ANTECEDENTS OF FUNDRAISING SUCCESS AND ENTREPRENEURIAL PERFORMANCE IN CROWDFUNDING PLATFORMS

By

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ABSTRACT

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The emergence of crowdfunding could provide novel opportunities for startup companies and potentially transform the nature of entrepreneurship and new firm creation. The prevailing modes of venture financing limit the types of business projects that get funded or limit the range of project choices availability to funder. In contrast, crowdfunding platforms present a diversified array of project choices and funds so that not just mainstream, but also "long tail" effect might prevail. Crowdfunding platforms could connect entrepreneurs and funders, and provide new avenues for entrepreneurs to acquire legitimacy and engage with a broader pool of funders. However, despite the growing volume of research, more insight is needed about (a) what factors and social dynamics explain the ability to attract funding success, and (b) how are the patterns of fundraising related to project success? Using the comprehensive theoretical lens of social network, electronic word-of-mouth, bandwagon effects, entrepreneurship and innovation theories, I address two research questions.

In the first essay, I examine the impact of crowds' and entrepreneurs' behaviors and online community engagement along with entrepreneur characteristics on fundraising success in crowdfunding platforms. We collect data about startup projects and funders from a reward-based crowdfunding platform in the U.S., as well as additional data from online social network sites and blogs. Our sample includes a total of 722 technology-related projects (March 2012 - January 2013) and more than 177,700 funders. The empirical results show that the networks of interactions among funders as well as the entrepreneurs' social engagement with the crowdfunding community are key antecedents of funding success. Along with fundraising success in crowdfunding platforms, for start-ups both obtaining financial resources and creating innovation are important for their survival. However, there is lack of attention as to whether successfully funded projects deliver outcomes.

In my second essay, I investigate the existing dynamics in fundraising process, and how the fundraising patterns are related to crowdfunding projects performance. The current finding shows the various impacts of fundraising patterns on entrepreneurs' performance. This study will contribute to crowdfunding and entrepreneurship literature and offer practical implications by providing a comprehensive theoretical framework and the supporting empirical evidence.

Keywords: crowdfunding, network, community engagement, entrepreneurial performance, fundraising patterns

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Using a two-essay format, I would like to investigate how entrepreneurs successfully raise money in a crowdfunding platform, and how dynamic fundraising patterns influence entrepreneurial performance. Essay 1 examines the impact of community engagement of funders and entrepreneurs, and an electronic word-of-mouth effect, as well as the entrepreneurial characteristics on the probability of fundraising success. Essay 2 explores different dynamic fundraising patterns, how these patterns are related to funders' type, entrepreneurial improvisation, and project outcome type, and influence entrepreneurial project performance and innovation performance. An overview of the two essays is given below.

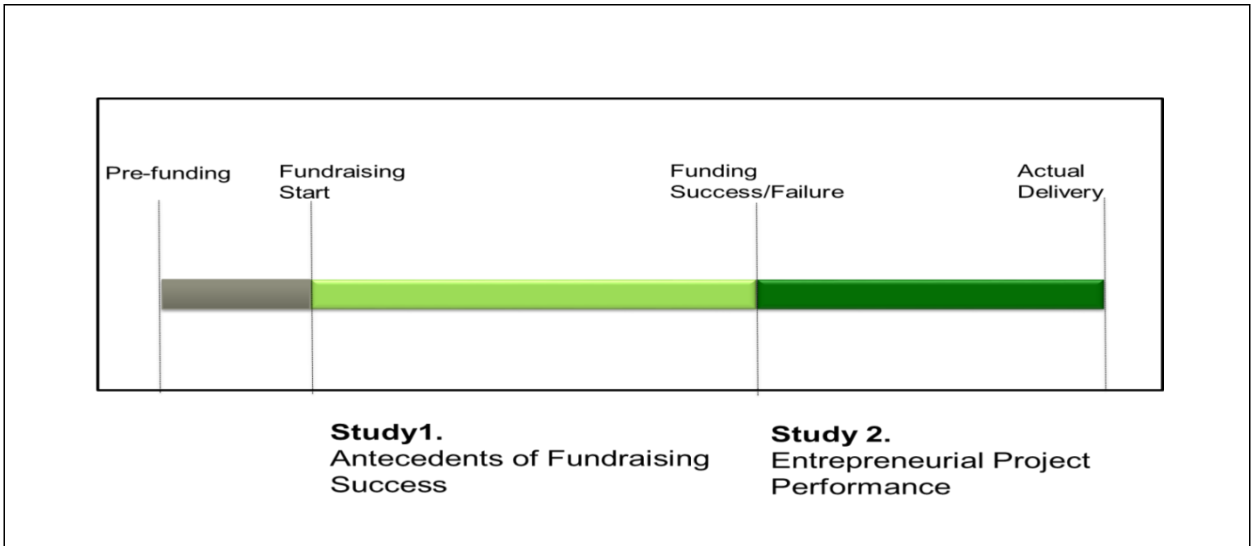

Figure 1.1 Overview of Dissertation

CHAPTER 2.
ESSAY 1: COMMUNITY ENGAGEMENT AND COLLECTIVE EVALUATION IN CROWDFUNDING

"Innovation is not led by lone inventors in their garrets but is the product of a collaborative process"

--Samuel J. Palmisano, former CEO of IBM

2.1 INTRODUCTION

Digitally mediated social networks have transformed social, economic, and business activities (Agarwal, Gupta, and Kraut, 2008; Aral, Dellarocas, and Godes, 2013). These networks foster social interactions and create new types of interactions, such as electronic ties with partners, interactions with customers, and collaboration within communities (Agarwal et al., 2008; Singh, Tan, and Mookerjee, 2011). Along with social and economic transformation, these networks engender new business models whereby companies can tap into collaborative platforms as a way to acquire resources and new ideas. One such novel model of digital value creation is crowdfunding, whereby project creators from a variety of arenas can tap into a community to raise funding via the Internet (Schwienbacher and Larralde, 2010; Mollick, 2012). Based on prior research, we define crowdfunding as "a novel method for generating funds by tapping into the collective and allowing project creators (e.g., entrepreneurs) from various areas to request funding from many individuals via the Internet" (Schwienbacher and Larralde, 2010; Mollick, 2012). Any individual or entrepreneur can create or fund projects in crowdfunding platforms. According to recent reports, there are around 452 crowdfunding platforms active worldwide. In 2012, these raised almost $2.7

billion and successfully funded more than one million projects (crowdsourcing.org, 2012). Kickstarter, one of the most popular crowdfunding platforms, had received about $450 million in funding in 2012[1]. Figure 2.1 shows the web search volume of 'Kickstarter' and 'crowdfunding' from 2009 to 2014. The trend graph (of Kickstarter) shows a steep growth of web search volume. The Jumpstart Our Business Startups (JOBS) Act of 2012 in the U.S. allows startup companies to initiate equity-based projects in crowdfunding platforms, a move that could significantly ease the burden of raising funds for startup companies as well as reduce barriers for investors to participate in entrepreneurial investment. The Securities and Exchange Commission (SEC) has similarly moved to make regulatory changes that will enable equity participation through crowdfunding.

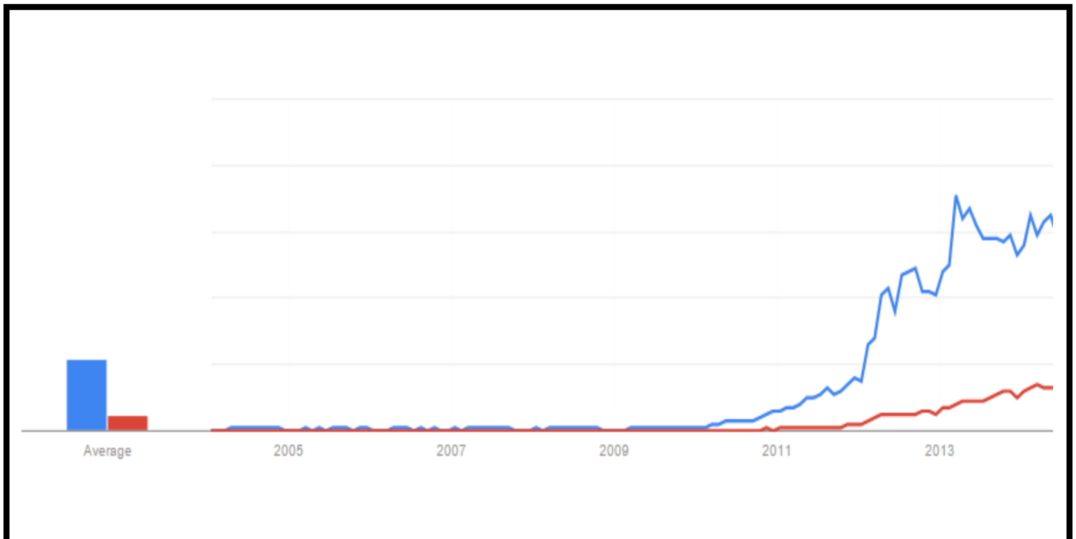

Figure 2.1 Web Search Volume
(Kickstarter: top & crowdfunding: bottom, Google Trends , 2014)

The emergence of crowdfunding could unleash substantial changes in the nature of entrepreneurship and new firm creation. Under traditional funding mechanisms, start-up companies have experienced considerable difficulties in obtaining external funding (Gompers and

[1] www.kickstarter.com/help/stats

Lerner, 2001; Hsu, 2007), and in creating visibility and establishing legitimacy (Zimmerman and Zeitz, 2002; Zott and Huy, 2007). Crowdfunding allows entrepreneurs to reach crowds of unprecedented scale at a low cost and provides a variety of avenues to enhance legitimacy for necessary resources. For example, *Pebble*, one of most popular Kickstarter projects, raised $10.2 million from 68,929 people within 37 days in 2012.

When investors lend, there is a problem of verifiability of effort or moral hazard. In traditional financing, lenders have an incentive to screen borrowers given the risk of default in lending to an inexperienced lender. Professional funding firms such as venture capitalists also have developed expertise and managerial routines to evaluate potential entrepreneurs (Kirsch et al. 2009). Crowdfunding marketplaces lack features of institutional lending such as certification. In traditional funding markets, project creators invest in time and effort in building relationships with large net worth individuals or angel investors. While individual investors make decisions on which projects to fund, in most crowdfunding platforms these decisions can only be executed once the projects reach a funding goal. That also means that for project creators, there is no upfront investment in building their company or creating a product; rather, they need to deliver the promised reward in return for the monetary contributions. How do the project creators' actions ensure that there is no moral hazard problem? How do funders mitigate information asymmetry?

Crowdfunding exhibits features of asymmetric information characteristic of Peer-to-peer lending since the lenders are mostly small investors and not as informed as institutional lenders in evaluating project quality and the capabilities of funders. According to Kickstarter Statistics[2], fewer than 50% of projects reached their funding goals in 2012. Further, there is also a lack of regulation relating to consumer protections, so investors have to rely on their judgment and the

[2] www.kickstarter.com/year/2012

collective evaluation of the crowd. Question is also what underlying value can be added by the crowd? So, how do they choose investments?

Recently, researchers have emphasized the critical role of co-value creation, a collaborative process between customers and companies or among actors in a various networks in innovations (Prahald and Ramaswamy, 2004; Nambisan and Sawhney, 2011; Lusch and Nambisan, 2015). Co-value creation not only facilitates relationship building but also creates shared knowledge and experience. Drawing on this perspective, customers are not passive recipients but are actively involved in innovation process (Nambisan and Sawhney, 2011). Information technology is a critical enabler of a co-value creation. Online communities and interactive web functions (web2.0) enable spontaneous conversation and richness of interactions among online community participants, and increase the reaches of audience (Prahald and Ramaswamy, 2004; Ray, Kim, and Morris, 2014).

A crowdfunding platform supports two-sided social interaction in that the digital platform facilitates interactions both between entrepreneurs and funders and interactions amongst funders. Such interactions allow entrepreneurs to convey more information about projects as well as allowing funders to share information about projects. Crowdfunding platforms also provide visibility of projects and entrepreneurs' track records. Funders can easily obtain detailed project information such as a goal, duration of project, descriptions, a video, total pledged amounts, entrepreneurs (project creators) and other funders' information, and project creators' embeddedness in the two-mode network of funders and creators. Entrepreneurs may be able to share both soft and hard information. Further, funders may persuade other funders to contribute money to entrepreneurs. Thus, crowdfunding platforms provide with an online social space which enables *"connection"*, interactions among funders and entrepreneurs or among funders, *"collaboration"*, more than simple involvement (i.e., share experience and knowledge about funding projects), and *"co-value creation"*, evaluating and supporting entrepreneurs. We suggest that the problems of information asymmetry in such settings can be mitigated by the collective evaluation mechanisms enabled by the online community aspects of crowdfunding.

Prior research examining social influence in crowdfunding has focused on the history of fundraising process (Agarwal, Catalini and Goldfarb, 2011; Burtch et al., 2013; Mollick, 2012) rather than the participants' social network and social interactions. Prior studies also pay less attention to the entrepreneurs' characteristics, though they have been important factors in venture capital investment. A theoretical explanation of the underlying phenomena will not only contribute to related literatures, but will help entrepreneurs who want to initiate projects and obtain legitimacy, as well as in assisting potential funders and platform designers. We draw upon multiple theoretical perspectives such as theories of social networks, theories of online communities and theories of entrepreneurship to examine how entrepreneurs' involvement with the crowdfunding platform and the funders' involvement with a project lead to success. The main research questions we will address are as follows:

(1) *How does funders' involvement with projects (community engagement, e-WOM) influence the likelihood of success in fundraising?*

(2) *How does entrepreneurs' community engagement affect likelihood of success in fundraising?*

We examine our research questions using data collected about startup projects and their funders from multiple sources. We collected startup projects and funder data from Kickstarter, one of the most popular reward-based crowdfunding platforms in the U.S. Additional data were gathered from online social network sites and blogs. Our sample includes a total of 722 technology-related projects (March 2012 - January 2013) and more than 177,700 funders. The empirical results show that the embeddedness of funders contributing to a specific project, the external electronic word of mouth (from outside the crowdfunding community) for a project and the engagement of entrepreneurs into the community of funders are key antecedents that a project is successfully funded. Interestingly, these factors dominate the effects of the entrepreneurs' human capital.

Identifying the impacts of online community engagement on the probability of fundraising success poses several econometric challenges. First, a critical issue in the estimation process is reverse causality between entrepreneurial engagement (i.e., updating information about projects) and fundraising success. Not only the increase of updating actions influence fundraising, but also entrepreneurs who get higher funding amounts may engage in updating more often. To deal with this issue, we used three sets of instruments which are correlated with entrepreneurial engagement actions but are not correlated with fundraising performance. Second, selection-bias problem may exist in the research context. The unobserved characteristics of successfully funded projects may create estimation bias in the model of pledged percentage amounts model. We employ Heckman's two stage selection model to deal with selection bias problem. Additionally, to consider the potential heterogeneity in projects and e-WOM, we analyze the sentiment of e-WOM.

This paper can make several contributions to the literature. First, we provide a comprehensive theoretical framework to understand fundraising mechanisms in a novel funding market. Second, although there are several studies on crowdfunding, the extant literature mainly emphasizes the role of project attributes (i.e., goal, duration, demo materials such as videos etc.), impacts of entrepreneurs' (project creators') social networks, geographical proximity, and contribution history in crowdfunding success. In this paper, we explicitly focus on the factors enabled by features of online communities such as funders' network embeddedness, funders' and entrepreneurs' community engagement with the online crowdfunding community, electronic word of mouth effects and entrepreneurs' human capital. Therefore, we contribute to multiple streams of research on crowdfunding, crowdsourcing, and entrepreneurship literatures. The rest of the paper proceeds as follows. Section 2 provides theoretical background and research hypotheses. In Section 3, we explain our sample data, data collection process, and introduce our empirical models of crowdfunding success. Section 4 provides results of empirical test. In Section 5, we conclude by providing theoretical and managerial implications of study, limitations of current study, and future directions.

2.2 THEORETICAL BACKGROUND AND RESEARCH HYPOTHESES

2.2.1 Theoretical Background

In general, there are four types of crowdfunding: donation, reward, lending, and equity-based (Burtch et al., 2013). Academic research has begun to investigate the antecedents of funding success and contributors' behavior. Burtch et al. (2013) examined the effect of others' initial contributions on latter participants' contribution decisions in donation-based funding. Ordanini et al. (2011) investigate how participants' motivations vary across different platforms. Mollick (2012) analyzed the impacts of project quality, social network of project creators, and project characteristics on funding success. Agarwal et al. (2011; 2013) presented the positive effects of offline relationships on funding investments, and the decreased effects of geographical distance between investors and artist-entrepreneurs on investments. Kuppuswamy and Bayus (2013) examine how funders' support on Kickstarter varies depending on project characteristics and timing. Table 2.1 summarizes existing crowdfunding studies.

Recently, the innovation literature has emphasized the critical role of co-value creation, a collaborative process between customers and companies or among actors in a various networks in innovations (Prahalad and Ramaswamy, 2004; Nambisan and Sawhney, 2011; Lusch and Nambisan, 2015). Information technology is a critical enabler of a co-value creation, which enables spontaneous conversation and richness of interactions among online community participants and increases the reaches of audience (Ray, Kim, and Morris, 2014). Researchers have also investigated the role of online community with interactive web technology in innovation and firm performance (Prahalad and Ramaswamy, 2004; Ray et al., 2014; Ma and Agarwal, 2007). Online platforms facilitate opportunities for two-sided markets by bringing together different groups of users within a platform and creating economic values for both sides. Several studies have looked at the price structure strategies for two-sided markets, network externalities of one-side network, and cross-side network effects in online platforms (Eisenmann, Parker, and Van Alstyne, 2011). For a given user, the value of the platform depends largely on the number of users on the network's other side; and each side typically plays a distinct role in the platforms (Eisenmann et al., 2011). However, transactions in two-sided networks often also involve sets of social relations. Thus, two-sided platforms also facilitate a network of user social interactions, across both sets of users and within each user's side. Boudreau and Lakhani (2013) suggest that there is an essential dichotomy between the roles of a platform in enabling contests vs. in enabling a collaborative community. Prior research suggests that interpersonal contact is especially important in persuasion and information dissemination, and online platforms provide participants with initial contact points for an innovation (Phelps et al., 2004). Therefore, rather than elaborating on the economic perspective of two-sided networks, we focus on the social relationships of two-sided participants in crowdfunding platforms. A considerable literature on online communities examines social capital and participants' incentives to share information (Wasko and Faraj, 2005), the role of member attachment (Ren et al., 2012) and the ability of an online community to enforce norms and sanctions (Chua et al., 2007). Ren et al.(2012) distinguish between member attachment that arises from attachment to a group from that of interpersonal bonds that center member attention on individuals. Using their typology, the member attachment in crowdfunding platforms such as Kickstarter exhibits both features of identity-based attachment, wherein there is considerable community engagement and communication as well as attachment to individual funders wherein a funder's background and personal information could be salient for funding decisions.

Table 2.1 Current Crowdfunding Studies			
Reference	**Independent Variable**	**Dependent Variable**	**Key Finding**
Mollick (2012)	• Project quality • Project characteristics • Social network	Funding Success	• Antecedents of funding success • Significant role of Project quality (video) and social network on funding success
Agrawal et al. (2011, 2013)	• Geographical distance • Social network (prior offline relation) • Project characteristics	Investment value	• Local and distant investment patterns • A reduced role for spatial proximity (distance is still significant) • Online platform does not eliminate social-related frictions. Local investors invest relatively early • The geography effect is driven by investors who likely have a personal connection with the artist entrepreneur
Schwienbacher & Larralde (2010)	• Compare pre-ordering mechanism vs. profit sharing mechanism	Reward mechanism	• Crowd funders are rewarded by "community benefits" that increase their utility • The entrepreneur prefers pre-ordering if the initial capital requirement is relatively small, and profit-sharing otherwise
Bellefalammet et al.(2010)[3]	• Modelization of crowdfunding: pre-ordering, price discrimination,	No empirical test	• Rewards mechanism • The conditions under which crowdfunding in preferred to traditional forms of external funding (1) for-profit vs. non-profit; (2) choice of funding method (3) customers as investors

Table 2.1 (cont'd)			
Gerber, Hui, and Kuo (2012)	• Creator's and Funder's motivation: (1) autonomy (2) competence(3) relatedness	Participation	• Identify six creator and four supporter motivations Creators: raise funds, expand awareness of work, connect, gain approval, maintain control, to learn (unmotivated to ask for money, spend time, fail, gain publicity, waste money) • Supports: to collect external rewards, to help others, to be part of a community, to support a causes analogous with their personal beliefs (unmotivated: to wait for or not receive rewards, to be pestered for support
Ordanini et al. (2009)	• Investor's motivation • Platform characteristics	Participation	• Crowdfunding participants : (1) purposes: patronage, investment, social participation; (2) characteristics: innovative orientation, identification, exploitation; (3) roles and task: agent, shareholder(growth and development), donor(help); (4) investment size: small, large, small • Crowdfunding firm: (1) purpose: empower artist and fans, raise alternative venture capital, fund social projects online; (2) service roles: relational mediator, engine of growth, social gatekeeper; (3) network effects: substitute an existing intermediary, disintermediate from an existing intermediary, add a new intermediary
Lin et al. (2012)	• Hard (credit information) vs. soft information(social capital)	Funding success	• Significant impacts of social capital
Burtch et al. (2013)	• Contribution frequency	Contribution amounts	• Significant role of accumulated amounts on additional funding
Kuppuswamy and Bayus (2013)	• Contribution pattern and timing • Project characteristic • Existing social network	Contribution amounts	• How the backers' support in Kickstarter varies depending on project and timing

2.2.2 Information Asymmetry and Collective Evaluation in Crowdfunding

In traditional financial markets, while start-ups have several avenues for external funding such as venture capital companies, friends and families (F&F), and angel investors, in practice it is considerably difficult to obtain external funding (Gompers and Lerner, 2001; Hsu, 2007). It has been posited that an entrepreneur's ability to raise funds depends on her human capital such as education level, history, and prior related experience (Stuart, Hoang, and Hybels, 1999; Busenitz et al., 2005), since funders may interpret such observable information as a signal of the potential quality of the projects (Stuart et al., 1999). Entrepreneurs' embeddedness in social networks also influence the probability of external fundraising success in traditional funding markets (Jenssen and Koening, 2002; Shane and Cable, 2002; Shane and Stuart, 2002).

Crowdfunding entails significant differences from traditional funding methods such as microfinancing and angel capital investment in terms of the economies of scale and scope of accessible resources (Mollick, 2012). However, in traditional funding methods, the size of project creator's social networks remain hidden and the social interactions among funders are not observable. For example, in a venture capital companies syndicate we may observe the formation but not what details they exchange with each other.

Rewards differ across crowdfunding platforms and monetary rewards are not always necessary. At the same time, however, since funders can contribute a small sum of money to projects without any professional expertise or the ability to evaluate either the quality of projects or an entrepreneur's potential, there is considerable asymmetry of information. Online Peer-2-Peer (P2P) lending is characterized by similar types of asymmetric information, in the sense that individuals can gather small amounts of money from crowds. In an online funding context, Lin et al. (2013) found that both soft information (online friendships) and hard information (credit information) were associated with the likelihood of credit being issued. However, there are significant differences in terms of rewards and processes of funding[4].

