, K., & Blackburn, K. 2015. The Development and Psychometric Properties of LIWC2015. Austin, TX: University of Texas at Austin.
Petty, R. E., & Cacioppo, J. T. 1986a. The Elaboration Likelihood Model of Persuasion. ***Advances in Experimental Social Psychology***, 19(1): 123-205.
Petty, R. E., & Cacioppo, J. T. 1986b. The Elaboration Likelihood Model of Persuasion, ***Communication and Persuasion***. New York: Springer.

Petty, R. E., & Wegener, D. T. 1999. The Elaboration Likelihood Model: Current Status and Controversies. In S. Chaiken, & Y. Trope (Eds.), ***Dual-Process Theories in Social Psychology***: 37-72. New York, NY, US: Guilford Press.

Phillips, D. J., & Zuckerman, E. W. 2001. Middle - Status Conformity: Theoretical Restatement and Empirical Demonstration in Two Markets. ***American Journal of Sociology***, 107(2): 379-429.

Pieters, R., & Wedel, M. 2004. Attention Capture and Transfer in Advertising: Brand, Pictorial, and Text-Size Effects. ***Journal of Marketing***, 68(2): 36-50.

Price, L. L., & Ridgway, N. M. 1983. Development of a Scale to Measure Use Innovativeness. ***Advances in Consumer Research***, 10: 679-684.

Quiamzade, A., & L'Huillier, J. P. 2009. Herding by Attribution of Privileged Information. ***Journal of Behavioral Decision Making***, 22(1): 1-19.

Richins, M. L., & Root-Shaffer, T. 1988. The Role of Evolvement and Opinion Leadership in Consumer Word-of-Mouth: An Implicit Model Made Explicit. ***Advances in Consumer Research***, 15: 32-36.

Riesman, D. 1950. ***The Lonely Crowd: A Study of the Changing American Character***. New Haven, CT: Yale University Press.

Rochet, J.-C., & Tirole, J. 2003. Platform Competition in Two-Sided Markets. ***Journal of the European Economic Association***, 1(4): 990-1029.

Rogers, E. M. 2003. ***Diffusion of Innovations*** (5 ed.). New York: The Free Press

Roure, J. B., & Keeley, R. H. 1990. Predictors of Success in New Technology Based Ventures. ***Journal of Business Venturing***, 5(4): 201-220.

Rozin, P., & Royzman, E. B. 2001. Negativity Bias, Negativity Dominance, and Contagion. ***Personality and Social Psychology Review***, 5(4): 296-320.

Rynes, S. L., Bretz, R. D., & Gerhart, B. 1991. The Importance of Recruitment in Job Choice: A Different Way of Looking. ***Personnel Psychology***, 44(3): 487-521.

Sabherwal, R., & King, W. R. 1995. An Empirical Taxonomy of the Decision-Making Processes Concerning Strategic Applications of Information Systems. ***Journal of Management Information Systems***, 11(4): 177-214.

Schumpeter, J. A. 2008. ***Capitalism, Socialism, and Democracy***: HarperCollins.

Schwienbacher, A., & Larralde, B. 2010. Crowdfunding of Small Entrepreneurial Ventures. Handbook of Entrepreneurial Finance, Oxford University Press, Forthcoming, Available at SSRN: http://ssrn.com/abstract=1699183.

Sen, S., & Lerman, D. 2007. Why Are You Telling Me This? An Examination Into Negative Consumer Reviews on the Web. ***Journal of Interactive Marketing***, 21(4): 76-94.

Senecal, S., & Nantel, J. 2004. The Influence of Online Product Recommendations on Consumers' Online Choices. ***Journal of Retailing***, 80(2): 159-169.

Silk, A. J. 1966. Overlap among Self-Designated Opinion Leaders: A Study of Selected Dental Products and Services. ***Journal of Marketing Research***, 3(3): 255-259.

Simonsohn, U., & Ariely, D. 2008. When Rational Sellers Face Nonrational Buyers: Evidence from Herding on eBay. ***Management Science***, 54(9): 1624-1637.

Singh, P. V., Sahoo, N., & Mukhopadhyay, T. 2014. How to Attract and Retain Readers in Enterprise Blogging? ***Information Systems Research***, 25(1): 35-52.

Spence, M. 1973. Job Market Signaling. ***Quarterly Journal of Economics***, 87(3): 355-374.

Steyvers, M., & Griffiths, T. 2007. Probabilistic Topic Models. ***Handbook of Latent Semantic Analysis***, 427(7): 424-440.

Summers, J. O. 1970. The Identity of Women's Clothing Fashion Opinion Leaders. ***Journal of Marketing Research***, 7(2): 178-185.

Sussman, S. W., & Siegal, W. S. 2003. Informational Influence in Organizations: An Integrated Approach to Knowledge Adoption. ***Information Systems Research***, 14(1): 47-65.

Swain, M. R., & Haka, S. F. 2000. Effects of Information Load on Capital Budgeting Decisions. ***Behavioral Research in Accounting***, 12: 171.

Tam, K. Y., & Ho, S. Y. 2005. Web Personalization as a Persuasion Strategy: An Elaboration Likelihood Model Perspective. ***Information Systems Research***, 16(3): 271-291.

Taylor, J. W. 1977. A Striking Characteristic of Innovators. ***Journal of Marketing Research***, 14(1): 104-107.

Thorndike, R. L. 1953. Who Belongs in the Family? ***Psychometrika***, 18(4): 267-276.

Train, K. E. 2009. ***Discrete Choice Methods with Simulation***. Cambridge: Cambridge University Press.

Van den Bulte, C., & Joshi, Y. V. 2007. New Product Diffusion with Influentials and Imitators. ***Marketing Science***, 26(3): 400-421.

Venezia, I., Nashikkar, A., & Shapira, Z. 2011. Firm Specific and Macro Herding by Professional and Amateur Investors and Their Effects on Market Volatility. ***Journal of Banking & Finance***, 35(7): 1599-1609.

Venkatraman, M. 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, D. J., & Dodds, P. S. 2007. Influentials, Networks, and Public Opinion Formation. ***Journal of Consumer Research***, 34(4): 441-458.

Wu, L. 2013. Social Network Effects on Productivity and Job Security: Evidence from the Adoption of a Social Networking Tool. ***Information Systems Research***, 24(1): 30-51.

Xu, T. 2015. Financial Disintermediation and Entrepreneurial Learning: Evidence from the Crowdfunding Market. Available at SSRN: http://ssrn.com/abstract=2637699.

Yang, L., & Hahn, J. 2015. ***Learning from Prior Experience: An Empirical Study of Serial Entrepreneurs in IT-enabled Crowdfunding***. Paper presented at the Thirty Sixth International Conference on Information Systems, Fort Worth.

Yin, D., Bond, S. D., & Zhang, H. 2014. Anxious or Angry? Effects of Discrete Emotions on the Perceived Helpfulness of Online Reviews. ***MIS Quarterly***, 38(2): 539-560.

Zhang, J., & Liu, P. 2012. Rational Herding in Microloan Markets. ***Management Science***, 58(5): 892-912.

Zhu, F., & Zhang, X. 2010. Impact of Online Consumer Reviews on Sales : The Moderating Role of Product and Consumer. ***Journal of Marketing***, 74(March): 133-148.

Zvilichovsky, D., Inbar, Y., & Barzilay, O. 2015. Playing Both Sides of the Market: Success and Reciprocity on Crowdfunding Platforms, ***Available at SSRN: http://ssrn.com/abstract=2304101***.