We suggest *"The Ladder Model of Co-Value Creation in Crowdfunding"* to explain the benefits which entrepreneurs can obtain by using crowdfunding platforms (Figure 2.2). Like co-creation of value in marketing literature which stresses different level of involvement or impacts at different points in the value chain, funders' roles, their communities, and co-creation processes are different in the crowdfunding model. First, entrepreneurs can obtain *financial resources*. Crowdfunding allows entrepreneurs to enhance legitimacy of their projects. Entrepreneurs can easily access potential investors and external financial resources, and interact with them. Some entrepreneurs raise more funding than their initial goals. Additionally, the success in crowdfunding projects creates legitimacy for additional funding. Furthermore, entrepreneurs can obtain non-financial or indirect potential benefits (i.e., social capital and potential customers, delivering initial products and achieving innovation, new opportunity and on-going business), which will become a source of potential revenue. The online community interactions and e-WOM not only attract funders, but also help entrepreneurial innovation. Funders are able to participate actively in *entrepreneurs' innovation process*. They evaluate and share ideas about the project and entrepreneurs' performance. Additionally, crowdfunding communities force entrepreneurs to *complete their initial innovation plans* (delivery outcomes). Lastly, based on the existing online social capital, additional funding, and credibility, entrepreneurs can initiate *new innovation*. Figure 2.2 summaries main benefits, which entrepreneurs can obtain from using crowdfunding.

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[4] Crowdfunding calls for entrepreneurs to provide monetary or non-monetary rewards to funders, which is different from paying interest on loans, as is done in P2P marketplaces.

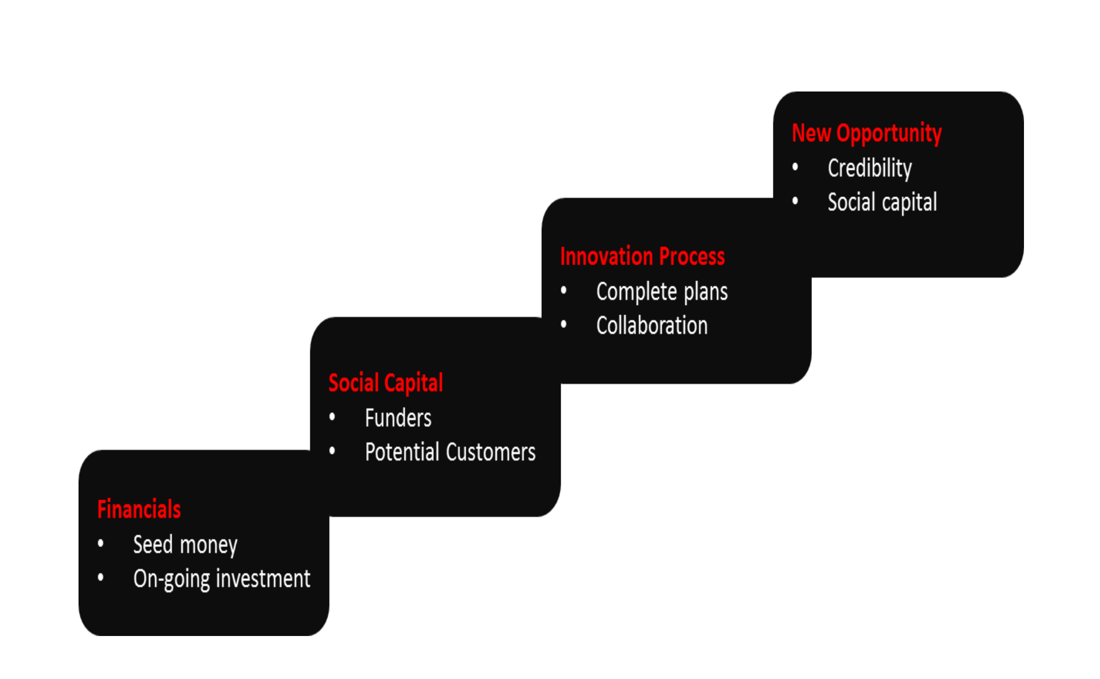

Figure 2.2 The Ladder Model of Co-Value Creation in Crowdfunding

Thus, Crowdfunding platforms provide with an online social space which enables *"connection"*, interactions among funders and entrepreneurs or among funders, *"collaboration"*, more than simple involvement (i.e., share experience and knowledge about funding projects), and *"co-value creation"*, evaluating and supporting entrepreneurs[5]. Figure 2.3 shows the three major roles of crowdfunding platforms: (1) Project creators launch their projects; (2) funders choose projects to which they want to contribute; and (3) platforms provide both participants with a place for online interactions and functions.

[5] We reframed Prahalad and Ramaswamy (2004)'s argument about co-creation in a crowdfunding context.

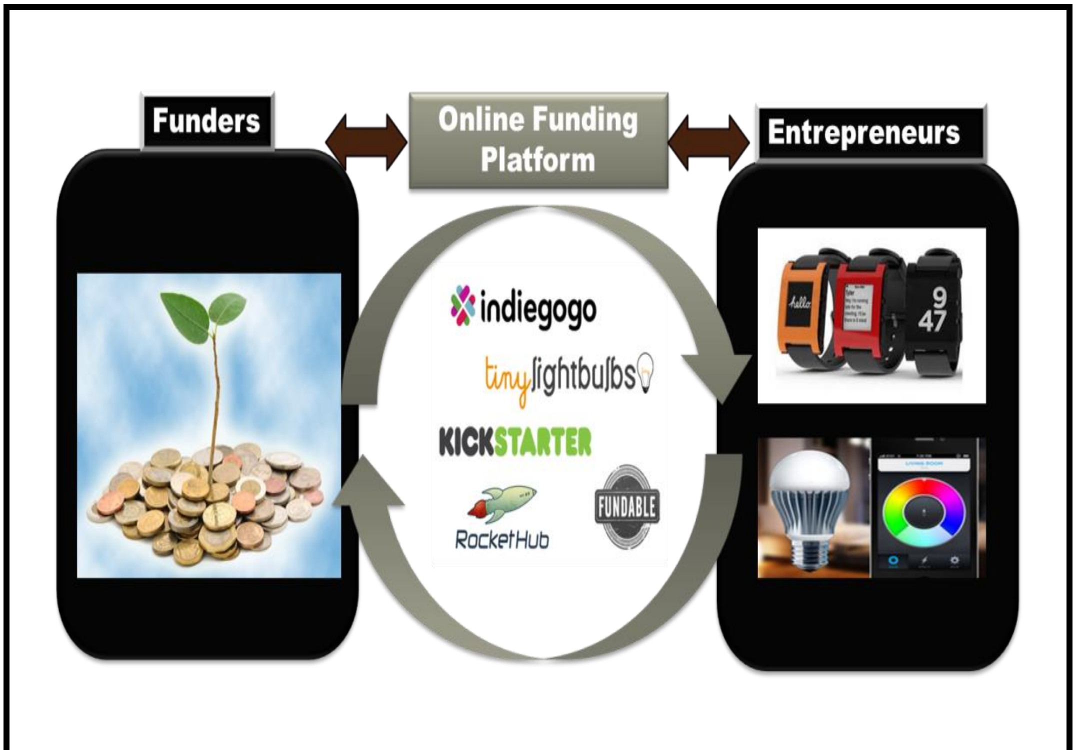

Figure 2.3. Two-sided Interaction in Crowdfunding Platforms

We consider three distinct aspects of crowdfunding platforms that translate to success in fundraising. First, funders in crowdfunding platforms are engaged in terms of providing ideas and input, and proactive in seeking details about the project from the entrepreneur, which requires entrepreneurs to provide business plans and details about how an idea how would executed. Thus, crowdfunding raises money from the "crowd" through a process of collective evaluation as well as crowdsourced input for problem-solving and project execution. In other words, crowdfunding platforms exhibit characteristics of online communities in enabling interactions between funders and entrepreneurs. We consider the role of network embeddedness and community engagement in fundraising success. Second, crowdfunding platforms facilitate interactions among participants within the platform and increase the visibility of the projects and the participants, entrepreneurs can easily interact with funders and convey their personal credibility, information about their professional organizational abilities, their achievements, track record, and information about key funders. Such entrepreneurial human capital enhances the visibility and legitimacy of a project, which raises the probability of success in fundraising (Zimmerman and Zeitz, 2002; Zott and Huy, 2007). Finally, online social media such as blogs, wikis, crowdsourcing, and online forums have become important intermediaries for information transmission and for forming online communities (Finin et al., 2008). Many studies have examined how electronic word-of-mouth influences consumer choices, content-generation behaviors, and product sales (Dellarocas, 2003; Pollock and Rindova, 2003; Grewal et al., 2003; Goes and Lin, 2014). Aggarwal et al. (2012) show how the valence of electronic word-of-mouth influences venture capitalists' decision-making. We therefore examine how e-WOM in online social media helps crowdfunding projects to succeed. To gain insights into the effects of social networks in crowdfunding, we analyze the connections between the fundraising results of projects on crowdfunding websites and the corresponding promotion campaigns in online social media.

Figure 2.4 shows the research model of our study and serves as a roadmap for hypotheses development. Our paper considers two-sided interactions in crowdfunding as occurring through two distinct social channels: (1) how social interactions and community engagement in crowdfunding influences fundraising success, finally, external impact and how e-WOM on social media influence fundraising success. Our study is different from the existing crowdfunding studies. First, we examine digitally enabled two-sided network effects such as the impact of funders' interaction (network embeddedness, engagement) and entrepreneurs' actions on fundraising success. We also examine the impact of e-WOM on fundraising success. In addition, we examine the effects of traditionally critical factors (entrepreneurs' human capital) in fundraising success.

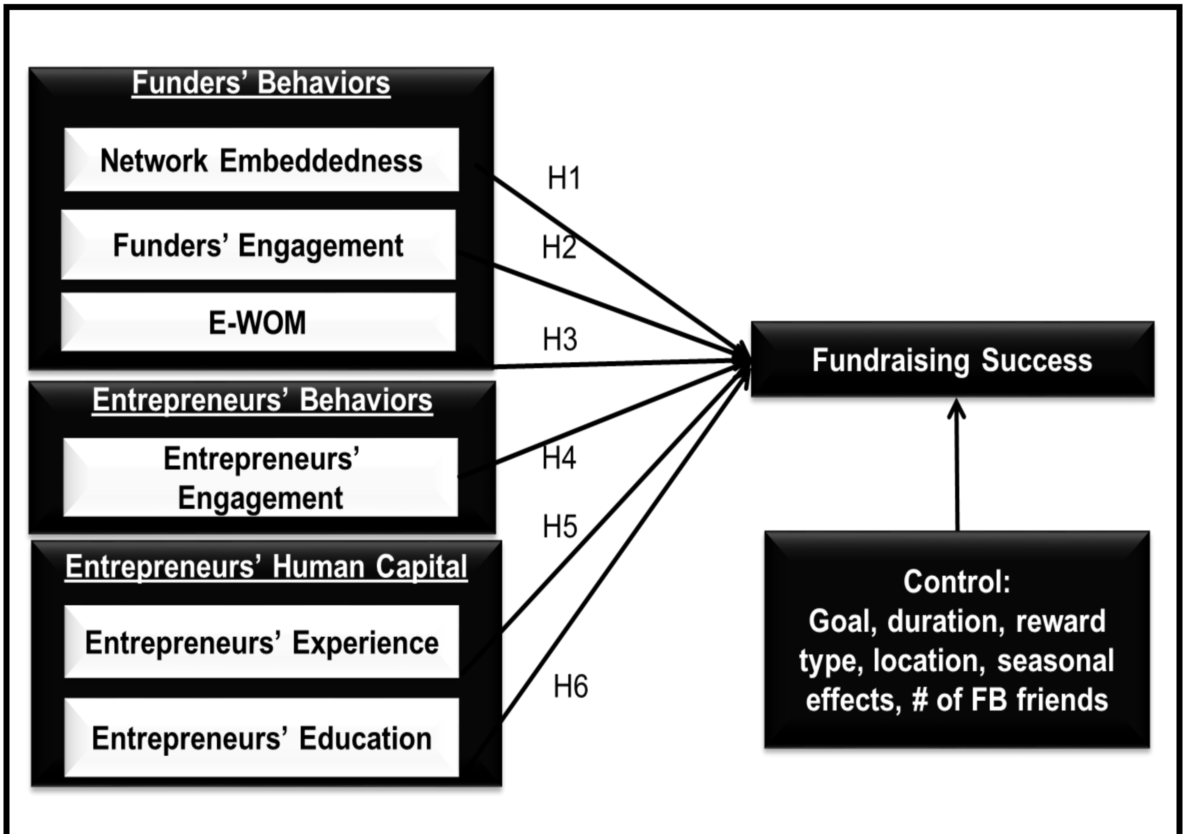

Figure 2. 4. Research Model

2.2.3 Hypotheses Development

Funders' Embeddedness

Social network theory explains how individuals' relationship with others and the characteristics of relationship influence various outcomes of interest, including behavior and performance (Ibarra and Andrews 1993; Lin, 1999; Wasserman and Faust, 1994). According to the theory, people can access more information and resources and influence others depending on the strength or ties and the structural position within the networks (Wasserman and Faust, 1994; Ibarra and Andrews 1993). Based on Social Information Processing (SIP) theory, Salancik and Pfeffer (1978) argued that the information available in people's social relationships influences their attitude development. In particular, SIP plays an important role in shaping attitudes under conditions of uncertainty or ambiguity, because people are more likely to follow social interpretations in those conditions (Ibarra and Andrew, 1993). Studies based on Social Network Theory elucidate the SIP mechanisms, and provide more adequate measures for exploring the relationship between network interactions and people's decisions (Dean and Brass, 1985; Rice and Aydin, 1991). Network centrality is a fundamental concept that shows the extent to which a node is connected to other nodes in a social network (Wasserman and Faust, 1994; Borgatti and Everett, 2006), and is commonly used to measure the effect of social influence on people's perceptions and attitudes (Dean and Brass, 1985; Ibarra and Andrew, 1993). Network centrality confers access to resources both through better access to information as well as through the ability of central actors to influence others that makes them more likely to engage in similar behaviors. A central network position of an entrepreneur represents greater information accessibility and resource availability (Jenssen and Koening, 2002). For example, entrepreneurs who have higher centrality within the entrepreneur-funder network have greater access to resources and their behaviors often influence others' behaviors. Equally important is the social influence of a funder amongst other funders, since such factors increase a funder's participation and shapes the process of a collective decision (Aral and Walker, 2012). Most prior studies on the role of social networks in funding opportunities have focused on friends and the small offline social network of entrepreneurs. However, our study takes a new perspective on the role of social networks enabled by digital platforms and how online social interactions create business values. We study the effect of the larger cohort of online participants and their interactions on the platforms, where the participants are mostly strangers rather than offline friends and acquaintances.

Several economic studies have emphasized the role of network embeddedness on economic outcomes (Burt, 1997; Uzzi, 1997; Granovetter, 2005). Granovetter (2005) claimed that people's actions or decisions are embedded in social relations, thus economic actions are influenced by these relations. Since any social interaction transmits information, the embeddedness of social interactions or transactions in a network promotes the formation of collaboration and improves performance (Granovetter, 1985). Network embeddedness facilitates more efficient spread of information about what members are doing and enhances the ability to shape others' behaviors. According to the traditional embeddedness literature, people's economic behaviors are embedded in their social relationships and if people have higher embeddedness they will have more chance to get information and resources or influence others. Recently the effects of network embeddedness have often been reviewed in a digitally mediated community context along with traditional social network and social influence studies. Grewal, Lilien and Mallapragada (2006) examined the effects of the network embeddedness of projects and developers on project success in an open source system (OSS). They found significant heterogeneity exists in the network embeddedness of open source projects and managers, and that network embeddedness influences technological and commercial success. Singh (2010) also find that a project's embeddedness raises OSS success. Entrepreneurship literature likewise suggests that network embeddedness helps with fundraising (Venkataraman, 1997).

In a crowdfunding context, network embeddedness refers to the network centrality of the project's funders. Fundraising success will rely on funders who have higher network centrality within a whole crowdfunding network. Those funders will have more chance to interact with, to motivate, and to attract each other (highly centralized funders) and other funders through the social influence mechanisms, which ultimately helps projects reach their goals. The more connected people are to each other, the more they may be opinion leaders (Rosen, 2009). However, funders who have low centrality have less social interactions with others and have limited means to persuade others within a network, while they individually fund projects. Many studies on the process of social influence argue that individuals tend to ignore their preferences and private information, and follow the crowd, who are presumed be better informed when making investment decisions under conditions of uncertainty (Pollock et al. 2003). Therefore, projects which have higher funders' embeddedness will have a better chance of reaching funding goals. Thus, we propose the following hypothesis.

Hypothesis 1: *The network embeddedness of project' funders will influence its probability of fundraising success.*

A digital platform enables people to transmit information, share knowledge and engage in discussions (Finin et al., 2008). Online feedback mechanisms foster cooperation among community members and the publicly shared knowledge influence the entire community (Dellarocas, 2003). People may participate in online communities because of informational and instrumental values and "social benefits derived from establishing and maintaining contact with other people" (Dholakia et al. 2004). Venkataraman (1997) argues that investors can overcome the problem of information asymmetry using social relationships. In the crowdfunding platform, funders are able to freely share comments and knowledge about projects, and to ask and to answer each other's questions. Funders, who post comments in the platforms, often share in-depth insights on projects, and the reasons behind the choice they made as funders. Funders can share more knowledge about the projects and entrepreneurs through interactions within the digital platforms. By posting those comments, they can engage in the crowdfunding community. The volume of comments on a project is a reflection of social engagement and enthusiasm of the community members. More comments and discussion are proxies of how much funders are engaged in the community. Therefore, funders' engagement for each project will influence the probability of fundraising success.

Hypothesis 2*: The community engagement of project's funder will influence its probability of fundraising success.*

In the marketing literatures, there has been the rich discussion on the power of electronic word-of-mouth, in which many prior studies has shown the positive e-WOM effects on product sales and advertisement (Reichheld, 2003). Aggarwal et al. (2012) find the significant impact of e-WOM from blogs on the probability to get venture capitals. However, there is no study on how e-WOM from online social networking site such as Twitter and Facebook influence investors' behaviors and entrepreneurs' fundraising success in crowdfunding context. Therefore, we would like to investigate the e-WOM effects from popular social networking sources and private blogs on project creators' fundraising success in crowdfunding platforms. We expect that e-WOM during the fundraising period will increase the probability of fundraising success. Not only does e-WOM increase the visibility of projects and entrepreneurs, but it also substitutes for unavailable quality data, which helps potential funders in assessing the quality of projects and entrepreneurs' potential performance (Aldrich and Fiol, 1994; Sanders and Boivie, 2004). Individuals seek out e-WOM messages to get more information about products and services (Schindler and Bickart, 2005). Thus, the increase in volume of e-WOM may increase the probability of funding success, because it increases the awareness and familiarity about projects and entrepreneurs. We suggest following the hypotheses.

Hypothesis 3: *The volume of overall e-WOM for a project will be positively related to its probability of fundraising success.*

Entrepreneurs' Engagement with the Crowdfunding Community

Entrepreneurs' can purposely seek legitimacy through specific actions (Suchman 1995; Zimmer and Zeitz, 2002; Zott and Huy, 2007). According to entrepreneurship literatures, legitimacy (acceptance of an entrepreneur' actions as proper or appropriate) helps new ventures to overcome the liability of newness and influences the acquisition of necessary resources (Suchman, 1995; Zott and Huy, 2007). Ventures can increase their legitimacy through several actions such as sharing information about their performance (patents; prior performance), credentials, endorsement, and social connections (Lousbury and Glynn, 2001; Zott and Huy, 2007).

Crowdfunding facilitates entrepreneurs to increase their visibility and the opportunities to access necessary resources by enhancing legitimacy of a project. First, the crowdfunding platform allows each entrepreneur to communicate with funders simultaneously and frequently. Entrepreneurs can continuously provide project information, project progress, and their credibility information, and such actions will make funders draw interpretations about the character of the entrepreneur and projects. For example, sharing a photo of products (or a prototype) in the platform can cause funders (viewers) to perceive the entrepreneur as having professional process. Those actions can make them more credible and knowledgeable and are interpreted as a good signal about their performance (Zott and Huy, 2007). Also, funders within the platform can respond to the entrepreneurs' updated information and entrepreneurs can also respond back to the comments. The interaction can be extended to the interaction among participants. Such three-way interactions (between entrepreneurs and funders, funders and entrepreneurs, and among funders) will help to increase legitimacy of a project. Also, entrepreneurs can leverage their funders to diffuse information and project stories. Once entrepreneurs share any stories about projects within the platform, funders can choose to indicate their interest in that information and comment on and share it with others. Thus, entrepreneurs' engagement (updating behaviors) will influence the probability of fundraising success. We propose the following hypothesis:

Hypothesis 4: *The volume of entrepreneurial engagement with the crowdfunding community positively influences the probability of the project's fundraising success.*

Entrepreneurs' Human Capital

Considerable information asymmetry exists in crowdfunding. Funders may not have prior information about entrepreneurs, offline-relationships, or prior experience with entrepreneurs. Funders can contribute small amounts of money to projects without any professional expertise or the ability to evaluate the quality of projects as well as entrepreneurs' potentials. There is also a hidden information problem, in that the quality of the innovation (Agarwal et al., 2013; Sanders and Boivie 2004), entrepreneurial vision and ability are all difficult for potential funders to infer. Where substantial information asymmetries exist, there is high possibility of adverse selection (Leland and Pyle, 1977). Therefore, in entrepreneurial context potential funders deploy quality signals to navigate the asymmetry of information between what they know and they need to know (Agarwal et al., 2013; Janney and Folta, 2003).

Spence (1973) defines signals as *'those observable characteristics attached to the individual that are subject to manipulation by him"* and demonstrated that education is a signal in the labor market. In entrepreneur finance literature, investors assume that signals from entrepreneurs' observable characteristics such as prior education level and history covariate with their actual performance (Deeds, Decarolis and Coombs, 1997; Stuart et al., 1999). Such observable characteristics are germane to the viability, competence and potential value of start-ups (Busenitz et al., 2005). Positive information signals will increase the probability of potential funders' contribution. Therefore, entrepreneurs should convey positive quality signals to outsiders to become viable (Prasad, Bruton and Vozikis, 2000; Agrawal et al. 2011). In crowdfunding platforms the signals from entrepreneurs' observable attributes will influence the fundraising success. In this study, we consider two attributes such as education level and prior experience. Higher education can be a proxy for start-ups' innovation capability. Also, entrepreneurs who have prior project experience will have more skills to manage projects. We propose the following hypotheses:

Hypothesis 5: *Entrepreneurs' education levels influence the probability of the project's fundraising success.*

Hypothesis 6: *Entrepreneurs' prior experience influences the probability of the project's fundraising success.*

2.3 DATA AND METHODS

2.3.1 Data Collection

The data have been collected from Kickstarter.com. To participate in the platform, individuals or entrepreneurs need to sign up with the site and submit their basic personal information and social network information. Based on this, the platform provides an individual's profiles and social media information. Any individual or entrepreneur can create[6] as well as fund projects in a variety of areas. Project creators pay fees only when their goals have been reached, in the same way project funders can only fund a project when the pre-announced goal has been reached. Members can easily access project information such as goal, pledged amount, creators' profile information, a project video, and detailed project information. Members can also observe the cumulative number of funders and each backer's information, the accumulated amounts pledged, the number of comments and updates. We collected projects, funders, and entrepreneur data. Our sample focuses on the projects initiated within the Technology category. There are a total of 722 projects (March 2012 – January 2013) in the dataset. We have a total of 303 successful projects and 419 failed projects, which is almost the same as Kickstarter.com statistics[7]. Figure 2.5 shows the screenshots of a project and a funder's profile pages.

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[6] Currently, Kickstarter.com only allows people in the United States or United Kingdom to create projects.

[7] 30 additional projects are removed from our dataset, because of insufficient information.

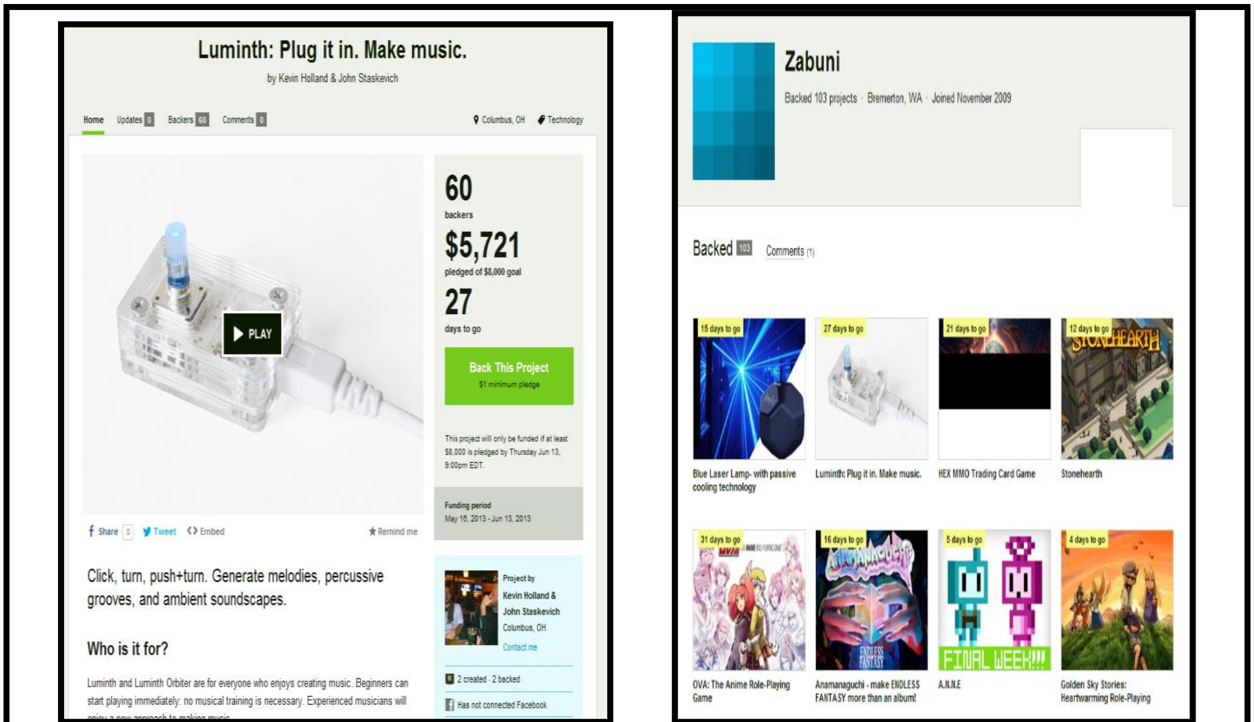


Figure 2.5 Screenshots of a Project and a Funder's Profile

We gathered project information (goal, duration, category, description, number of funders, comments, updates, and so on) and funder's information (location, funded or created projects) from each page. We also gathered project creators' location, descriptions, joined date, and activities in Kickstarter platform (funded and created projects). Additionally, we gather entrepreneurs' detailed attributes from LinkedIn. During our observation window, we collect e-WOM data for each project from online social networking sites (Twitter, Facebook and online websites) using a web-crawler. We also relied on Google searches, archive searches and data from the Kickback machine[8], a site that archives Kickstarter webpages.

[8] It is closed now (2014).

2.3.2 Network Analysis

The projects on Kickstarter.com are classified into more than 13 categories. We consider each category to be a network boundary. Our sample focuses on the projects initiated within the Technology category (e.g. technology, open source, and hardware). There are a total of 722 projects and more than 177,000 funders in the dataset. Following Wasserman and Faust (1994), we created two-mode affiliation networks of projects and funders (Figure 2.6). We measure network embeddedness using network centrality measures (Everett and Borgatti, 2005). To measure network embeddedness of funders, we follow three steps. First, we formed a two-mode network by connecting funders through projects. After that we generated the one mode network of funders and calculate their centrality score within the whole platform. Lastly, based on those score, we calculated aggregated network embeddedness for each project.

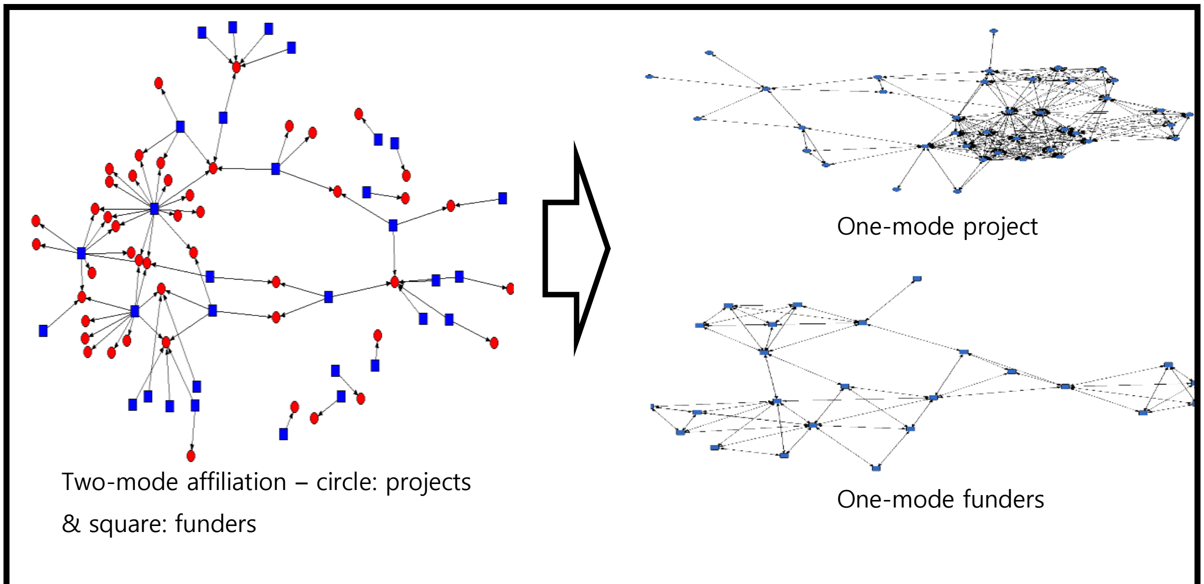


Figure 2.6 Transpose Two-Mode Network to Two One-Mode

2.4 EMPIRICAL MODEL

2.4.1 Funding Success Model

Crowdfunding success is influenced by multiple factors such as funders' social interactions, entrepreneurial actions, and project characteristics. Fundraising success is (i) a binary variable, i.e., whether a project reaches its fundraising goal or not, and (ii) percentage of pledged amounts.

$$
\begin{aligned}
&CFS(Crowd\ Funding\ Success)_i \\
&\qquad = \beta_0 + \beta_1\ Network\_E_i + \beta_2 S\_Engagement_i + \beta_3 E\_Education_i \\
&\qquad + \beta_4 E\_engagement_i + \beta_5 E\_Experience_i + \beta_6 Reward_i \\
&\qquad + \beta_7 E\_WOM_i + \beta_8 logGoal_i + \beta_9 Location_i + \varepsilon_i
\end{aligned}
$$

In this model, we examine the impact of network embeddedness, the volume of social interaction among funders, e-WOM, entrepreneurs' engagement, and entrepreneur human capital. We controlled for project characteristics such as size of goal and duration, and control the geographical impacts, seasonal impact, and reward types. Since the observed outcomes of CFS is binary (1=success, otherwise 0), we assume $\varepsilon_{\mathrm{it}} \sim$ N (0,1) and use the general probit model.

$$Pr\ (y_i = 1) = \Phi\ (CFS_i)$$

Where y_i is 1 when *i* project get successfully funded, otherwise it is zero.The positive and significant β_1 and β_2 will suggest that the projects are more likely to be successful if higher network embeddedness, or community interactions exist. The positive and significant β_3 and β_5 will suggest that the projects are more likely to success in fundraising if higher entrepreneurs' characteristics (education and prior experience) exist. The impact of entrepreneurs' engagement on the probability of funding success is measure by β_4 and E-WOM is measured by β_7, respectively. In the same vein, we analyze the percentage amounts model using an OLS model.

$$
\begin{aligned}
CFPAM_i = \beta_0 &+ \beta_1\, Network\_E_i + \beta_2 S\_Engagement_i + \beta_3 E\_Education_i \\
&+ \beta_4 E\_engagement_i + \beta_5 E\_Experience_i + \beta_6 Reward_i \\
&+ \beta_7 E\_WOM_i + \beta_8 logGoal_i + \beta_9 Location_i + \varepsilon_i
\end{aligned}
$$

2.5 RESULTS AND DISCUSSION

2.5.1 Results

Table 2.2 shows the definition of variables and descriptive statistics. The maximum value of pledged percentage is 6264, the goal is 750,000, and the maximum total pledged amounts are 2,945,885. The standard deviation of pledged percentage is 440.89 and mean is 170.77. We use two success variables such as Success (fundraising success) and percentage of pledged amounts (= goal/total funded amounts). Each project has initial fundraising goal and duration. The average duration is 27 days. During fundraising period, we collect comments about each project in online social networking sites (e.g. twitter, Facebook) and calculate the total volume of electronic word of mouth. The maximum volume is 984, and we used square of total volume (range between 0 and 31.37, mean = 2.09, and SD=3.77) in the analysis. There are three education levels: BS, MS, and PhD. If we cannot observe project creators' education information, we input 0. We used information from both Kickstarter.com and LinkedIn site. We looked at whether each project creator has prior crowdfunding experience (whether they created other project) or not. However, the quality of information is different based on project creators' prior performance. Thus, we calculated net positive prior experience (Total positive experience – negative experience), which ranges from -2 to 2. We measure entrepreneurial actions and funders' engagement within the crowdfunding platforms. Also, based on our network analysis, we calculate the network embeddedness of each project. For the empirical analysis, we use log (Network embeddedness). We also control reward type of each project if the final outcome is physical products (either hardware or software) or warm glow type (gift, invitation, etc.).

Table 2. 2 Variable Definitions and Descriptive Statistics						
Variables	Definition	No. Obs.	Mean	Std. Dev.	Min	Max
Success	=1 if a project reach the goal, otherwise =0	722	0.42	0.50	0	1
%_pledged	Percentage of funded amounts	722	170.77	440.89	0	6264
Goal	Funding goal (amounts)	722	39715.7	70100	75	750000
Amounts	Total funded amounts	722	41152.34	175034	1	2945885
Duration	Initial Length of the funding cycle for each projects (days)	722	26.89	13.77	1	60.04
E-WOM	Total quantity of comments in social network sites	722	18.54	70.50	0	984
Education	Entrepreneurs' education level (1=BS,2=MS, 3=PhD, otherwise 0)	722	0.67	.84	0	3
Experience	Entrepreneurs' prior net experience (Positive – Negative)	722	-0.04	0.38	-2	2
Entrepreneur Engagement	The volume of actions (# of updates for a project)	722	4.37	5.11	0	33
Network embeddedness(log)	Embeddedness of a project within a community	721	5.59	1.81	0	9.97
Funders Engagement	Total quantity of discussion for each project	722	52.98	168.54	0	1660
Num. of FB Friend	Total number of project creators' friend, if there is no FB sites = 0	722	268.58	471.59	0	5088
Word Count	Total number of words in entrepreneur's profile	722	82.39	94.92	0	1603
Social Presence	=1 if each entrepreneur share her personal social network site links, otherwise =0	722	0.68	0.47	0	1
Reward Type	=1 physical outcome, otherwise =2	722	1.20	0.40	1	2
Image	=1 if each entrepreneur share her personal image, otherwise =0	722	0.66	0.48	0	1

Figure 2.7 shows the distribution of percentage of total pledged amounts and project goals. The distribution figures show the evidence of prevailing "long tail" effect in crowdfunding, which

provides diverse project choices to funders and financing opportunity for project creators. For the empirical analysis we do a log transformation of the goal and percentage of pledged percentage amounts. Table 2.2 provides more detailed information.

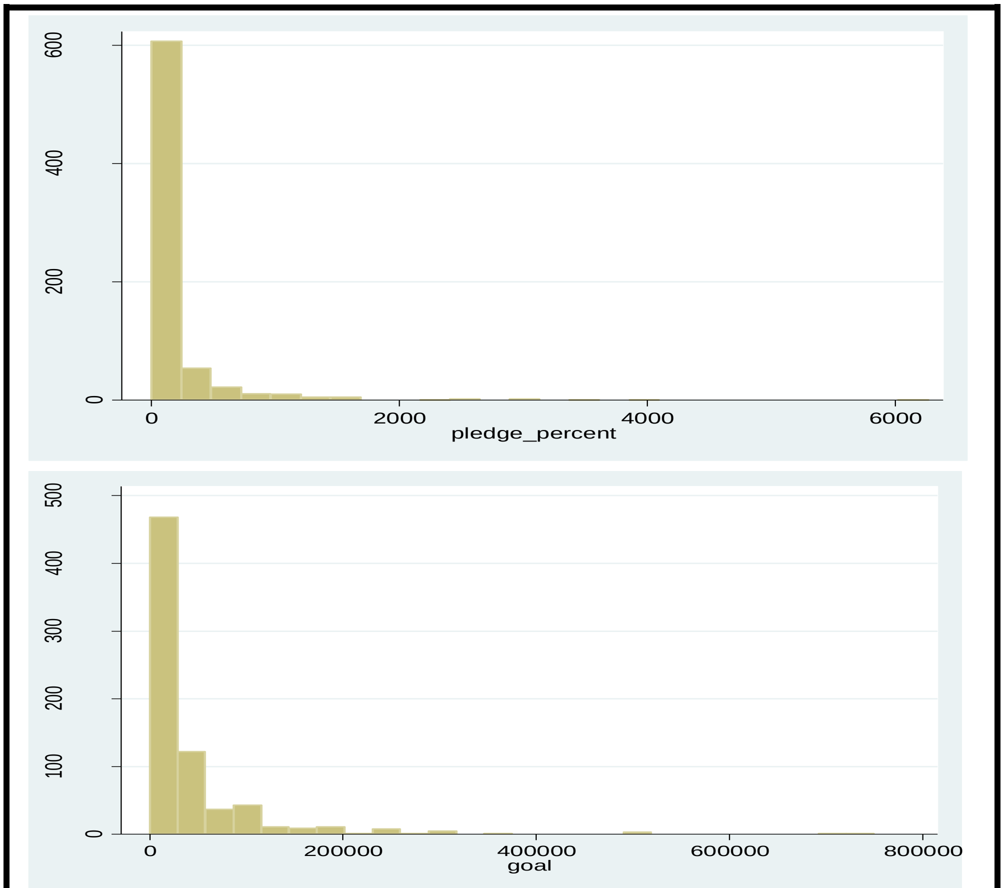


Figure 2. 7. Distribution :Pledged Percentage and Project Goal

Table 2.3 represents the correlations of variables.

Table 2.3 The Correlations of Variables

	SG	PA	Goal	RW	DR	ED	EP	MO	EA	SEG	NE	LC	EW	NF
SG	1.000													
PA	0.784	1.000												
Goal	-0.294	-0.365	1.000											
RW	-0.089	-0.128	-0.157	1.000										
DR	0.284	0.197	0.101	0.010	1.000									
ED	0.001	-0.0083	0.097	-0.031	0.106	1.000								
EP	0.065	0.020	0.100	-0.007	0.106	-0.001	1.000							
MO	0.017	0.032	0.006	0.032	-0.447	-0.125	-0.025	1.000						
EA	0.412	0.426	0.173	-0.188	0.242	0.024	0.033	-0.030	1.000					
SEG	0.338	0.363	0.216	-0.136	0.172	0.043	0.014	-0.013	0.385	1.000				
NE	0.611	0.714	0.126	-0.285	0.228	0.059	0062	-0.044	0.526	0.500	1.000			
LC	0.069	0.062	0.030	-0.118	-0.041	-0.013	0.020	0.095	0.075	0.061	0.081	1.000		
EW	0.271	0.267	0.188	-0.044	0.115	0.129	0.087	0.044	0.258	0.337	0.365	0.031	1.000	
NF	0.013	0.010	0.004	0.065	0.020	0.073	0.025	-0.061	-0.029	-0.015	-0.038	0.010	0.052	1.000

SG: Goal Achieve; PA: log pledged amounts; Goal: log goal; RW: reward type; DR: duration;
ED: education; EP: experience; MO: Month; EA: entrepreneurial action;
SEG: social engagement; NE: network embeddedness; LC: location; EW: EWOM; NF: number of Facebook friend

We examine two models: (1) Fundraising success model and (2) Percentage Amount of Funding. We examine the first model using probit model and OLS for the second model. To deal with heterogeneity of projects, we use cluster robustness errors. Table 2.4 shows the empirical results of our analysis. The R^2 is 0.68 in fundraising success model (pseudo) and 0.760 in log percentage of pledged amounts model. Network embeddedness positively influences both fundraising success (0.804***) and log percentage of pledged amounts (0.851***), which supports Hypothesis 1. Projects which have highly embedded funders will have more chance to get funding, because funders who have higher embeddedness influence others' participation and increase the probability of fundraising success. Funders' engagement within the platform also positively influences crowdfunding success (0.014***, 0.001*** respectively; support Hypothesis 2). When people share more information about the project and actively interact with others within the platform, the project can attract more funders. We also observe the significant impact of e-WOM on fundraising success (0.079***, 0.33** respectively; support Hypothesis 3). We observe the significant impacts of entrepreneurs' engagement on fundraising success (0.056***, 0.051*** respectively; support Hypothesis 4). We operationalize entrepreneurs' engagement as the volume of updates on crowdfunding platforms. The entrepreneurs can convey more knowledge than a simple project description through updating actions. These actions will signal the quality of projects and potential innovation capability. Also the effort, time, and dedication make entrepreneurs appear to be trustworthy. However, we cannot observe the significant influence of entrepreneurs' human capital such as prior experience and education on fundraising success in our initial test. We then measure the volume of net positive prior experience (Successful prior experience minus failed experience) rather than using total prior experience. We find that projects are more likely to get funding if project creators have prior positive success experience (only this model supports Hypothesis 6), but we cannot observe the significant impact of positive experience on the percentage of pledged amounts. Traditional funding literature emphasized the role of trust and reputation in fundraising success. Thus, start-ups who do have prior positive history, relationship, or reputation will be more likely to get funding from funders, but the prior positive experience does not significantly influence total funding amounts. Additionally, none of education level has significant influence on either fundraising success or percentage of pledged amounts (do not support Hypothesis 5). Overall, compared to traditional funding methods, funders in crowdfunding may value social information more than the entrepreneur's quality.

Table 2.4 Results				
Independent Variable	**Fundraising Success**		**OLS on LogPert_Amounts**	
	Coefficients	**Std. Err**	**Coefficients**	**Std. Err**
LogGoal	- 0.95***	0.082	-0.77***	0.030
Duration	0.046***	0.007	0.018***	0.004
Prior Experience	0.476*	0.243	0.066	0.118
Education1	-0.196	0.191	-0.069	0.101
Education2	0.011	0.260	0.109	0.143
Education3	-0.323	0.510	-0.316	0.226
Entrepreneur's Engagement	0.056***	0.021	0.051***	0.010
Funders' Engagement	0.014***	0.004	0.001***	0.0003
Network Embeddedness	0.804***	0.094	0.851***	0.033
Electronic Word of Mouth	0.079***	0.023	0.033**	0.013
Num. of FB Friends	0.0002*	0.0001	0.0002**	0.0001
Month	0.126***	0.030	0.087***	0.033
Location	-0.000	0.0004	0.0000	0.0002
Reward Type	0.096	0.211	0.071	0.117
Log-likelihood	-154.80		-	
R	0.684 (Pseudo)		0.760 (Adjust R2: 0.755)	
Number of observation	721		721	
two-tailed significance levels p<0.1, *; p<0.05, ** ; p<0.01, ***				

We also looked that distribution of technology projects. Traditionally, technology projects have been often initiated in the west-coast (Agarwal et al., 2011), but in crowdfunding context we can see that projects are dispersed across the U.S. (Figure 2.8). The empirical results also show the non-significant effect of location on fundraising success. Thus, crowdfunding platforms bring together large numbers of geographically dispersed funders and allow them to participate in interactions in online communities, contribute to start-ups, and create economic and social values.

Figure 2.8 Geographical Distribution (Technology Projects)

2.5.2 Robustness Checks

Endogeneity: Instrument Variable

To address the robustness of our estimation model, results, and model identification, we did implement a series of robustness checks. First, we checked potential endogeneity issues. A critical issue in the estimation process is reverse causality between entrepreneurial actions (i.e., updating information about projects) and fundraising success. Not only the increase of updating actions influence fundraising, but also entrepreneurs who get higher funding amounts may engage in updating more often. To deal with this issue, we used three sets of instruments, which are correlated with entrepreneurial actions but are not correlated with fundraising performance.

We collected entrepreneurs' profile data from Kickstarter.com and check whether entrepreneurs share their personal image and personal social network sites. Additionally, using profile description we calculated the length of entrepreneurs' profile using basic text-mining techniques (1.sentence extraction, 2. tokenization, 3. stemming, and 4. removing stop words). Prior studies show the relationship between entrepreneurial action and their narcissistic characteristics. Entrepreneurs are more likely to be optimistic and have narcissistic characteristics (Busenitz and Barney, 1997). Narcissistic entrepreneurs tend to be overconfident on their decisions and have the tendency to overestimate their ideas, future performance, and their own abilities (Benabou and Tirole, 2002; De Meza and Southey, 1996; Lee, Hwang, and Chen, 2014). This tendency contributes to entrepreneurial activities (Hirshleifer, Low, and Teoh, 2010).

Table 2.5 Instrumental Variable Models					
Variables		Probit Model: Fundraising Success		OLS on LogPert_Amounts	
		Coefficients	Std. Err	Coefficients	Std. Err
Fundraising Success	LogGoal	-0.94***	(0.082)	-0.787***	(0.047)
	Duration	0.046***	(0.007	0.014	(0.009)
	Prior Experience	0.473*	(0.243)	0.083	(0.126)
	Education1	-0.193	(0.189)	-0.039	(0.124)
	Education2	0.010	(0.255)	0.107	(0.146)
	Education3	-0.297	(0.508)	-0.265	(0.258)
	Entrepreneur Action	0.043**	(0.022)	0.119	(0.154)
	Funders' Engagement	0.014***	(0.004)	0.001	(0.001)
	Network Embeddedness	0.770***	(0.095)	0.776***	(0.174)
	Electronic WOM	0.077***	(0.023)	0.030*	(0.016)
	Num.of FB Friends	0.0002	(0.0002)	0.0002**	(0.0001)
	Month	0.130***	(0.030)	0.082***	(0.019)
	Location	-0.000	(0.0004)	- 0.000	(0.0002)
	Reward Type	0.153	(0.210)	0.107	(0.144)
Entrepreneur Action	Word count(profile)	- 0.001*	(0.0005)	-	
	Personal Image	- 0.310***	(0.115)	-	
	Social Presence	0.412*	(0.234)	-	
rho		0.265		-	
Likelihood Ration test rho=0: Chi2=3.522		Prob> Chi2 =0.061		-	
Log-likelihood		-527.76			
R2				0.746	
Wald Chi2 (Prob >chi2)		180.33 (0.000)		2132.43 (0.000)	
Number of observation		721		721	
two-tailed significance levels p<0.1, *; p<0.05, ** ; p<0.01, ***					

Entrepreneurs who have narcissistic characteristics enjoy explaining their vision and ideas because of own overconfidence and the desire to get others' agreements about their ideas, which can be represented in the entrepreneurs' profile in crowdfunding project pages. Those entrepreneurs tend to provide longer profile and to share own personal images. Additionally, entrepreneurs who share their personal social networking website may want share more information about projects information in order to show how much she (or he) is trustworthy.

According to accounting and finance literature, executives are becoming active on social media channels (Blankespoor, Miller and White, 2013). Their personal social networking sites (e.g., Facebook, Twitter, or LinkedIn) can provide both indirect and direct information about a project, specific news about a project, funding status, and entrepreneurs' day-to-day activities. Thus, potential funders can observe entrepreneurs' personal life, conversation and status and get better informed about project creators and projects. Prior literature suggests that executives' activation of personal social network sites are related to the increasing the levels of disclosure and alleviating information asymmetry (Saxton and Anker, 2013; Blankespoor et al., 2013). Therefore, entrepreneurs who activate their online social networking sites and share them in the profile page are more willing to provide information about projects and interact with funders. We performed the seemingly unrelated bivariate probit regression for the goal achievement model and used the two-stage least square method for the percentage of pledged amounts model. Table 2.5 shows the significant influence of all social interactions variables in probit model with instruments variable of goal achievement. However, in the percentage of pledged amounts model, entrepreneurial actions do not significantly influence the percentage of pledged amounts. This information can explain entrepreneurial and funders behavior patterns. Because of the "all or nothing" funding mechanism, project creators try to convey more information about their projects and interact with funders. However, once a project reaches the initial goal, entrepreneurs may not pay too much attention or effort to raise additional funding. Thus, entrepreneurial action may not be a critical factor for additional fundraising. At the same time, funders who fund projects after projects have less risk (already reached the goal), may care about social information (e.g., who fund the projects, how others think of, and popularity of projects) more than information from entrepreneurs. Thus, in the percentage of pledged amounts model social information plays an important role. This also explains how "the popularity of projects" influences total pledged amounts. Figure 2.9 depicts an apparent power-law distribution, which the 20% of projects accounts for nearly 80% of cumulative funding amounts in our dataset. The increase in popularity of projects may depend upon projects' current popularity. This is a commonly observed phenomenon, rich-get-richer or preferential attachment in networks (Barabasi and Albert, 1999; Easley and Kleinberg, 2010). Not every project gets the same amount of attention in crowdfunding platforms, and a few projects might achieve higher visibility. Funders will contribute "preferentially" to projects, which already have high popularity among members in online communities, and show some positive outcomes.

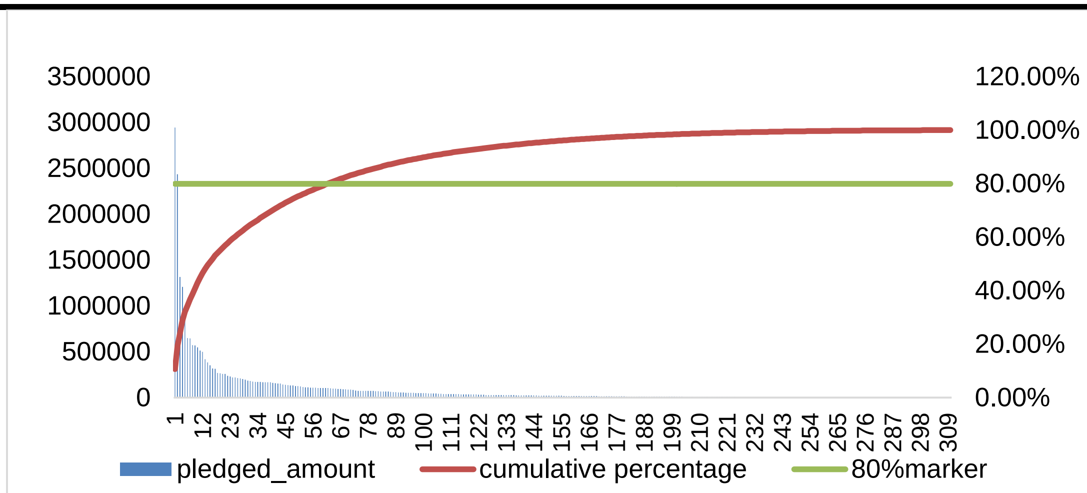


Figure 2.9 % of Cumulative Amounts and Number of Projects

Selection Bias - Heckman Selection Model

We are suspicious of whether selection bias exists in the OLS model, because the unobserved characteristics of successfully funded projects may create estimation bias in the model of pledged percentage amounts. In order to deal with this selection biases problem, we perform Heckman's two stage selection model (Heckman, 1979). First, we estimate a probit model (dependent variable: fundraising success =1, otherwise 0) to obtain estimates of θ and compute λ (the inverse Mills ratio λ,). If projects reach the original funding goals, $S_i = 1$ otherwise $S_i = 0$.

First Stage Model: Pr ($S_i = 1$) = Φ ($Z_i r_i$), $S_i = Z_i r_i + v_i$;

Second Stage Model: $Y_i = X_i \beta_i + \varepsilon_i$

Next, we estimate the expected value of *Y*, conditional on *S*=1, and X_i:

$$E(Y_i|X_i,\ S_i = 1) = X_i\beta_i + E(\varepsilon_i|S_i = 1),\ E(\varepsilon_i|S_i = 1) \neq 0,\ S_i = 1\ (v_i > -Z_i r_i)$$

If the residuals are correlated with one another and we estimate OLS Model without considering the first model, we will get the biased estimation. To test for bias, we examine the relationship between the residuals for the two stages (stage1 and stage2).

$$E(Y_i^*|X_i,\ S_i = 1) = X_i\beta_i + \theta_i\lambda_i,\quad E(\varepsilon_i|S_i = 1) = \theta_i\lambda_i\ ,\ \lambda \text{ : the inverse Mills ratio}$$

⇨ Second Stage Model: $Y_i = X_i\beta_i + \theta_i\lambda_i + \varepsilon_i$, $E(Y_i^*|X_i) = X_i\beta_i$ ($\because$ $E(\varepsilon_i|X_i = 0)$)

If the unobservable in the selection model are correlated with the unobservable in the stage 2 model, in other words the coefficient on the inverse Mill's ratio in OLS (outcome equation) model is significant, we have biased estimates without correction. This is basically saying that the unobservable in the selection of the probit model (Fundraising success) are also affecting the stage 2 model. If the unobservable in stage 1 are unrelated to the unobservable in stage 2, then we can say that the stage 1 does not affect stage 2 results. This is another way to say that selection into the sample of stage 2 is a random process, unaffected by different unobservable. Table 2.6 shows the results of Heckman's Two Stage Selection Estimation. There are 721 projects are used for the first stage probit model and 303 projects are used for the second stage OLS Model (Log_Pert). The model estimation is statistically significant (Wald χ^2 = 235.50***). We add the highest education level (PhD) to the probit model as an exogenous covariate, but do not add to the second stage OLS Model. Our results show that the significant coefficient of λ and a positive rho value in the OLS model, which indicates that the second stage model has selection bias. Thus, we want to explain the results based on Heckman Selection model. The results show the significant impact of Funders' engagement and network embeddedness along with LogGoal (negative), but we cannot observe effects of other independent variables. Compared to the goal achievement model, pledged percentage amounts mainly depend on the social interaction within the platform. Both positive prior experience and entrepreneurial actions do not significantly influence percentage of pledged amounts.

Table 2.6 Heckman's Two Stage Selection Model						
Independent Variables	**Probit Success Model**		**OLS LogPert (Success=1)**		**Heckman Selection Model**	
	Coefficients	**Std. err**	**Coefficients**	**Std. err**	**Coefficients**	**Std. err**
LogGoal	- 0.95***	0.082	-0.3223***	0.030	-0.430***	0.050
Duration	0.046***	0.007	-0.005	0.004	0.001	0.004
Prior Experience	0.476*	0.243	-0.061	0.079	-0.016	0.080
Education1	-0.196	0.191	-0.003	0.081	-0.049	0.082
Education2	0.011	0.260	0.111	0.106	0.104	0.106
Education3	-0.323	0.510	-	-	-	-
Entrepreneur Engagement	0.056***	0.021	0.001	0.007	0.001	0.007
Funders' Engagement	0.014***	0.004	0.001***	0.0002	0.001***	0.0002
Network Embeddedness	0.804***	0.094	0.395***	0.035	0.531***	0.050
E-Word of Mouth	0.079***	0.023	0.003	0.003	0.008	0.009
Num.of FB Friends	0.0002*	0.0001	0.000	0.000	0.000	0.000
Month	0.126***	0.030	0.006	0.012	0.159	0.013
Location	-0.000	0.0004	-0.000	0.000	-0.000	0.0001
Reward Type	0.096	0.211	-0.101	0.103	-0.053	0.102
λ	-		-		0.491***	0.124
rho	-		-		0.79	
Log-likelihood	-154.80		-		-	
R^2	0.55 (Pseudo)		0.529(Adjust R^2: 0.507)		0.55	
Number of obs	721		303		303	
two-tailed significance levels p<0.1, *; p<0.05, ** ; p<0.01, ***						

Sentiment Analysis of Electronic Word of Mouth

To test the effects of e-WOM, we used total volume of online comments on an each project. Prior studies on e-WOM show contradictory results (Aggarwal et al., 2012). Thus, we expect that the sentiment of e-WOM may differently influence fundraising success. To analyze e-WOM and sentiment of comments, we used web crawling tools we collect comments that mention each crowdfunding project. Considering relevance, we used data only talked about each project during fundraising period. To identify sentiment of each comment, we followed Lexicon based sentiment analysis approach. The sentiment (negative, neutral, positive), were extracted from translated messages through the sentiment analysis based on Lexicon (Taboada et al., 2011; Pang and Lee, 2008; Melville et al., 2009). To calculate the valence of e-WOM, we use Janis-Fadner coefficient of imbalance, which is the most popular valence measurement in communication research (Pollock, Shier & Slattery, 1995; Pollock & Whitney, 1997). The Janis-Fadner Coefficient of Imbalance (single-score content analysis) is calculated as follows:

If f> u (or the sum of the "favorable" attention scores is greater than the sum of the "unfavorable" attention scores), Coefficient of Imbalance (answers lie between 0 and +1): $\mathrm{C(f)} = \frac{(f^2 - f*u)}{r^2}$

If f < u (or the sum of the "unfavorable" attention scores is greater than the sum of the "favorable" attention scores), then use the following formula: Coefficient of Unfavorable Imbalance (answers lie between 0 and –1): $\mathbf{C(u)} = \frac{(\boldsymbol{f*u-f^2})}{\boldsymbol{r^2}}$

where, *f* = sum of attention scores coded positive or favorable; *u*= sum of attention scored coded unfavorable or negative; n=sum of attention scores coded balanced or neutral; $r = f + u + n$.

The statistics yielded from these formulas can vary from +1.00 to –1.00 and permit quantitative comparison of each e-WOM coverage of crowdfunding projects. Scores ranging between zero and +1 indicate favorability while scores between zero and –1 show unfavorability toward crowdfunding projects. However, our results do not show the significant impacts of the valence of e-WOM and significantly different sentiment effect on fundraising success. There are two possible interpretations. First, most of e-WOMs (during fundraising periods) have positive sentiments, because funders cannot experience and see the actual outcomes of projects and evaluate their experience. Funders often write comments to share project information and attract additional funders in order to successfully fund the projects to which they want to contribute. Because of that, the total volume of e-WOM does significantly influence, but the valence does not significantly influence fundraising success.

Heterogeneity of Projects

Figure 2.10 shows the percentage of projects and backers by reward types in our dataset. Funders can receive a tangible outcome, such as the final outcome of a project, or simple gifts (e.g., thank-you message, small gifts). 48.0% of crowdfunding projects in Technology category need to deliver hardware and 20% of projects provide funders with simple gifts or invitation. Different types of reward may influence individual's motivation and funding behaviors. Some funders may contribute to a project with non-economic motivation but others contribute to a project to pre-order the product. To explain people's charity giving behaviors, Andreoni et al. (1990) introduce the warm glow theory, an internal satisfaction that comes from the act of giving. Unlike the perfect altruism, under this theory, funders view others' contribution as imperfect substitutes of own contribution. To deal with the unobserved heterogeneity of projects result from expected rewards, we employ Levene's Test for equality of variances and t-test for equality of means. To test this, we first aggregate current categories into two groups based on if outcomes are physical products (hardware, software, both) or warm glow type (gift, invitation, other product, nothing). The Levene's Test shows the variance difference in prior experience and entrepreneurial actions in two groups. We observed the significant mean difference in the size of project (goal, percentage pledged amounts, network embeddedness, and entrepreneurial actions). However, we cannot find difference in other variable such as e-WOM and funders' engagement. Projects which deliver physical products (hardware, software) usually have larger goal than warm-glow type of projects. Therefore, those projects should attract more funders and money (regardless the size of project goal), and entrepreneurs also need to actively engage in projects to obtain sufficient funding to manufacture physical products. However, it is interesting that funders' community activity (engagement, eWOM) does not vary across projects and reward types.

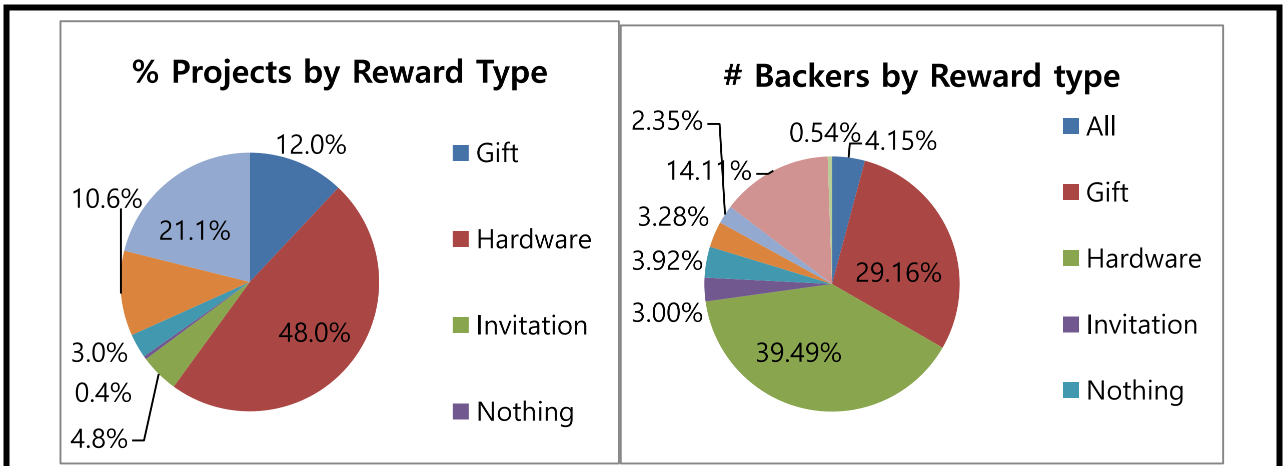


Figure 2.10 % of Projects and Backers by Reward Types

2.6 CONCLUSION AND IMPLICATIONS

In digitally mediated networks, most funders are anonymous; often they are not part of the same social network as the entrepreneurs. Rather than being influenced by traditional social norms, funders are likely to be influenced by social interactions and peer influence within the community that forms around the project. Despite the important role of network characteristics in social influence of an online funding community on funding success, these topics have not received much prior attention. However, there is a great deal of literature that emphasizes the role of social influence in different areas, such as online reviews (Moe and Schweidel, 2012) and user-generated contents (Susarla et al., 2012). In this study, we focus on the factors enabled by features of online communities such as funders' network embeddedness, funders' and entrepreneurs' community engagement with the online crowdfunding community, electronic word of mouth effects and entrepreneurs' human capital. Our empirical results show significant impacts of features of online communities on fundraising success in a crowdfunding platform.

This study makes several contributions to the literature. First, we demonstrate the significant impacts of two-sided networks on crowdfunding success. We examine the impact of "social learning" through social influence and interactions on the probability of fundraising success. A few prior crowdfunding researchers have investigated the impact of social influence and the social networks, but they have not actually measured social influence from the network characteristics. Additionally, while an each individual can decide to contribute to a certain project, the funding decision (i.e., whether each project creator will get funding or not) only depends upon the collective intelligence. Therefore, online collaboration and interactions are more important in crowdfunding context. The interactions in online communities and social networking sites will easily provide funders with project information which alleviates the information asymmetry problem.

Our empirical results support the significant impact of network embeddedness, both community and entrepreneurs' engagement, and e-WOM effects on probability of fundraising success. However, in the model examining the percentage of pledged amounts, entrepreneurs' engagement do not significantly influence the percentage of pledged amounts. The results explain entrepreneurial and funders behavior patterns. Because of "all or nothing" mechanism, project creators need to achieve their initial goals to get funding. Therefore, until a project reaches the initial goal a project creator attempts to contact more funders and provides them with project information. Once a project reaches the original goal, the project creator may pay less attention or effort to raise additional funding. Therefore, entrepreneurial engagement may not be a critical factor for additional fundraising. Our results in the selection bias model also support this mechanism.

A Rich-get-rich (or preferential attachment) model can provide an alternative explanation about funders' behaviors. Funders who contribute to projects which already reached the initial goal may care about social information (e.g., who funded the projects, how others think of them, and popularity of projects) more than information from entrepreneurs. Funders' engagement and network embeddedness within the crowdfunding platform significantly influence the percentage of pledged amounts. Entrepreneurs' positive prior experience influences the probability of fundraising success. However, we do not observe the impact of entrepreneurs' characteristics such as education level on fundraising success. In crowdfunding platform, funders' decisions depend more on social relationship, social interactions, e-WOM, and relationship with entrepreneurs than entrepreneurs' characteristics.

Entrepreneurs can obtain many benefits by using crowdfunding projects. First, they can easily access and obtain *financial resources*. Crowdfunding allows entrepreneurs to enhance legitimacy of their projects. Compared to the traditional financing context, entrepreneurs can easily access potential investors and interact with them. Additionally, the success in crowdfunding project creates legitimacy for additional funding. According to Mollick and Kuppuswamy (2014)'s survey, entrepreneurs who successfully get funding from crowdfunding platforms are more likely to get the high percentage of ongoing venture investment and the high level of revenue (over $100,000). Furthermore, entrepreneurs can obtain non-financial or indirect potential benefits (i.e., social capital and potential customers, delivering initial products and achieving innovation, new opportunity and on-going business), which will become a source of potential revenue. Crowdfunding projects can be featured within the platform and outside of the platform (social media), and entrepreneurs can obtain *social capital* (funders and friends in online social media) from their own projects. Entrepreneurs easily access potential customers who are either ardent funders or the anonymous public. The online community interactions and e-WOM not only attract funders, but also help entrepreneurial innovation. Funders are able to participate actively in *entrepreneurs' innovation process*. They evaluate and share ideas about the project outcomes. Additionally, crowdfunding communities force entrepreneurs to *complete their initial innovation plans* (manufacture & delivery outcomes). Lastly, based on the existing online social capital, additional funding, and credibility, entrepreneurs can initiate *new innovation*.

However, this study has a few limitations. First, we measure social interactions and entrepreneurs' engagement using the volume of transactions. Secondly, we only focus one platform and a specific category (Technology). In future research, we intend to investigate the nature of comments and their impacts on fundraising success. For example, entrepreneurs' updating action can be categorized into a few criteria based on the characteristics of contents and information. Future work can apply our empirical models in different category and crowdfunding platforms.

Despite a few limitations, our study helps researchers, potential funders, and entrepreneurs to understand the role of online communities (i.e., funders' network embeddedness, funders' and entrepreneurs' community engagement with the online crowdfunding community, electronic word of mouth effects) in crowdfunding success, and to explain why some projects are more likely to succeed in attracting funding. Start-ups have suffered because of the lack of legitimacy (Aldrich and Fiol, 1994). Crowdfunding offers the promise of allowing start-ups to enhance their legitimacy and provide a new venue for external resources. At the same time, however, lack of success in fundraising could hurt entrepreneurs' reputations. Indeed, more than 50% of Kickstarter projects fail to reach their goal. We also provide insights for potential funders and entrepreneurs as well as provide managerial implications to entrepreneurs who participate in crowdfunding platforms about what kind of entrepreneurial strategies should be pursued. The results also provide important tips for crowdfunding platform designers on how to design their platform.

CHAPTER 3.
ESSAY 2: DYNAMIC FUNDRAISING PATTERNS AND ENTREPRENEURIAL PERFORMANCE IN CROWDFUNDING PLATFORMS

"All Ideas are brilliant before they are executed", Tim Berry

3.1 INTRODUCTION

The emergence of crowdfunding has demonstrated strong potential to unleash considerable changes in the business environment. This online fundraising platform provides entrepreneurs with new opportunities for funding, and ultimately fosters entrepreneurship and new firm creation. The question of how entrepreneurs successfully raise money using such a platform has recently captured the interest of numerous researchers. Despite crowdfunding's popularity, certain issues have also come to light. According to CNN Money (December 18, 2012), 84% of Kickstarter's most successfully funded projects either failed to deliver or were delayed in delivering the promised products. On May 1st, 2014, the first lawsuit was brought against crowdfunding project creators who failed to deliver the promised outcome[9]. Mollick (2013) demonstrated that only 24% of successfully funded projects in Kickstarter delivered their promised outcomes—ranging from simple thank-you cards to physical products (e.g., hardware, software, games, and so on)—to funders on time. The predicted success of project creators lacks external measures of validation that could help in screening the quality of creators. Project quality also lacks quantifiable information. Hence, the crowdfunding platforms may have the ones that have ability to raise financial resources, but they are less likely to be successful at generating successful

[9] http://www.washingtonpost.com/blogs/govbeat/wp/2014/05/02/the-first-state-lawsuit-over-a-crowdfunding-project-is-about-a-deck-of-cards/

innovations. Additionally, many crowdfunding platforms do not have strict enforcement mechanisms in place to eliminate hoax projects or to prevent moral hazard problems among project creators[10]. Kickstarter, one of the most popular crowdfunding platforms, does state that "Kickstarter is not a store," where sellers scrutinize products and should be responsible for the quality of the products (Kickstarter blog, 2012). Rather, the platform does guarantee the quality of projects or project creators' ability to complete their projects than it shifts the responsibility to validate the quality of projects and creators' potential on to backers. Kickstarter allows funders who have neither the professional expertise nor the ability to evaluate the quality of a project or the entrepreneur's potential to contribute small amounts of money to projects. Therefore, some funders may be drawn to a particular project based on its external visibility and bandwagon effects, rather than on the project's intrinsic quality or the entrepreneur's performance. Although crowdfunding is beneficial to entrepreneurs for accessing financial resources, they have a fundamental responsibility to initiate and execute innovation, and to deliver the promised outcome by the predefined delivery deadline. Yet, more than 50% of technology projects funded through Kickstarter.com failed to deliver their outcomes on time. A negative entrepreneurial performance hurts an entrepreneur's reputation and diminishes future funding opportunities, as funders' negative experiences influence their funding behaviors. This will ultimately influence the overall ecology of digital funding and entrepreneurship. Therefore, it is necessary to investigate entrepreneurs' project performance in crowdfunding platforms, as well as the factors influencing that performance. There is a dearth of research, however, on entrepreneurial performance after

[10] In 2014, Kickstarter changed their policy about refunds and project creation to improve the rate of execution success and to eliminate moral hazard and agent problems, but it still does not have a strict policy on project execution and delays. 5% of projects are fraudulent projects, as determined by entrepreneurs returning funded amounts or failing to update their pages through the promised delivery date in Kickstarter (Mollick, 2013)

fundraising success or on the mechanisms that help to explain why some successfully funded projects could not deliver their promised outcomes on time. To date, crowdfunding research has mainly focused on the antecedents of fundraising success. A few exploratory studies have examined how project delays are influenced by wording errors in project pages, by the number of backers, and by the percentage of funded amounts (Mollick, 2013). Nonetheless, the insights gained from such research are insufficient to explain the critical variables that lead to successful (or failed) project performance. Moreover, they ignore why some projects with similar pledged amounts fail to deliver outcomes; why some over-funded projects cause negative project performance; and what the underlying mechanisms are for over-funded projects.

Success in technology project execution and innovation are driven by multiple factors such as inherent project characteristics, investor types, entrepreneurs' characteristics and their capacity for innovation, project management skills, available resources, and environmental factors (Tatikonda and Rosenthal, 2000; Shane and Stuart, 2002; Lee, Lee, and Pennings, 2001). Success in project execution is related to project characteristics such as the novelty, complexity, and outcome types of the project; the level of product newness and project complexity often lead to undesirable project performance (Tatikonda and Rosenthal, 2000). Entrepreneurs spend more time, money, and effort on producing physical products, with the risk and uncertainty of innovation increasing as the level of newness rises. Project development appears to be a struggle when entrepreneurs have limited experience and execution capability (Gupta and Wilemon, 1990; Wheelwright and Clark, 1992). Prior entrepreneurship and innovation studies have emphasized the critical role of entrepreneurial characteristics on entrepreneurial innovation performance (Shane and Stuart, 2002). Entrepreneurs with a higher education level and more relevant experience are more likely to perform innovation successfully than others, because such resources are highly associated with entrepreneurs' innovation capability (Lee et al., 2001; Leonard-Barton, 1992; Stuart and Abetti, 1990). However, entrepreneurial performance in crowdfunding projects may not depend only on their characteristics or innovation capability because of the unique attributes of fundraising in crowdfunding platforms. Entrepreneurs who have similar levels of experience and education will perform differently depending on the fundraising environment, which includes the type of funders, the project characteristics, funding amounts and trends, and interactions between funders and entrepreneurs. Entrepreneurs may fail to manage a project because of a lack of early momentum (resources) or because of sudden hype-demands, which disperse their resources to other activities (i.e., attracting more funding, revising original plans, or finding necessary resources).

Therefore, understanding the dynamics of fundraising could explain more about why some projects with similar funding percentages differ in their performance or have different fundraising patterns. The few existing studies that link the total percentage of accumulated amount of funding with delays in delivery have not taken the history of fundraising dynamics over the fundraising period into account. The heterogeneity of the dynamics of crowdfunding projects cannot be explained sufficiently by simply looking at the total pledged amounts, overfunding (above the initial fundraising goal amounts), and their impact on crowdfunding project performance, especially regarding on-time delivery. This paper investigates dynamic fundraising patterns in crowdfunding projects, how/why those patterns exist, and how different dynamic patterns are associated with project performance. The main research questions we address are:

(1) Are there different dynamic fundraising patterns among crowdfunding projects?

(2) Do the identified fundraising patterns help predict entrepreneurial performance? If so, how do the fundraising patterns influence entrepreneurial performance?

We explain the mechanisms using such theoretical lenses as entrepreneurship, innovation, and bandwagon effects. Fundraising trends in crowdfunding combine three different mechanisms: (1) funders' enthusiasm; (2) entrepreneurs' improvisation; and (3) project characteristics. Entrepreneurs' performance in crowdfunding projects tends to be contextually dependent on heterogeneous combinations that can be either a positive or negative "perfect storm" for entrepreneurial performance. By employing the functional data analysis (FDA) method, this study examines the impact of fundraising trajectories on entrepreneurs' performance. Daily funding data enables us to explain the different trajectories. We treat each funding trajectory as a unit of analysis, and identify four of the most critical fundraising patterns by performing functional principal component analysis (FPCA). Data from technology crowdfunding projects were collected from a reward-based crowdfunding platform in the U.S. We scrutinized the performance of projects initiated and successfully funded from March 2012 to January 2013. There were a total of 303 successfully funded projects that provided delivery information and daily funding data. After eliminating projects with goals of less than $200 and duration of fewer than 7 days, the study had a sample of 285 successfully funded projects. Project performance was measured in three ways. First, did the project creators deliver the promised outcome on time? In project management, budget, time, and cost are key performance measures. In crowdfunding platforms, project creators set a specific delivery date when they initiate a project. In this context, on-time delivery is an important and observable performance measurement. Prior innovation studies have suggested different innovation performance measures. Commercialization—bringing new products successfully to market—is one important measure because introducing a new product to market is a signal of the first stage of successful innovation (Balachandra and Friar, 1997). Thus, we also investigated factors that influence the commercialization of a final project outcome. Crowdfunding provides benefits to entrepreneurs by creating legitimacy for additional funding opportunities. We therefore investigated which project creators received additional funding (e.g., venture capital, private equity) after successful fundraising in crowdfunding platforms. We measured project performance in three ways: (1) delivery, (2) commercialization, or (3) venture capital funding. A functional regression model (FReg) shows that late infusion patterns (higher than average funding near the ending date) predicts negative performance in on-time delivery. The pattern also shows that under-funding in the middle of fundraising and a sudden hyper-infusion in the last few days have negative impacts on on-time delivery and commercialization. Our main model does not observe the significant impact of early funding on performance. In our sample, only 3.7 % of projects had early funding patterns. This can explain a limitation of crowdfunding, in which it is difficult to raise early funding in crowdfunding platforms due to the inherent nature of projects and entrepreneurs. The study also finds a positive, critical role of entrepreneurs' prior experience in on-time project delivery and obtaining venture capital funding. However, entrepreneurial characteristics do not significantly influence commercialization. The FDA allows us to identify shapes in the trajectory curves that are associated with superior crowdfunding performance. We find that the shape of the curve adds power to predicting a crowdfunding project's performance by enhancing model fit and forecasting accuracy, when compared with accumulated funding measures. This indicates the important role of the history of funding dynamics on performance.

We adopted a latent instrumental variable (LIV) approach (Ebbes et al. 2005) to control for potential endogeneity concerns with respect to the effect of fundraising patterns on project performance. Unobserved entrepreneurial quality factors may influence both fundraising type and project performance, which could lead to a spurious effect of funding patterns on project performance. In particular, such unobserved quality factors could influence both early momentum and project performance. In this study, we used a Bayesian statistical estimation method and a Markov Chain Monte Carlo Simulation (MCMC) for LIV to increase the accuracy of the estimation. We observed that significant coefficients of latent classes on early funding (the posterior means do not include zero in 97.5% of credible intervals). Additionally, to address the heterogeneity of projects, we classified projects into two groups such as crowd-based projects and experts–based projects based on the proportion of funders' contribution amounts. Functional ANOVA (FANOVA) results show that different mean values between the two groups, and the permutation F-Test represent significant F-values at 60% of the entire campaign's duration. Crowd-based projects have a significant increasing pattern at that point in time. This also provides evidence of how dynamic fundraising patterns can address the heterogeneity of crowdfunding projects and the underlying funding mechanisms.

This study contributes to the entrepreneurship and crowdfunding literature by providing a comprehensive model to explain both project performance in crowdfunding markets and how fundraising patterns themselves influence project performance in crowdfunding markets. This study identifies the dynamic fundraising pattern using fine-grain data and advanced statistical models; it explains the underlying mechanisms of those dynamics and examines the impact of those patterns on crowdfunding project performance. Finally, it explains how fundraising patterns influence project performance in crowdfunding markets. The empirical evidence provides meaningful managerial and theoretical implications.

In the following section, we review the extant theories and the relevant entrepreneurship and crowdfunding literature, proposing research hypotheses that link fundraising patterns with project performance. Next, we explain the data and introduce our empirical model. We then present the empirical results of our analysis. Finally, we discuss the theoretical and managerial implications of this study and suggest future research directions.

3.2 THEORETICAL BACKGROUND AND RESEARCH HYPOTHESES

3.2.1 Literature Review

Funders' Enthusiasm

There are different types of investors, based on their tendency to select projects and make investment decisions. Prior literature on finance, angel investments, and venture capital investments have demonstrated different types of investor strategies (tendencies), how those are formed, and the relationship between investor strategies and financial performance. Grinblatt et al. (1995) discussed herding behaviors in combination with the alleged tendency of investors to follow momentum-based fads in mutual funds purchases. Tyszka et al. (2008) argued that investment decisions are based on an individual's belief in the occurrence of the next event, and demonstrate a prevailing momentum strategy in investment. Other researchers have argued that individuals' investment decisions mainly depend on investors' risk-taking attitudes (Siegel and Hoban, 1982; Filbeck, Hatfield, and Horvath, 2005).

In the entrepreneurship literature, researchers have focused on identifying investors' characteristics (e.g., passion, overconfidence, perception of entrepreneurial potential and attributes, and subjective judgement), and examined how those characteristics lead the investment decision-making in angel and venture capital investments (Mitteness, Sudek, and Cardon, 2012; Maxwell, Jeffrey, and Levesque, 2011). Gompers and Lerner (2000) propose that the start-up evaluations depend on start-up characteristics as well as those of the investors. Others proposed that the impact of the available information and knowledge about a project and entrepreneurs on individual's investment decision (Campbell and Kirmani, 2000; Edmiston and Fisher, 2006; Wang, 2009).

Unlike traditional efficient market hypothesis (EMH), lots of private or internal information which could not timely reflect the value of start-up projects exists in start-up investment. Since not all information is publicly available, there are information asymmetry issues. Moreover, investors' investment behaviors in start-up investment cannot always be explained by popular economic theories such as the Expected Utility Theory. A few prior studies of start-up investments that were based on behavioral economics have pointed out the appearance of investors' irrational investment tendencies, caused by investors' personal preferences, subjective judgements (heuristics), and cognitive biases (i.e., overconfidence, overreaction, representative bias, and human errors) in information processing and decision-making (Koellinger et al., 2007; Maxwell et al., 2011). Additionally, in contrast to economic theory, which assumes individuals consider only their own wealth and will not sacrifice to help others, it is not difficult to observe investors who pursue "social utility" (altruistic behaviors, reciprocity, etc.) in many types of early-stage start-up funding (Angel investments and crowdfunding). Along with the behavioral economics perspective, social relationships and attachment influence investors' funding amounts. For example, a lot of early funding comes from people who know the entrepreneurs personally (i.e., friends and family), and are often for relatively large amounts of money (Agrawal et al., 2011). Table 3.1 provides a summary of the extant literature on investors, investment types, and start-up investments.

Although prior studies have addressed different aspects of investor characteristics, investment tendencies, and related financial performance, none of them provide a comprehensive frame for investor types using multiple criteria. Since investment behaviors often occur for multiple reasons, it is valuable to integrate multiple perspectives and different defined investor types. Furthermore, there is no prior study on crowdfunding that addresses either the types of investors or defines them with multiple criteria. Compared to other funding methods (such as Angel investments and VC investments), crowdfunding is an online investing process that has a specific goal and duration. Additionally, this platform provides high visibility of both the projects and the fundraising process. Thus, investors can easily observe the probability of fundraising success for the projects, and update their own belief in them. Offline investment (e.g. angel and venture capital investments) could not provide a real-time fundraising process, nor is it easy for funders to observe others' contribution behaviors.

Participants in crowdfunding platforms have very diverse background knowledge, experiences, motivations and social relationships. According to prior crowdfunding studies, the majority of funders in crowdfunding are laymen who do not have professional knowledge of projects and entrepreneurs. Therefore, in a crowdfunding platform, funders experience substantial uncertainty about a project's quality and an entrepreneur's potential performance before making funding decisions. Most crowdfunding platforms do not scrutinize either the projects or the project creators. Instead, they shift this responsibility to the funders (Kickstarter blogs, 2012). As a result of the uncertainty and onus, a funder's contribution strategy is shaped by: available information and knowledge about a project and an entrepreneur (Campbell and Kirmani, 2000; Edmiston and Fisher, 2006; Wang, 2009); his/her level of enthusiasm for the project (Barnewall, 1987; Filbeck et al., 2005); risk tolerance (Siegel and Hoban, 1982; Filbeck et al., 2005; Wang, 2009); resource allocation strategies (Christensen and Bower, 1996); and others' funding behaviors (Bikhchandani, Hirshleifer, and Welch,1992).

By combining prior studies, we classify investors with multiple criteria. Table 3.2 provides the summary of the characteristics of investor types. We classify funders into three categories: (1)

Enthusiastic funders, (2) *Momentum funders*, and (3) *Conservative funders*. First, enthusiastic funders are people who are excited about projects ideas, have ample knowledge and experience, are willing to take a risk and contribute larger amounts of money to projects in the early funding stage. The enthusiastic funders enjoy finance and analysis, and want to be fully engaged in decision-making for their investments (Barnewall, 1987). The financial literature indicates that investors' personality types and characteristics are an important influence on their financial risk behaviors and risk tolerance (Siegel and Hoban, 1982; Schooley and Worden, 1999; Filbeck et al., 2005). Active investors are more likely to take risks (Barnewall, 1987) and their higher knowledge levels lead to different information search and investment behaviors (Campbell and Kirmani, 2000). Using the Myers-Briggs Type Indicator (MBTI), Filbeck et al.(2005) found that the higher levels of risk tolerance are related to investors' characteristics such as extraversion, intuition, thinking, and perception. Thus, enthusiastic funders will make funding decision in the early stages, with larger amounts of funding. They tend to a have higher risk tolerance level than other types of investors.

Second, momentum funders believe large increases in the funding amounts will be followed by good performance. The basic idea of their funding strategy is that once a trend is established, it is more likely to continue in that direction, rather than move against the trend, thus they ride "hot" projects during the "hot" time. In crowdfunding platforms, people can easily observe others' contributions, accumulated funding amounts, and entrepreneurs' information. Thus, funders are likely to monitor others' funding behaviors over time to make their own funding decisions because they reflect others' interest and information about the probability of fundraising. Bandwagon effects refer to a tendency for people to follow the previous behaviors of critical mass—which corresponds to the crowd under conditions of uncertainty or ambiguity—and adopt or defer to the same behaviors that others have already accepted (Abrahamson and Rosenkopf, 1993; Fiol and O'Connor, 2003; Rosenkopf and Abrahamson, 1999). Earlier studies emphasized the idea that individuals would make rational decisions to follow others based on their utility (Leibenstein, 1950). The more recent approach on bandwagon effects does not always involve rational decisions (Abrahamson and Rosenkopf, 1993; Fiol and O'Connor, 2003). Bandwagon effects may occur because of individuals' or organizations' rational expectations about the benefits that will accrue from adopting a behavior (rational efficiency theories), or because of social, environmental or external pressures force those involved to adopt an idea, technology, policy, and product that a number of organizations or individuals have already adopted (fad theories) (Abrahamson and Rosenkopf, 1993; Fiol and O'Connor, 2003; Teo et al., 2003). Thus, bandwagon effects are motivated by several sources, including legitimacy, social relations, peer pressure, external visibility, and so on (Fiol and O'Connor, 2003, Sunstein, 2005). The literature on bandwagon effects have documented the momentum effect—where a person's attitude or behavior can be influenced by a trend in others' interests or behaviors (Xiong and Bharadwaj, 2014). Momentum funders will wait until projects achieve a certain threshold level and then contribute to them.

Finally, conservative funders seek to preserve their money by investing in lower risk projects (Barnewall, 1987; Filbeck et al., 2005) that have already reached their funding goals or were initiated by project creators with high visibility and prior relevant experience. The superstar (or "winner-takes-all") effects often lead to extreme distribution patterns such as power-law distribution or Pareto distribution (Brynjolfsson, Hu, and Smith, 2003; Easley and Kleinberg, 2010). Conservative investors have risk tolerances ranging from low to moderate.

Table 3.1 Literature Review			
Section	Topic areas	Authors	Key findings
Funders' Enthusiasm	Investment strategy (Investor types)	Grinblatt et al. (1995)	-analyzed the extent to which mutual funds purchase based on their past returns as well as their tendency to exhibit herding behaviors (the tendency to invest with the herd, in combination with the alleged tendency of investors to follow momentum based fads by buying past winners) -momentum investing affects the performance of the funds: purchase above intrinsic values cause lower future performance
	Investment strategy (Investor types)	Tyszka et al. (2008)	-identified four types of investment strategies (long-run momentum strategy, long-run contrarian strategy, short-run momentum strategy, and short-run contrarian strategy) for predicting uncertain next events; - argued that investment decisions are based on an individual's belief in the occurrence of the next event -show the tend to predict that the next event will be a continuation of the recent rend (momentum strategy); found that under the uncertainty about the next events, short-run momentum strategy is prevail.
	Information sharing among Investors	Shiller and Pound (1989)	-herding behaviors -found that the impact of direct interpersonal communications and word of mouth communications on individual investors investment
	Investment strategy (Investor types)	Hirshleifer, Subrahmanyam, and Titman (1994)	-herding Behaviors -analyzed trading behaviors and equilibrium information acquisition when some investors receive common private information before others -found that herding patterns (mimicking earlier trades)
	Investment strategy (Investor types)	Morrin et al. (2002)	-explored patterns of decision making among professional security analysists and observed different investment patterns (momentum and contrarian patterns)
	Investment strategy (Investor type and characteristics)	Kubinska, Markiewicz, and Tyszka (2012)	-examined disposition effect for stock trading participants -found that contrarian investors are more prone to the disposition effect thant are momentum traders

Table 3.1 (cont'd)			
Funders' Enthusiasm	Investment strategy	De Bondt (1993)	-found that non-experts expect the continuation of past 'trends' in prices (momentum strategy: financial laymen consistently bet on trend continuation)
	Investors' Characteristics	Mitteness, Sudek, and Cardon, (2012)	-angel investor characteristics -perceived passion is likely to play a significant role in the funding decision process. -angel investors' characteristics influence how perceived passion translates into evaluations of funding potential.
	Investors' Characteristics	Maxwell, Jeffrey, and Levesque (2011)	-studied early stage business angel decision making -found that angel investors do not use a fully compensatory decision model wherein they weight and score a large number of attributes. Rather, they use a shortcut decision making heuristic known as elimination-by-aspects to reduce the available investment opportunities to a more manageable size. -Investment decisions are made according to two stages
	Investors' Characteristics	Madill, Haines, and Rlding (2005)	-identified aspects that differentiate business angels as early stage investors from other investors.
	Investors' Characteristics	Gompers and Lerner (2000)	-how start-up evaluations might not depend on start-up characteristics only, but also those of the investors -show that market conditions impact VC valuations
	Social relationships	Hochberg, Ljungqvist, and Lu (2010)	- found networking affect valuations of newly founded companies.
	Information	Cumming and Dai (2011)	-showed u shape relationship between fund size and firm valuations - found that how VCs' reputation, size, and limited attention impact their bargaining power and valuations in addition to venture quality and market conditions

Table 3.1 (cont'd)			
Funders' Enthusiasm	Information	Sanders and Boivie (2004)	-how information asymmetry can lead to opportunistic behaviors in form of adverse selection (i.e., hidden information) and moral hazard (i.e., hidden actions). For this reason investors struggle to get valuable and reliable information.
	Information	Zheng, Liu, and George (2010)	-two kinds of information that influence investor evaluation: internally generated information on the start-up's innovative capability and externally verifiable information on the start-up's inter-company network attributes
	Information	Binks, Ennew, and Reed (1992)	-information asymmetry (investors try to evaluate companies based on the information they are provided by the founders or able to collect
	Risk and Investment	Siegel and Hoban, 1982	-investors' personality types and characteristics are an important influence on their financial risk behaviors and risk tolerance
	Investors' characteristics	Mitteness et al.(2012)	-identified investors' characteristics (e.g., passion, overconfidence, perception on entrepreneurial potential and attribute, and subjective judgement) and examined how those characteristics lead investment decision making in angel investment and venture capital investment
	Entrepreneurial characteristics	Hsu (2007)	-characteristics of founders are important determinants in VC evaluations. (prior experience in founding, both human capital (e.g., training and prior professional experience), social capital (e.g. social skills and charisma) of the start-up founders are all positively correlated with higher evaluations.
	Investors' characteristics	Gompers and Lerner (2001)	-start-up evaluations depend on start-up characteristics as well as those of the investors.
	Investors' characteristics	Koellinger et al.(2007)	-own subjective judgement (heuristics), cognitive biases (i.e., overconfidence, overreaction, representative bias, and human errors) in information processing and decision making based on the behaviors economics
	Investors' enthusiasm	Barnewall (1987)	-enthusiastic funders enjoy finance and analysis, and want to be fully engaged in decision-making for their investments
	Information and Professionalism	Campbell and Kirmani (2000)	-higher knowledge levels lead to different information search and investment behaviors

Table 3.1 (cont'd)

Funders' Enthusiasm	Risk and enthusiasm	Filbeck et al. (2005)	-higher levels of risk tolerance are related to investors' characteristics such as extraversion, intuition, thinking, and perception.
	Bandwagon Effects	Abrahamson and Rosenkopf, 1990; Fiol and O'Connor, 2003	-bandwagon effects refer to a tendency for people to follow the previous behaviors of critical mass—which corresponds to the crowd under conditions of uncertainty or ambiguity—and adopt or defer to the same behaviors that others have already accepted
Entrepreneurial improvisation	Resource dependency	Zimmerman and Zeitz, 2002	-resources are crucial to new venture growth
	Resource dependency	Christensen and Bower, 1996	-argued that the failure of a firm's innovation can often be ascribed to insufficient resources or expertise
	Resource dependency	Salancik and Pfeffer, 1978;	-argued that entrepreneurs have strong external resource dependence; and should attract external actors to provide those resources by motivating their beliefs and feelings that the entrepreneurs are worthy, appropriate, and competent.
	Resource dependency	Baker, Miner, and Eesley (2003)	-found that entrepreneurs' strategic orientation and innovation success are often constrained by external resources, and their actions are contingent upon the availability of resources
	Resource dependency & acquisition of resources	Lounsbury and Glynn, (2001)	- define cultural entrepreneurship as the process of storytelling that mediates between extant stocks of entrepreneurial resources and subsequent capital acquisition and wealth creation
	Heterogeneous resource and performance	Teece, Pisano, and Shuen (1997)	- company capabilities are heterogeneous among the market participants which lead to different company performance
Project characteristics	Project newness	Wallace, Keil, and Rai (2004)	- technological newness and application size influence project failure
	Project newness	Cooper (1980)	- project newness negatively influence new product success
	Novelty, complexity	Tatikonda and Rosenthal (2000)	-technology novelty, project complexity, and product development project execution success: a deeper look at task uncertainty in product innovation

Table 3.2 Investors Types			
Criteria	**Investor Type**		
	Enthusiastic Investors	*Momentum Investors*	*Conservative Investors*
Funding Timing	Early	Relative	Late
Risk Tolerance	High	Low to medium	Low to medium
Level of Enthusiasm	High	Medium	Low
Resource Allocation	Large amounts	Small to medium	Small
Susceptible to Others' Behaviors	Low	High	High

Entrepreneurs' Improvisation

Entrepreneurs ultimately seek to generate new business value, so they engage in efforts to identify resources and opportunities (Shane & Venkataraman, 2000). Resources are crucial to new venture growth (Zimmerman and Zeitz, 2002), and the failure of a firm's innovation can often be ascribed to insufficient resources or expertise (Christensen and Bower, 1996). The degree of newness and difficulty, relative to the skills and experience of the firm influences their survival (Christensen and Bower, 1996). However, most start-ups lack the financial, human, and technological resources because of their limited or nonexistent records of performance (Zimmerman and Zeitz, 2002). As a result, entrepreneurs have strong external resource dependence (Salancik and Pfeffer, 1978; Christensen and Bower, 1996; Zimmerman and Zitz, 2002), and should attract external actors to provide those resources by motivating their beliefs and feelings that the entrepreneurs are worthy, appropriate, and competent. Therefore, entrepreneurs' strategic orientation and innovation success are often constrained by external resources, and their actions are contingent upon the availability of resources (Baker et al., 2003; Christensen and Bower, 1996; Lounsbury and Glynn, 2001; Shepherd, Douglas, Shanley, 2000). Entrepreneurs' improvisation behavior, which is defined as "deliberate extemporaneous composition and execution of novel action," can to be used to evaluate currently available funding, and whether it meets existing goals and potential possible outcomes (Baker et al., 2003; Moorman and Miner, 1998; Hmieleski, Corbett, and Baron, 2013). Accordingly, entrepreneurs must be capable of framing executable strategic decisions to achieve their original goals and to move their firms in a more promising direction using the resources available to them in the moment (Hmieleski et al. 2013).

There is heterogeneity in entrepreneurs' perception of funders' behaviors, of the opportunities and risks of their projects, according their own innovation capabilities (e.g., prior experience, knowledge) and funding trends, which will appear in different strategic actions (i.e., resource allocation and social engagement). Entrepreneurs experience conflicts and challenges when facing the two main dilemmas of crowdfunding platforms: (1) failure to attract adequate initial funding, causing a distraction from their focus, and (2) the risks associated with unexpected hype-funding. Because of limited resources, entrepreneurs need to effectively allocate resources such as time and effort. Entrepreneurs who achieve early funding momentum in the overall fundraising process can put more effort into actual production than those who need to focus on raising money. To attract more funding, the latter type of entrepreneurs will be more likely to engage in the social community to explain the plausibility and credibility of their business. These contingent actions will influence entrepreneurs' performance differently. The former scenario may positively influence performance, whereas the latter one may not have a positive impact on performance.

Entrepreneurs' prior related experiences and knowledge from higher education are associated with increased innovation performance (Shane and Stuart, 2002). Entrepreneurs who have a higher education level and greater relevant experience are more likely to achieve performance than others. Indeed, such resources are highly associated with entrepreneurs' innovation capabilities, including project management skills (Lee et al., 2001; Leonard-Barton, 1992; Stuart and Abetti 1990). However, their innovation capability is often contingent on the availability of resources. According to the previous literature, improvisation behaviors can generate different effects on the performance of firms under specific circumstances (Miner, Bassoff, and Moorman, 2001). Thus, depending on the availability of resources and their own ability to cope with risks, entrepreneurs with prior experience and a deep knowledge of their projects may or may not do justice to their innovation's execution. For example, over-funded projects will burden entrepreneurs with the obligation to fulfill their commitments to funders by the deadline because of unexpected high demands with constrained resources and time.

Project Characteristics

Project execution success is related to project characteristics such as novelty, complexity, and outcome types. Tatikonda and Rosenthal (2000) pointed out how project technology novelty (i.e., the newness of products) and project complexity (i.e., the number of product functions embodied in the product) influence performance in product development. Highly novel and complex projects increase the level of task (e.g., new project development) uncertainty. Table 3.3

In crowdfunding, each funder will receive rewards, such as the final outcome of a project, or simple gifts (e.g., thank-you messages, small gifts). In the Technology group (from March 2012 to January 2013) in Kickstarter, 48.0% of crowdfunding projects needed to deliver hardware, and 21.2% of them needed to deliver software, respectively. 20% of the projects provided funders with simple gifts or invitations (Figure 3.1). Entrepreneurs need to spend more time, money, and effort on producing physical products than intangible ones, and the risk and uncertainty of innovation increases as the level of newness rises. Project and innovation performance is rooted in multiple factors such as inherent project characteristics, entrepreneurs' characteristics, project management skills, and available resources (Lee et al., 2001; Tatikonda and Rosenthal, 2000; Shane and Stuart, 2002).

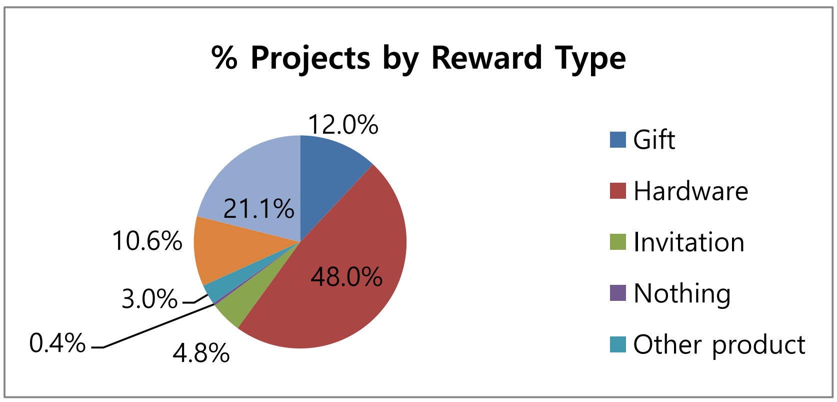


Figure 3. 1. % of Projects by Reward Types

Moving Toward Conceptualization of Fundraising Patterns in Crowdfunding

Landstrom (1998) argue that investment as a process in which decision making criteria may vary in the course of time, and the complexity of the investment decision process can be better understood if that process is broken down into several stages. The purpose of theoretical development is to highlight the importance of considering the shape of the fundraising patterns, as researchers can miss important information regarding entrepreneurial performance in crowdfunding projects. Most crowdfunding platforms[11] use all-or-nothing mechanisms in which

[11] We collected data from a platform using the all-or-nothing mechanism.

each project has a predefined duration and funding goal. In order to obtain funding from the platform, project creators must raise funds by the predefined deadline, while funders are only able to contribute to a certain project within that time period, otherwise the entrepreneurs do not get funding nor do funders have a chance to contribute to the projects. Before the predefined funding deadline, there is little information available about the final outcome, and funders cannot judge its value, entrepreneurial potential or innovation performance. Additionally, entrepreneurs who launch crowdfunding projects can neither assure fundraising success upfront nor predict the exact demands for the outcomes. These uncertainties lead to different perceptions, attitudes, and behaviors of funders and entrepreneurs toward crowdfunding projects. Those differences are represented by the heterogeneity found in fundraising patterns. In this paper, we argue that fundraising trends in crowdfunding combine three different mechanisms: (1) Funders' enthusiasm (orientation toward crowdfunding projects); (2) Entrepreneurs' improvisation; and (3) Project characteristics. The different speeds and directionality of the three mechanisms will engender various combinations, representing diverse fundraising trajectories and patterns. Entrepreneurs' performance in crowdfunding projects tends to be contextually dependent on such heterogeneous combinations that can be either a positive or negative "Perfect storm" for entrepreneurial performance.

In crowdfunding platforms, project creators raise money for the "crowd through a process of "collective evaluation mechanisms." Funders can contribute small amounts of money to projects without any professional expertise or the ability to evaluate the quality of projects as well as entrepreneurs' potentials. Accordingly, some funders will be more likely to be drawn to a particular project based on its external visibility and bandwagon effects rather than the project's intrinsic nature or entrepreneurial performance. Additionally, entrepreneurs who have similar levels of experience and education will achieve different performance levels depending on the fundraising environment. Such environments include project characteristics, funding amounts and trends, funders, and interactions between funders and entrepreneurs. In turn, the fundraising process results are a combination of dynamics among funders, entrepreneurs, and inherent project characteristics, which may vary across the projects. Previous research in marketing has shown that the history of people's intentions and growth patterns can have a significant impact on future sales and prerelease buzz dynamics can continuously influence the dynamics of purchase intentions (Chintagunta and Lee, 2012). Xiong and Bharadwaj (2014) found ways in which the trajectory of buzz influences future marketing performance; they demonstrated the critical role that trajectory plays in increasing the predictive power of their research model. As we discussed earlier, there are heterogeneities in funder types, entrepreneurs' improvisation behaviors, and project characteristics. By taking time and space dimensions into account in explaining the dynamics among the three forces (funders, entrepreneurs, and projects), we are able to identify previously unobserved dynamic patterns that influence project performance. The fundraising trajectory can explain the heterogeneity of the dynamics of crowdfunding projects. Fundraising dynamics can continuously reflect the probability of fundraising success and others' funding interest, and influence the dynamics of entrepreneurial performance. Understanding the dynamics of fundraising could explain more about why some projects with similar funding percentages differ in their performance or why they have different fundraising patterns. In order to study the relationship between dynamic fundraising patterns in crowdfunding projects and the subsequent performance of entrepreneurs, we have conceptualized four possible fundraising patterns that consider the characteristics of the three forces (funders, entrepreneurs, and projects): (1) Early momentum pattern, (2) Bandwagon and late infusion funding pattern, (3) Underfunding and late burst pattern, and (4) Rational funding pattern (average growth pattern). The four fundraising patterns are conceptually related to the phenomenon of resource scarcity, bandwagon effects and the characteristics of the three forces. Early momentum funding patterns imply a low level of financial resource scarcity for the entrepreneur in the early stage. Bandwagon and late infusion funding pattern represents projects which attract funders continuously throughout the funding period, and then suddenly attract a huge number of funders. Underfunding and late burst patterns represent projects which do not have high visibility (either projects or entrepreneurs) and fail to attract funders during the majority of the time period, but reach the funding goal right before the ending date. In rational funding patterns, funders may contribute to the projects not because of the bandwagon or momentum effect, but because of project and entrepreneurial characteristics. Furthermore, entrepreneurs can predict the future demand and will be able to make executable product development plans. Table 3.3 explains four fundraising patterns and their characteristics.

Table 3.3 Fundraising Patterns and Characteristics

Factors	**Fundraising Patterns**			
	Early momentum	*Late infusion*	*Underfunding late burst*	*Rational funding pattern*
Funding Variation Time	Early	Late	Late	Steady
Reaching Thresholds	Early	Early to mid	Late	Mid
Slack Resource	High	Mid	Low	Mid
Entrepreneurs' Attention	Execution	Execution	Fundraising	Execution
Risks from Demands Prediction	Low	High	High	Low
Entrepreneurs' Visibility	High	High or Mid	Low	Mid or Low

3.2.2 Research Model

Different dynamics in fundraising patterns exist in crowdfunding projects, and these dynamics may influence entrepreneurial performance because they can explain more about the impact of unobserved entrepreneurial contingent behaviors or the nature of funding. We measure project performance in three ways: (1) delivery, (2) commercialization, and (3) funding from alternative sources such as venture capital and private equity after projects are initiated in crowdfunding platforms. Figure 3.2 shows the research model of our study and serves as a roadmap for hypotheses development.

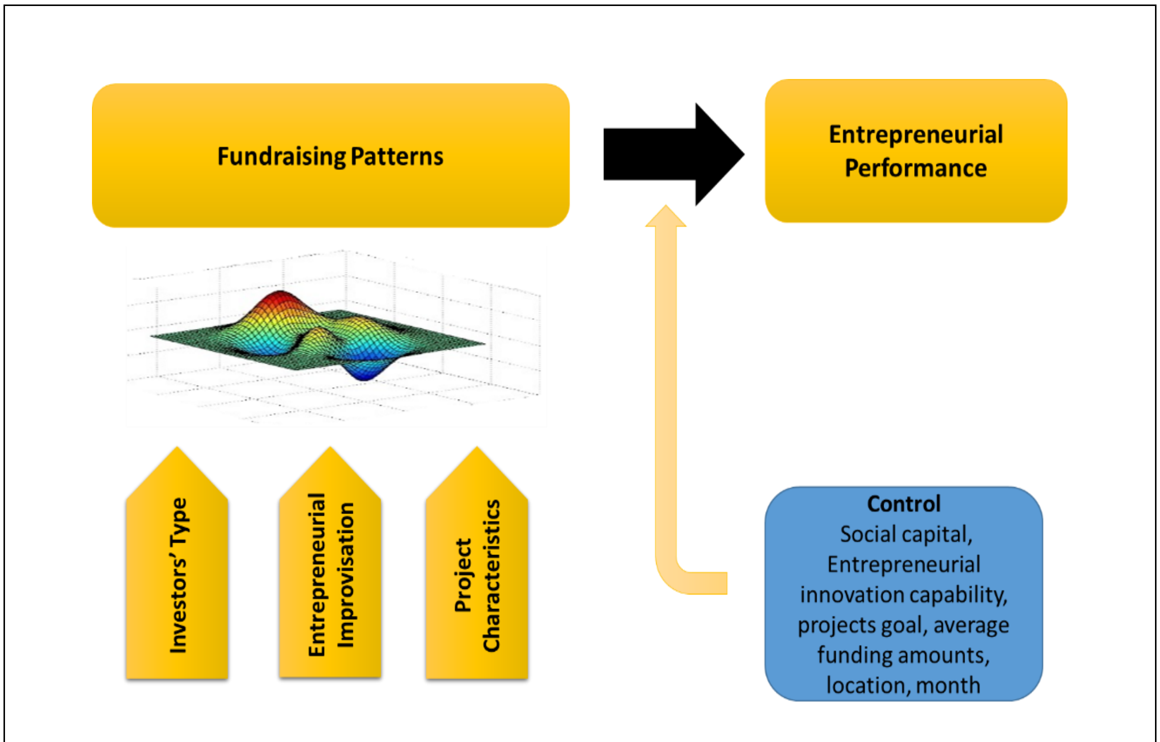


Figure 3.2. Research Model

3.2.3 Hypothesis Development

Fundraising trajectories can explain the heterogeneity of the dynamics of crowdfunding projects. Understanding the dynamics of fundraising could explain more about why some projects with similar funding percentages differ in their performance, or why they have different fundraising patterns. The fundraising patterns will differently influence entrepreneurial performance. Early momentum funding patterns imply a low level of financial resource scarcity for the entrepreneur in the early stage. Prior studies have shown that early funding in a campaign is often driven by friends and families, or by experts who have more knowledge about the projects (Agrawal et al., 2013). Thus, earlier funding momentum may represent a high probability of success in project execution. Early stage funding can create slack resources, which are defined as resources in excess of what is required, allowing an entrepreneur time to adapt successfully to internal and external pressure and changes (Bourgeois, 1981; Sharfman, Wolf, Chase, and Tansik, 1988). Slack resources can positively influence entrepreneurial performance (Sharfman et al., 1988). Project execution and innovation performance can be negatively influenced by hyper-funding (late infusion) in two ways. First, hyper-funding creates risk regarding the execution of more outcomes, and resource allocation decisions could be suboptimal, with resources being constrained by the entrepreneur fulfilling commitments to his or her backers. Entrepreneurs are less likely to manage increased expectations, thus undermining their performance. Also, entrepreneurs may fail to manage a project because of a lack of early momentum (resources) and sudden hyper-demands that disperse their resources to other activities (i.e., attracting more funders, seeking necessary resources, and changing original project plans). Projects might experience fundraising success because of others' behaviors, fads, or popularity of projects. Bandwagon effects, as noted above, are not always based on rational decision-making. On occasion, overconformity can have a negative impact on society (Sunstein, 2005). The effects can often cause problems of over-legitimacy, raising money that exceeds initial goals and that overstate an entrepreneur's ability. Over-legitimacy enforced by social communities in crowdfunding platforms may, in some cases, negatively influence project performance. To have stunning success, significantly beyond an entrepreneur's initial fundraising scope, can be either a plight or an opportunity. It all depends on how the entrepreneur copes with it. Entrepreneurs will face the challenge of dealing with a large and complex order fulfillment process. It is difficult for entrepreneurs to fathom, in advance, the exact scale of a project. In crowdfunding projects, when a late hyper-growth pattern is observed, the bandwagon effects may negatively influence potential performance. After all, the projects may be of poor quality or the entrepreneurs may be ill-prepared to execute them.

Additionally, some projects are underfunded for most of the fundraising period and then have a late infusion; such a pattern is likely to negatively influence project performance. These projects do not have high visibility of projects or entrepreneurs and do not actually attract a crowd's attention during the fundraising period. The late burst is mainly driven by the entrepreneurs' fundraising efforts. The combination of a lack of crowd attention and the entrepreneurs' resource scattering reflects the quality of the projects and entrepreneurial potential. Thus, this type of trajectory negatively influences project performance.

Lastly, projects with average growth patterns are likely to be positively associated with project performance, because entrepreneurs do not experience sudden demands and crowds have consistently paid attention to the projects. Thus, entrepreneurs are more likely to make executable product development plans and focus on project execution. In addition, funders may contribute to the projects not because of bandwagon or momentum effect, but because of project and entrepreneurial quality. Therefore, the fundraising patterns will differently influence entrepreneurial performance. We propose the following hypothesis.

> **Hypothesis**: *Entrepreneurial performance is differently influenced by fundraising patterns.*

3.3 DATA

3.3.1 Data Collection

We collected funding projects data from Kickstarter.com, one of the most popular reward-based crowdfunding platforms in the U.S. Our data focuses on projects in the Technology category, which were initiated and successfully funded between March 2012 and January 2013. A prior study has shown that, within a crowdfunding platform, the project performance patterns (delivery rate) do not differ across categories (Mollick, 2013). There were 303 successfully funded projects. After eliminating projects that did not provide any delivery information or longitudinal data, had small-size funding (less than $200), were short duration projects (less than 10 days), and those that canceled projects after fundraising success, there were a total of 285 projects that provided delivery information. The observation window was closed on December 2014.

3.4 METHODOLOGY AND EMPIRICAL MODEL

3.4.1 Functional Data Analysis

We employed the Functional Data Analysis (FDA) method to identify fundraising patterns, model the longitudinal fundraising process, and test our hypotheses. FDA has become important in statistics in other disciplines (Sood, James, and Tellis, 2009) though it is not common in Information Systems. The central paradigm of FDA is to treat each function or curve as a unit of observation. Each function was examined as a unit of observation, and this approach assumed smoothness and permitted as much flexibility as required by the data (Ramsay and Silverman, 2005; Sood et al., 2009). We applied the FDA approach by treating the daily cumulative funding data of each project as 285 curves or functions. By taking this approach, we could extend several standard statistical methods for use on the curves themselves (Sood et al., 2009). FDA can effectively incorporate entire fundraising histories (Ramsay and Dalzell, 1991). To explain the relationship between fundraising patterns (observed daily funding dynamics for each project until the project's ending date) and entrepreneur's performance (delivery, observed for each product at a single point of time), we faced the challenge of dimensionality and regressing multi-dimensional vectors on a scalar variable.

The FDA approach helps overcome this challenge because it allows most of the variability in fundraising across the fundraising days to be captured with a few functional principal components, significantly reducing the dimensionality (Ramsay and Silverman, 2005). Functional principal component analysis (FPCA) helped us to identify the shape patterns in the fundraising. FPCA provides a parsimonious, finite-dimensional representation for each curve, which helps us to understand variations among the curves. Additionally, this allowed us to perform functional regression by treating the functional principal component scores as independent variables. Prior studies show that a functional data analysis approach provides more accurate predictions than other traditional approaches that use information from only one curve (Sood et al., 2009).

To identify fundraising patterns, we created functional data and assessed the trends of the data. We have data from each project's daily funding dynamics, comprised of daily observations. We used penalized smoothing splines (PENSS) to recover the underlying continuous smooth fundraising dynamic curve $X_j(\mathrm{t})$ for each new product j (j= 285) by removing random influences (Ramsay and Silverman 2005, Sood et al., 2009). The spline basis is defined by the sequence of knots on the daily interval. $X_j(\mathrm{t})$ denotes the observed data at time t (1,2, …,T, T=60). Then the smoothing spline estimate is defined as the function, h(t), which minimizes for a given value of λ>0 (Sood et al., 2009).

$$PENSS_{\lambda,m} = \sum_{\mathrm{t=1}}^{\mathrm{T}}(\mathrm{X(t)} - \mathrm{h(t)})^2 + \lambda \int \{\mathrm{h}'^{\mathrm{m}}(\mathrm{t})\}^2 \mathrm{dt} \quad (1)$$

$$\text{Roughness penalty} = \int \{\mathrm{h}'^{\mathrm{m}}(\mathrm{t})\}^2 \mathrm{dt}$$

The first squared error term in Equation (1) forces h(t) to provide a close fit to the observed data. The smoothing parameter λ controls the trade-off between the smoothness of function h and data fit (Foutz and Jank, 2010). We followed the standard practice of choosing λ as the value that provides the smallest cross-validated residual sum of squared errors (Sood et al., 2009). Figure 3.3 shows the mean of general cross-validation (GCV) criterion for different smoothing parameter λ. As λ approaches 0, the fit of the function to the observation improves. From $\lambda=10^{-2}$, the mean of GCV is close to zero and stable. Thus, a smoothing parameter λ is equal to 10^{-2} in our analysis.

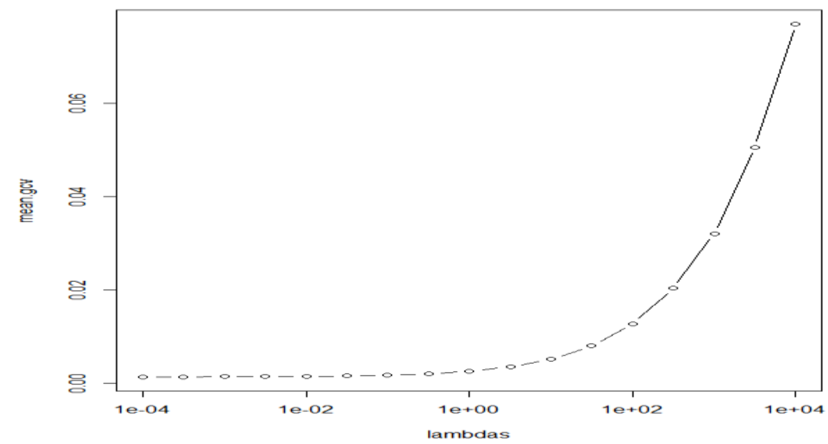


Figure 3.3 Smoothing Parameter Lambda(λ) and Mean of GCV

3.4.2 Functional Principal Component Analysis

Next, we performed a functional principal component analysis (FPCA) to identify the most critical features of fundraising patterns by displaying the modes of functional variation. FPCA is used to extract the common temporal characteristics of a set of curves (Ramsay, Hooker, and Graves, 2009). Smoothing techniques were incorporated into the functional principal components analysis. We decomposed curves into functional principal scores. We denoted by $X_1(t), X_2(t), X_3(t), \dots, X_n(t)$ the *i* smooth curves that are our approximations to the fundraising curves for each project.

$$X_i(t) = \mu(t) + \sum_{j=1}^{\infty} e_{ij}\varphi_i(t) \quad i = 1, \dots., n \quad (2)$$

Subject to the following orthogonality constraints:

$$\int \varphi_j(t)\varphi_i(t)dt = 0\,, \;\int \varphi_{j\;j}^2(t)dt = 1, \;\; 1 \le j \le i. \;(3)$$

Where, $\varphi(t)$ is the eigenfunction, which represents the principal component functions and $\mu(t)$ the average curve over the entire population. The principal component scores, e_{ij}, correspond to the ith curve representing the amounts that $X_i(t)$, which varies in the direction defined by $\varphi_i(t)$.

3.4.3 Empirical Model (Functional Regression Model)

We performed functional regression to predict entrepreneurs' performance. To examine the impact of the fundraising patterns on entrepreneurs' performance, we used the functional principal component scores as the independent variables. We examined the impact of the identified fundraising patterns on entrepreneurs' performance. While project performance is influenced by multiple factors, our study focuses on the impact of fundraising patterns on entrepreneurial performance. Project performance refers to whether entrepreneurs delivered promised outcomes on time, commercialized projects, and obtained venture capital funding. Project performance was measured with a binary variable (deliver: 1, otherwise: 0; commercialization: 1, venture funding: 1, otherwise: 0). To test the causal relationship between functional observations and the scalar response variable, we used a functional regression model, in particular, we used a functional logistic regression model to forecast a binary response variable from a functional predictor whose observations are functions (Aguilera, Escabias, and Valderrama, 2006). The following is our performance model. The impact of fundraising patterns ($\beta_p c_{jp}$) on project performance was examined along with controlling other variables (γ).

Performance Model: $$\mathbf{y_j = \beta_0 + \sum^{P}_{p=1} (\beta_p c_{jp}) + \sum^{J}_{j=1} \gamma_j + \varepsilon_j} \quad (4)$$

Where β_p is the coefficient of the pth FPCA score c_{jp}, and γ is the vector of the coefficients of other variables.

Control Variables

We also controlled several covariates to eliminate alternative explanations. We controlled entrepreneurial characteristics (i.e., prior experience, education), social capital (the number of funders, the volume of online community interactions), project characteristics such as size of goal, average funding amounts, outcome type, seasonal effects, entrepreneurial actions during the fundraising period, and geographical location. According to the signaling theory, entrepreneurs' performance is signaled by their observable characteristics such as education and prior experience (Shane and Stuart, 2002; Stuart, Hoang and Hybels, 1999). Entrepreneurs who have a higher education level and more relevant experience, knowledge, and skills will be more likely to have successful innovations than others, because those resources are highly associated with entrepreneurs' innovation capabilities (Lee et al., 2001; Leonard-Barton, 1992; Stuart and Abetti 1990). Using the resource-based view theory, prior research in strategic management has emphasized the significant role that entrepreneurs' internal capabilities (i.e., idiosyncratic resources) play in their performance. Start-ups' performance is influenced by their focus on the acquiring of intangible resources for survival or growth, and on internally accumulated resources or capabilities (Barney, 1991; Lee et al., 2001). Lee et al. (2001) examined the influence of internal capabilities (i.e., technological knowledge, production skills) on technological start-ups' success. Additionally, in IT project management research, the success of a project often depends on entrepreneurs' characteristics such as education, skills, experience, and leadership style (Belout and Gauvreau, 2004). In venture capital literature, the most important criteria for venture capitalists' funding decisions are the quality of the entrepreneurs and their team, as well as the entrepreneur's experience (Sapienza, 1992). Therefore, entrepreneurs' innovation capability and characteristics are important factors in crowdfunding project performance. Prior entrepreneurship and strategy literature has emphasized the role of social capital in entrepreneurial performance (Leenders and Gabbay, 1999; Lee et al., 2001). A firm's ability to mobilize external resources is often conditional on its social network (Granovetter, 1985). There is a correspondence between the level of projects' social capital within a crowdfunding platform and entrepreneurs' performance. The crowdfunding community networks can provide both available resources and community knowledge and ideas about projects, which enhance entrepreneurs' performance. Therefore, entrepreneurs who have a strong network within a crowdfunding community are more likely to achieve a higher performance. Additionally, in crowdfunding platforms, online crowds can work as information regulators, because they can easily post their opinions and questions about project performance and share them with other participants. Entrepreneurs in crowdfunding platforms cannot ignore these actions because it will negatively impact their legitimacy. Furthermore, the current community participants are more likely to be repeat funders or future customers. Thus, entrepreneurs might try to complete the projects due to their own will and the pressure of online communities. We measured online social capital using the accumulated volume of funders' participation in online community as well as the total number of funders.

Measurement

Adams et al.,(2006) reviewed prior innovation performance literature and summarized innovation management measurement areas as being (1) inputs, (2) knowledge management, (3) innovation strategy, (4) organization culture, (5) portfolio management, (6) project management, and (7) commercialization. To measure crowdfunding project performance, this study distinguished three outcomes, depending on the innovation process: (1) complete initial innovation plans (project performance), (2) introducing new products into the market (innovation performance), and (3) future growth and financial opportunities. The dependent variables are on-time delivery, commercialization, and obtaining additional funding (venture capital funding).

(1) Completing their initial innovation plans (delivery outcomes) -Input Process

We observed the actual performance of projects and gathered project delivery, and manufacturing data from the crowdfunding platforms, online social media, and entrepreneurs' blogs and websites. We defined project performance as whether entrepreneurs delivered their promised outcomes to funders. Project performance was coded using a binary variable (1: on time delivery, otherwise 0).

(2) Innovation performance: Introduce New Product into the Market

In addition to examining project performance in crowdfunding platforms, we also examined whether each entrepreneur commercialized his or her product in the market. Commercialization can be a good measure of innovation. Commercial success in the market should be explained with more sophisticated methods. This study, however, did not measure the actual sales or the commercial success. Funders hope to see positive outcomes from an entrepreneur's project that they've funded, but it is not necessary for them to see good sales performance in the market. Commercialization data was collected from the online marketplace, the company's website. If the final outcomes are sold in the market, we coded 1(otherwise 0).

(3)Growth/Financial Opportunity

The fundraising success in a crowdfunding project creates legitimacy for additional funding. Entrepreneurs who successfully obtain funding from crowdfunding platforms are more likely to get a high percentage of ongoing venture investment. Thus, we also wanted to investigate which types of projects received external funding after initial fundraising success in a crowdfunding platform. Venture capital investment data was collected from *PrivCo* and Crunchbase. If project creators received venture capital funding, it was coded 1, otherwise 0.

Table 3. 4 Frequency Table for Dependent Variables						
DV	**Delivery**		**Commercialization**		**Venture Capital Funding**	
Codes	Frequency	Percent	Frequency	Percent	Frequency	Percent
0	190	66.67	131	49.80	228	86.69
1	95	33.33	132	50.20	35	13.31
Total	285	100	263	100	263	100

Table 3.4 shows the frequency of the dependent variables. In our sample, 33% of projects delivered their final outcomes on time. Over 67% of the projects failed to deliver outcomes to funders by the estimated delivery date. With a two-year window, 50.2% of projects were ready to sell in the market. The study included projects sold in public market places such as Amazon and app-stores (Android, apple store) and private websites (company's websites). 13.31% of the projects were able to get additional funding from venture capital and private investors.

Table 3.5 shows the definition of the variables and descriptive statistics. The maximum value of the pledged percentage is 6264 (the maximum total pledged amounts are 2,945,885) and the log (goal) is 13.53($750,000). The standard deviation of the pledged percentage is 440.89 and the mean is 170.8. Funders' engagement within the crowdfunding platforms was collected during the fundraising period. The maximum volume of comments is 1660. There are three education levels: BS, MS, and PhD. If the project creators' educational information was not observable, we input 0. We looked at whether each project creator had prior crowdfunding experience or not (whether they created other projects or not). We also controlled for the reward type of each project if the final outcome was physical products (either hardware or software) or a warm glow type (gift, invitation, etc.). For the second and third model (commercialization and venture capital funding), we ruled out projects whose outcome was not a physical product (e.g., event, conference, one-time lecture). We used 263 projects for the second and third analyses.

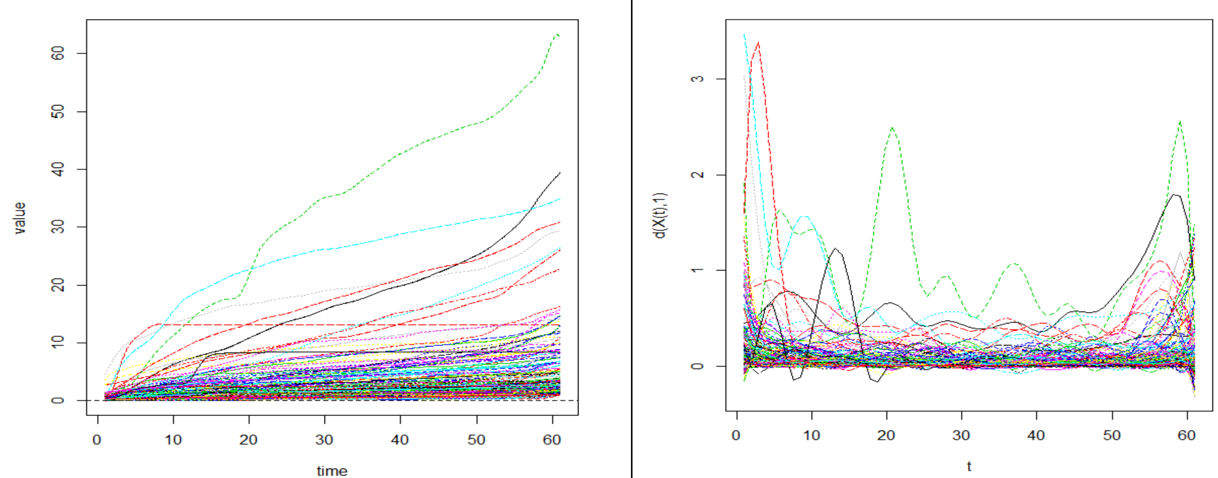
Table 3.5 Variable Definitions and Descriptive Statistics

Variables	Definition	# of Obs.	Mean	Std. Dev.	Min	Max
Delivery	=1 if a project deliver outcomes on time, otherwise =0	285	0.332	0.470	0	1
Commercialization	=1 if a project commercialize the product, otherwise =0	263	0.504	0.500	0	1
VC Funding	=1 if a project get additional external funding, otherwise =0	263	0.133	0.340	0	1
%_pledged	Percentage of funded amounts	285	170.8	440.89	0	6264
logGoal	Funding goal (amounts)	285	9.19	1.529	5.30	13.53
Avg_amounts	Average of funded amounts (total amounts/number of funders)	285	147.0	251.94	5.05	2469.8
Education	Entrepreneurs' education level (1=BS,2=MS,3=PhD, otherwise 0)	285	0.69	.831	0	3
Experience	Entrepreneurs' prior experience	285	0.154	0.36	0	1
Entrepreneur Engagement	The volume of actions (# of updates for a project)	285	3.59	4.42	0	29
Number of Funders	Total number of funders for each project	285	849.44	1715.7	4	11281
Funders Engagement	Total quantity of discussion for each project	285	134.89	258.48	0	1660
Num. of FB Friend	Total number of project creators' friend, if there is no FB sites = 0	285	274.73	398.11	0	3109
Location	Geographical location	285	345.50	218.38	110	999
Reward Type	=1 software, 2 hardware	263	1.693	0.462	1	2

3.5 EMPIRICAL ANALYSIS AND RESULTS

3.5.1 Exploring the Fundraising Patterns

We explored our data and found that different fundraising patterns exist. Figure 3.4 shows the overall fundraising trajectories of crowdfunding projects. The left panel shows the cumulated funding trajectory curves for crowdfunding projects and the right panel represents the corresponding velocity curves (the first order differentiation) which represent the rate of change in funding amounts. These figures show the different history and evolutionary path of fundraising across projects in our data.



[The Cumulated Funding Trajectory Curves] [The Corresponding Velocity Curves]

Figure 3. 4 Smoothing Splines of Crowdfunding Projects

* (Y axis: Cumulative Funding amounts/goal, X axis: Days)

Figure 3.5 shows the examples of funding trends for different crowdfunding projects in our data. Each project has different funding amounts and evolutionary paths.

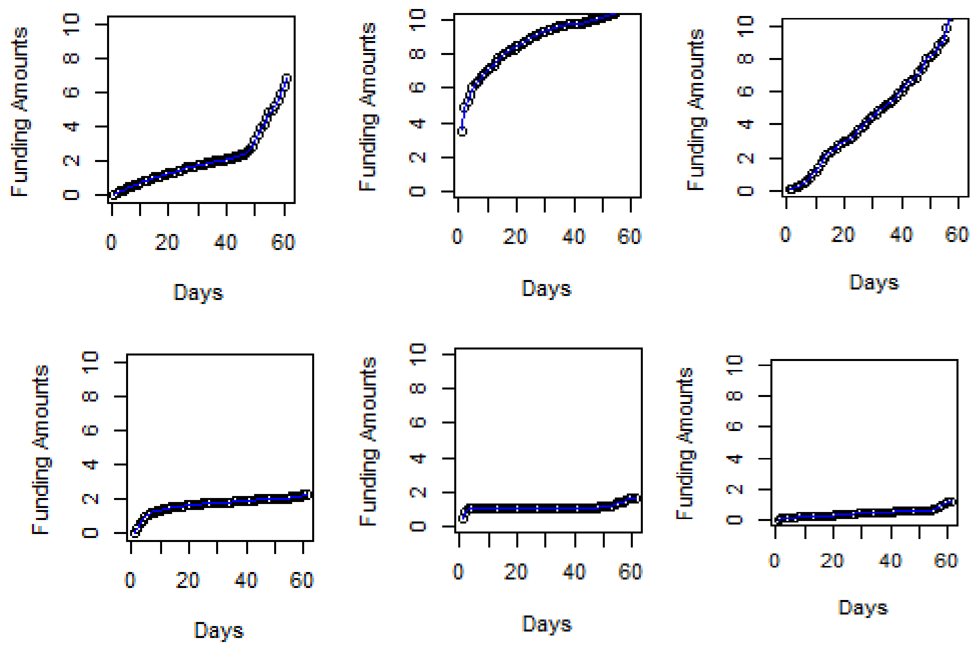


Figure 3.5 Examples of Funding Trajectory for Each Project

Figure 3.6 shows two projects that have similar total funding but have different fundraising trajectories. The momentum effect also indicates that an upward trend in early funding is not the same as a high volume of early funding. Project A and B have the same pledged percentage (193%, pledged amounts/goals) amounts,[12] however, we observed different fundraising trajectories. Project A got more funding at an early stage while Project B got funding at a late stage. The entire history of fundraising dynamics can contain additional information to forecast entrepreneurial outcomes above and beyond the accumulated funding amounts.

[12] In crowdfunding platforms, each project has a different goal (funding amounts); to standardize, we calculated the percentages of funding amounts.

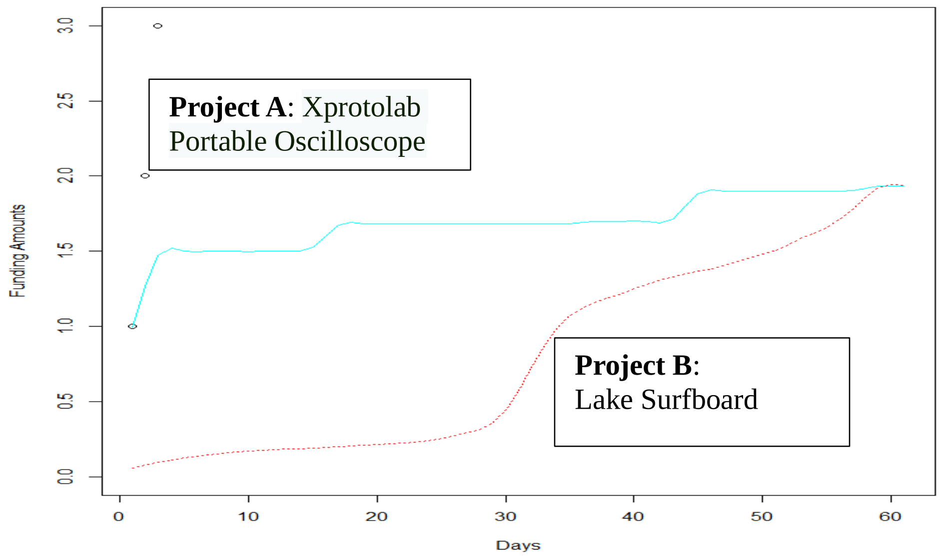


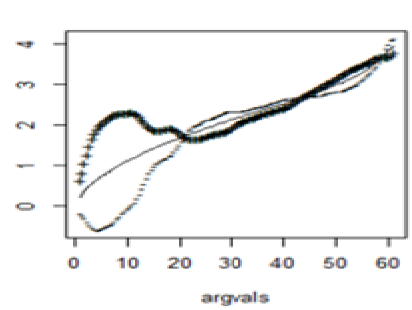
Figure 3.6 Examples of Different Fundraising Patterns

3.5.2 Results

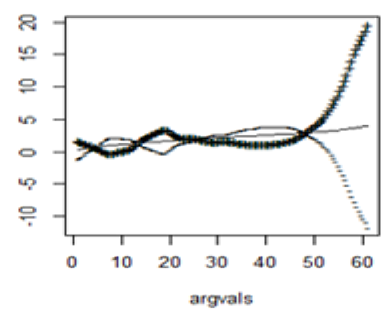
To reduce the dimensionality constraints, we conducted a functional principal component analysis (FPCA). The results of the FPCA showed the dominant modes of variation in the data. Because principal components are often easier to interpret if they are rotated, a VARIMAX rotation was performed. Figures 3.7 and 3.8 present the FPCA results (Figure 3.8: harmonics of FPCA) using a cumulative percentage of the daily funding amounts (= daily funding/project goal) with a VARIMAX rotation. We observed the four most popular fundraising patterns (see the eigen value numbers in Figure 3.9), which explain 99% of variation in funding. The eigenvalue graph shows that the optimal factors number 4.

The first fundraising pattern explains variations in the early stage of funding. This represents projects that obtain early infusions (above the average) in the first 30% of the funding duration, and then exhibit average growth after achieving a certain momentum. 3.7$ of projects follows this patterns. The second pattern explains the large variation of funding amounts in the late stage of fundraising, which represent a project that has average growth in most of fundraising period and then, hype-funding (a late funding infusion) in the late funding stage. We found that 21.6% of technology projects have late infusion patterns. The third model represents under-funding through most of the fundraising period, followed by late hype-funding. Projects in this group do attract some funders in the beginning of fundraising, before losing attention, and then get extra funding right before the ending date. This pattern is the most popular in crowdfunding context. More than 50% of projects have type 3 pattern. The fourth model shows average growth funding (19.1% of projects) patterns.

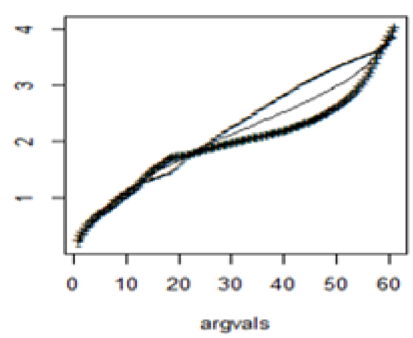
Type 1. Early Momentum
(3.7% of projects)



Type 2. Late Infusion
(21.6% of projects)



Type 3 Underfunding
(55.6% of projects)



Type 4 Rational Funding
(19.1% of projects)

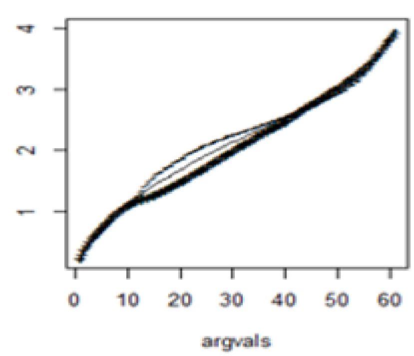


Figure 3.7 Funding Principal Component Analysis

* A principal component represents a variation around the mean. The solid line is the mean curve of funding (t), the +++++ (-----) line represents adding (subtracting) some amount of the FPCA.

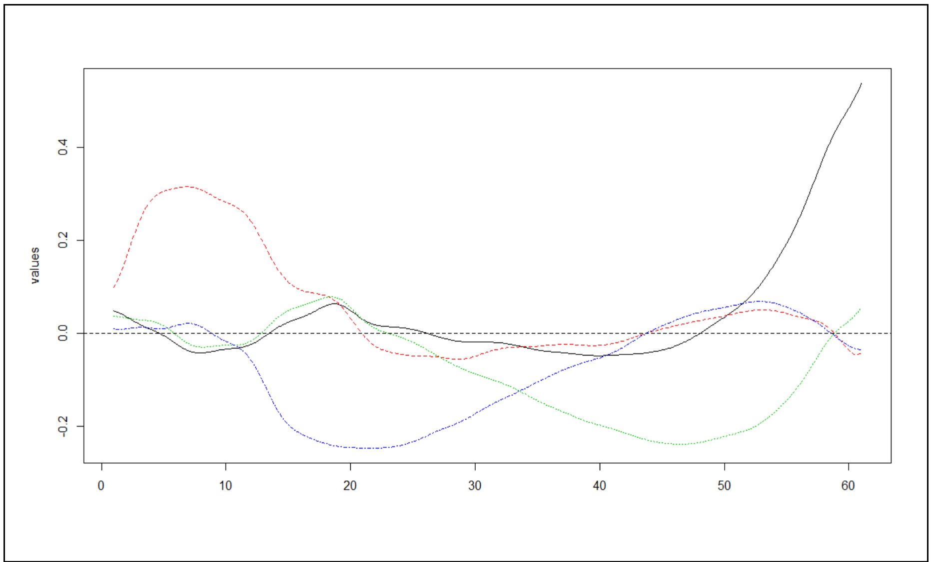


Figure 3.8 Harmonics of FPCA Patterns

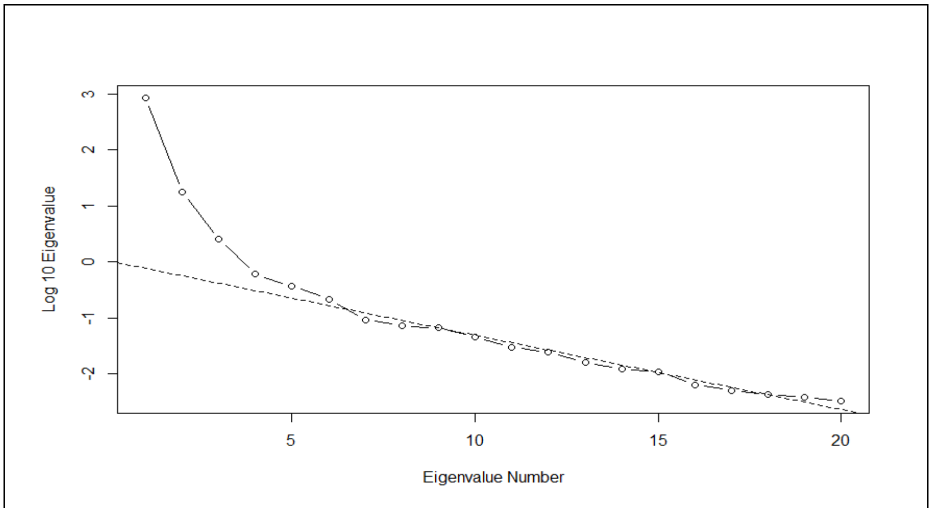


Figure 3.9 Eigenvalue Number

We examined the relationship between the shape of fundraising patterns and crowdfunding project performance. Table 3.6 presents the functional regression analysis results. To eliminate possible alternative explanations, we controlled for location effects, outcome types, and entrepreneurial experience. In the initial project model (delivery), the results showed that the second and third fundraising patterns have negative impacts on project delivery.

Table 3.6 Results of Initial Project Performance				
Independent Variable	**Initial Project Performance** On Time Delivery		**Initial Project Performance** On Time Delivery	
	Coefficients	**Std. Err**	**Coefficients**	**Std. Err**
Type 1 Early momentum	-	-	0.070	0.107
Type 2 Late infusion	-	-	**- 0.186***	0.108
Type 3 underfunding	-	-	**- 0.210****	0.106
Type 4 Rational funding	-	-	**0.206***	0.115
Pledged percent	-0.000	0.0000	-	-
Education1	0.206	0.2795	- 0.006	0.174
Prior Experience	**0.736****	0.356	**0.721****	0.363
LogGoal	**- 0.268****	0.127	**- 0.350*****	0.127
Num. of FB Friends	0.0003	0.0003	0.0004	0.0003
Funders' Engagement(t-1)	**- 0.003****	0.0014	**-0.003****	0.046
Number of funders	**0.0002***	0.0001	**0.0004***	0.0001
Average Funding	**0.001***	0.0007	**0.001***	0.0007
Month	**0.107****	0.048	**0.107****	0.048
Location	-0.005	0.0006	-0.005	0.0006
Reward Type	0.096	0.211	0.096	0.211
Log-likelihood	-162.203		-162.203	
R^2	0.10 (Pseudo)		0.110 (Pseudo)	
Number of obs.	285		285	
Two-tailed significance levels p<0.1, *; p<0.05, ** ; p<0.01, ***				

Projects that suddenly obtained hype-funding limit entrepreneurs' innovation capabilities, and make it difficult for entrepreneurs to perform their initial production plans. Additionally, underfunded projects with high variations in the late stage of funding, also negatively influence entrepreneurs' performance. Entrepreneurs may focus more on luring funders, to achieve fundraising success, and the inherent quality of the project and the entrepreneurs may not be good enough to deliver outcomes on time. Finally, rational funding (average growth trajectory) has a positive impact on performance. In this case, entrepreneurs can predict potential demands and prepare for them. In addition, longer horizontal fundraising to reach a funding goal may increase scrutiny from the crowd. However, the significant impact of early momentum model was not observed. This shows the limitation of crowdfunding projects. Only 3.7% of projects are of this type, which means projects in crowdfunding have difficulty raising early funding momentum. Although we did not find the significant impact of the early momentum model, we still found the positive directionality of this pattern on project delivery. We also observed the positive impact of entrepreneurial prior experience on project performance.

The second model is commercialization success (see Table 3.7). We found a significant negative impact of underfunding on commercialization. This result reinforces our argument about fundraising patterns and the quality of the project and entrepreneurs. The inherent quality of the project and of entrepreneurs may not be good enough to introduce a product to market. For commercialization, we found that entrepreneurs' experience had no significant influence on commercialization. This result indicates that commercialization requires other capabilities such as marketing and technology development. Thus the crowdfunding experience may not be sufficient to explain prior commercialization experience.

Table 3.7 Results of New Product into Markets				
Independent Variable	**New Product into Markets** Commercialization		**New Product into Markets** Commercialization	
	Coefficients (p-value)	**Std. Err**	**Coefficients (p-value)**	**Std. Err**
Type 1 Early momentum	-	-	0.136	0.135
Type 2 Late infusion	-	-	-0.170	0.113
Type 3 underfunding	-	-	**-0.190***	0.112
Type 4 Rational funding	-	-	0.119	0.119
Pledged percent	0.001***	0.0004	-	-
Education1	-0.250	0.280	-0.092	0.168
Prior Experience	-0.075	0.386	-0.076	0.399
LogGoal	**- 0.562*** **	0.142	**-0.591*** **	0.146
Num. of FB Friends	0.0004	0.0004	0.0005	0.0004
Entrepreneur Engagement(t-1)	0.007	0.032	0.021	0.034
Funders' Engagement(t-1)	0.0009	0.001	0.001	0.0009
Number of funders	**- 0.0003** **	0.0001	**- 0.0004*** **	0.0001
Average Funding	0.00005	0.0007	-0.00002	0.0007
Month	**0.094** **	0.049	**0.087***	0.049
Location	-0.002	0.0006	-0.0003	0.0006
Reward Type	-0.145	0.309	-0.181	0.311
Log-likelihood	-159.075		-155.44	
R^2	0.127		0.15	
Number of obs.	263		263	
two-tailed significance levels p<0.1, *; p<0.05, ** ; p<0.01, ***				

In the third model, we investigated factors that influence the opportunity to get extra funding from venture capitalists or private equity (see Table 3.8). We did not find a significant impact of fundraising patterns on venture capital funding. However, we found that experience is a critical factor in venture capital funding. Additionally, we observed the significant impact of size of projects on venture capital funding. Therefore, in venture capital funding, observable entrepreneurial experience and popularity of projects are more important than other factors

Table 3.8 Results of Growth/Financial Resource				
Independent Variable	**Growth/Financial Resource** Venture Capital Funding		**Growth/Financial Resource** Venture Capital Funding	
	Coefficients	**Std. Err**	**Coefficients**	**Std. Err**
Type 1 Early momentum	-	-	0.204	0.159
Type 2 Late infusion	-	-	-0.247	0.227
Type 3 underfunding	-	-	-0.224	0.192
Type 4 Rational funding	-	-	0.143	0.174
Pledged Percent	**0.001***	0.0004	-	-
Education1	**0.120**	0.264	0.153	0.485
Prior Experience	**1.052****	0.647	**1.075****	0.629
LogGoal	**1.283*****	0.595	**1.283*****	0.289
Num. of FB Friends	0.001	0.001	0.0006	0.0006
Entrepreneur Engagement(t-1)	-0.001	0.001	-0.002	0.044
Funders' Engagement(t-1)	0.0007	0.001	0.0005	0.001
Number of funders	-0.0001	0.0002	**-0.0004***	0.0002
Average Funding	0.0002	0.0007	0.0001	0.0007
Month	**0.150***	0.080	**0.151***	0.083
Location	-0.0001	0.001	-0.0007	0.001
Reward Type	**-0.812***	0.498	**-0.880***	0.524
Log-likelihood	-72.29		-68.82	
R^2	0.29		0.33(Pseudo)	
Number of obs.	263		263	
Two-tailed significance levels p<0.1, *; p<0.05, ** ; p<0.01, ***				

3.5.3 Robustness Checks

Potential Endogeneity: Latent Instrumental Variable Approach

Endogeneity can arise from multiple sources: (1) relevant omitted variables, (2) measurement errors in the repressors, (3) the problem of self-selection, (4) simultaneity, and (5) serially correlated errors in the presence of a lagged dependent variable (Zhang et al., 2009). One way to overcome problems of endogeneity is to find instruments, based on economic theory or intuition (Greene, 2000). Instruments are variables that correlated with independent variables, but are uncorrelated with the error term. Hence, instrumental variables cannot have a direct effect on the dependent variable. However, there are challenges in using instrument variables. In many cases, it is not easy to find available instrument variables, and some of those available might not be a good quality instrument. Using bad quality instruments may result in estimates that are even more biased than OLS estimates (Bound et al., 1995; Hahn and Hausman, 2003; Zhang et al., 2009).

We observed different fundraising dynamics and the influence of such patterns on entrepreneurial performance. To eliminate potential endogeneity issues from omitted variables, we controlled the impact of several covariates (project goal, average funding amounts, funders' community, and entrepreneurial characteristics) on entrepreneurial project performance. Additionally, reverse causality may not be problematic in our context, because there is a time gap between fundraising and entrepreneurial project performance. The only concern we have is, regarding potential endogeneity issues from unobservable variables that could influence both fundraising patterns and entrepreneurial performance. Especially, an unobservable entrepreneurial quality could influence both early momentum funding patterns and entrepreneurial performance. However, it is not easy to observe entrepreneurial quality information in crowdfunding projects.

Additionally, there is difficulty in identifying an observable instrument variable for dynamic fundraising patterns. To resolve this potential endogeneity problem, we adopted a latent instrumental variable (LIV) approach. This is a modeling approach to account for regressor-error dependencies and is used when observable instrumental variables are difficult to identify (Ebbes et al., 2005). The Latent Instrumental Variables (LIV) approach estimates regression parameters regardless of the presence of regressor-error correlations[13] (Zhang et al, 2009). This method solves the endogeneity problem without observable instrument variables (Ebbes et al., 2005; Zhang et al., 2009). As this method does not rely on observable instruments, we can also avoid issues of availability, validity, and weakness of the instruments (Zhang et al., 2009; Ebbes et al., 2005). The main idea of this approach is to introduce a binary unobserved instrumental variable that partitions endogenous predictors into two parts, one uncorrelated and the other correlated with the error term in the main equation (Ebbes et al., 2005; Zhang et al., 2009). The inclusion of a latent instrument in a system of regression equations is similar to a linear structural relations model, in which a latent factor that is uncorrelated with the error term is specified (Zhang et al., 2009). Ebbes et al. (2005) provide a way to estimate models with an endogenous explanatory variable. Zhang et al. (2009) extend the LIV approach by developing a Bayesian formulation that has the advantage of providing valid inferences and conducting significant tests.

To deal with a potential endogeneity problem (the early momentum pattern), we introduced an early momentum equation (m_i)[14]. We specified the model as follows:

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[13] Traditional instrumental variable (IV) is typically used to correct for regress-error correlations.

[14] We calculated and used the percentage of early funding amounts for $\widetilde{m}_i$ (total funding amounts for early 30% of duration to measure (i.e. if the duration is 60days, it will be the total percentage of pledged amounts of first 20days).

$$y_i = \beta_0 + \beta_1\widetilde{m}_i + \beta_2 c_i + \varepsilon_i^y \text{ (a)}$$

$$m_i = \widetilde{m}_i + \varepsilon_i^m = \alpha_1 x_i + \theta_1 v_i + \varepsilon_i^m \text{ (b)}$$

Where, y_i: project performance; β: coefficients of regressors; $\widetilde{m}_i$: instrumented variables; c_i: other covariates; x_i: manifest variable; α_1: coefficient of manifest variable; v_i:unobserved latent instrument variables; θ: coefficients of latent instrument variables

In the early funding model (Equation b), the instrumented average early funding ($\widetilde{m}_i$) is a function of entrepreneurial characteristics x_i and an unobserved LIV, v_1. We assumed that v_1 follows a Bernoulli distribution, $v_1 \sim$ B (π_{vi}), where π_{vi}= P (v_1=1) is the instrument probability. The latent instrument v_1 partitions the variation in m_i in such a way that a part of it ($\widetilde{m}_i$) is uncorrelated with entrepreneurial performance error ε_i^y and another part of it ε_i^m is correlated with ε_i^y. The parameter θ represents the effect of the latent instrument v_1 on the average early funding. The instrumented average early funding, $\widetilde{m}_i$, instead of observed average early funding (m_i), appears in the entrepreneurial performance model (Equation a). The LIV effectively removes early funding endogeneity from the model and enables consistent estimates of the effect of average early funding on entrepreneurial performance (β_1). We estimated the model with a Markov Chain Monte Carlo (MCMC) using R and WinBugs. We checked a few convergence diagnostics. A trace plot is a plot for the iteration number against the value of the parameter at each iteration. Figure 3.10 shows a well-mixed trace plot for each parameter and density plots of the parameters. We also do not find significant autocorrelation. To determine the optimal number of burn-in, we conducted Gelman-Rubin diagnostics with three chains. With 10,000 burn-in, we cannot observe over-dispersed starting points and three chains are well mixed. Next, we determined the optimal number of iteration (length of chain) using Rftery and Lewise's analysis (20, 000 iteration). The MCMC estimation results for the entrepreneurial performance and early funding equations appear in Table 3.9. We find significant parameters θ on average early funding. The Posterior coefficients of θ represent significant effects of unobserved two groups on m_i. This shows that early momentum could be endogenous and unobserved project or entrepreneurial quality influences early funding amounts. However, we did not observe the significant impact of $\widetilde{m}_i$ (early funding momentum) on entrepreneurial performance. This result shows that early momentum can be driven by prior visibility or unobserved entrepreneurial quality factors, but the early momentum alone is not sufficient to influence entrepreneurial performance.

Table 3.9 MCMC Bayesian Results of Latent Instrument Model (Posterior)
(Burn-in 10,000; Iteration 20,000) *** significant

Independent Variable	**Posterior**		Quantiles for each variable	
	Mean	**SD**	**2.5%**	**97.5%**
β_0	-1.780	0.059	-1.157	1.187
β_1	-2.347	0.077	-1.780	1.277
β_2	-1.309***	0.059	-2.476	-1.552
α_1	-1.702	0.039	-9.521	6.210
θ_1	-1.152***	0.039	-1.928	2.495
θ_2	5.185***	0.386	4.097	-4.039

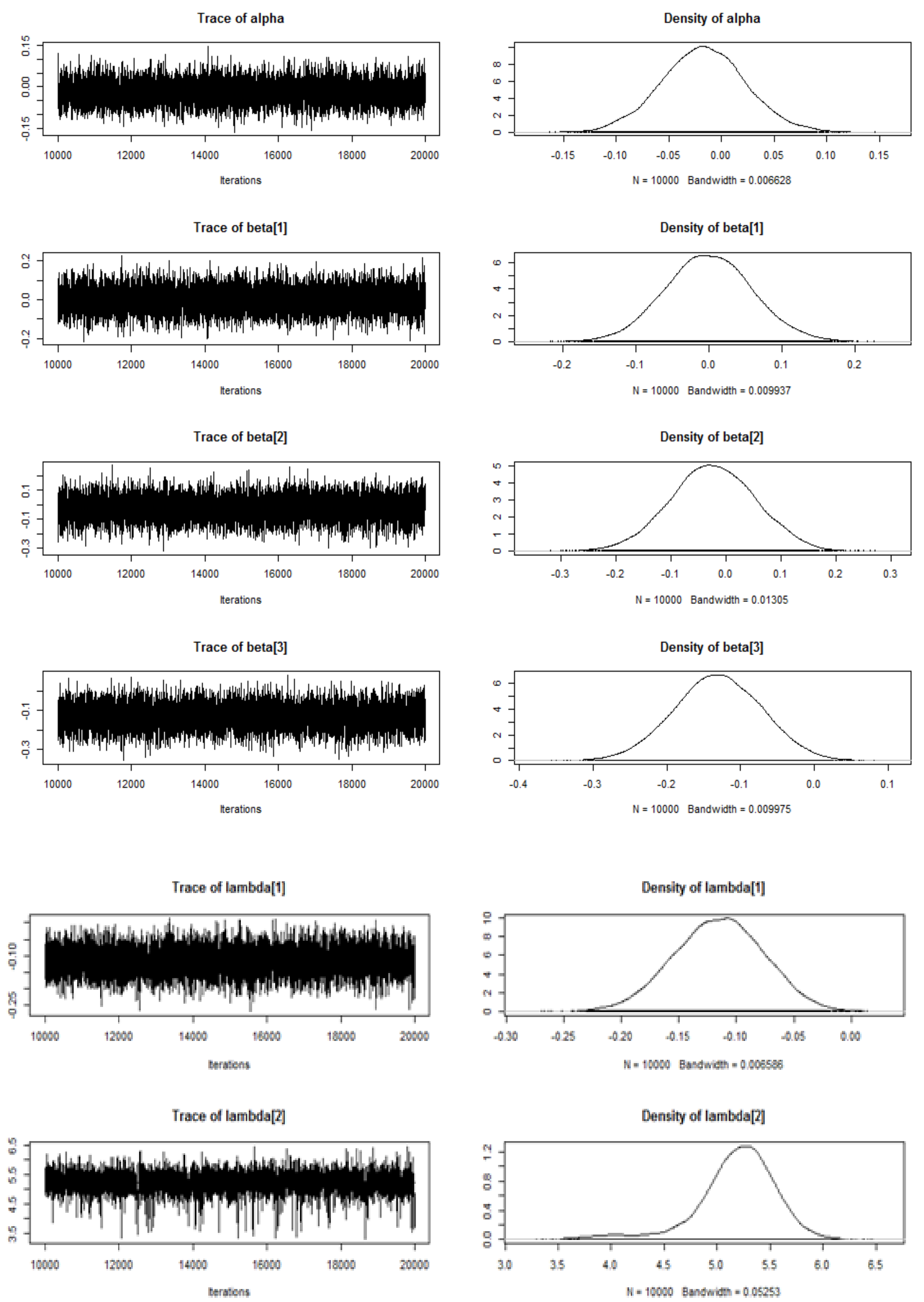

Figure 3.10 Trace Plots and Density Plots

Heterogeneity of Projects: Crowd- vs. Expert- Based Funding

As we discussed earlier in this paper, funders' contribution strategies-how much and when they contribute to projects- vary in accordance with their ability to evaluate project quality, their enthusiasm, and the tolerance of risk level. Thus, some funders contribute to projects with a great deal of knowledge and higher amounts of money in order to access an early version of innovation outcomes, while others are drawn to a particular project based on simple hedonic interest, philanthropy, fads, or bandwagon effects rather than the intrinsic quality of the projects. Such a motivation makes funders avoid high-risk investments, and leads to late funding participation with small amounts of money. Therefore, we expect that projects which gathered money from those investors will have more chances to represent the late hype-funding patterns than others. To address the heterogeneity of projects and the related fundraising patterns, we classified projects into two groups: (1) Crowd-based projects and (2) Expert-based projects based on the data we collected from Kickstarter.com. However, since Kickstarter.com does not provide each individual's contribution amounts, we classified these groups using reward data. First, we investigated every level of rewards, corresponding contribution amounts and the number of contributors for each project. With those data, we calculated the contribution percentages of each reward level. Next, we investigated whether a project received more than 50% of its funding amounts from the 50% of lower reward levels.[15] If projects belong to this group, we coded them as crowd-based projects, otherwise we coded them as expert-based projects. Figure 3.11 shows the evolutionary fundraising paths (left figure: funding trends; right figure: velocity of funding trends) for the two groups. Blue lines represent expert-based funding projects and red lines represent crowd-based projects. In general, red lines more represent hype-funding projects than blue ones in

[15] A lower rewards level is equivalent to lower contribution amounts.

the figures. To analyze the effect of a project's type on the shape of crowdfunding curves (i.e., the fitted curves as responses), we adopted a functional analysis of variance (FANOVA) method.

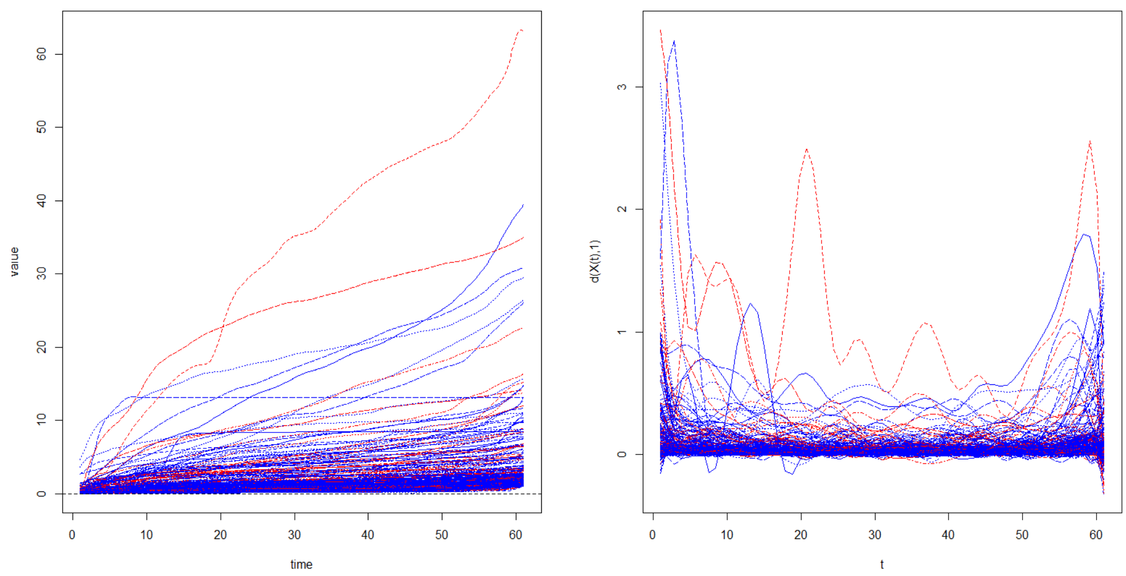

Figure 3.11 Plots of Crowd Vs. Expert-based Model (Red line: Crowds; Blue: Experts)

To perform a FANOVA, we need to define a linear model. We can then find the best parameters (using regression). Y(t) is a functional response, $\beta_i$is the weights, x_i is either 0 or 1.

$$y(t) = \beta_0(t) + \beta_1 x_i(t) + \varepsilon_i(t)$$

There are 69 projects in Group 1 (crowd-based, funding from relatively small amounts) and 216 projects in Group 2 (expert-based, funding from relatively higher amounts). Figure 3.12 shows the means of the fitted funding curves for the crowd-based projects (n=69, black curve) and the expert-based projects (n=216, grey curve). As we see in this figure, crowd-based projects have a higher mean value of funding in the late stage than the expert-based funding.

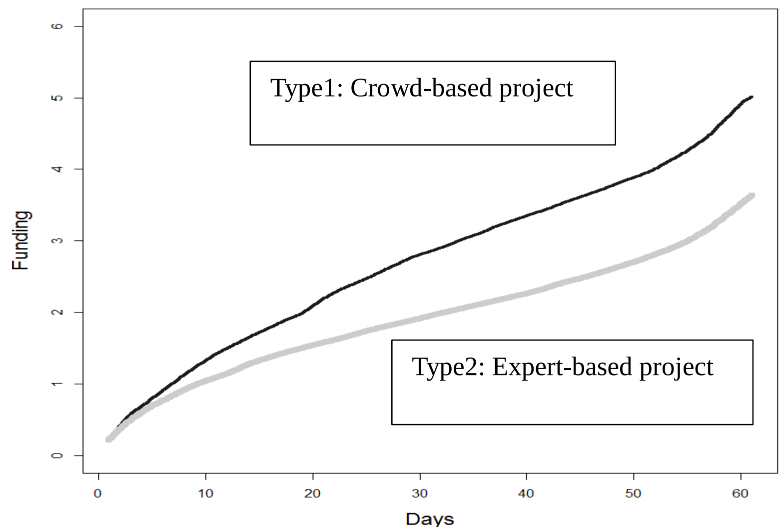

Figure 3.12 Mean Curves for Crowd and Expert Types

Figure 3.13 represents the estimated functional regression coefficients (right figure: β_0, left figure: β_1) with corresponding confidence Intervals (shaded). With the crowd-based projects as the reference group, the estimate discrepancy to reference group (β_1) is different from the reference group.

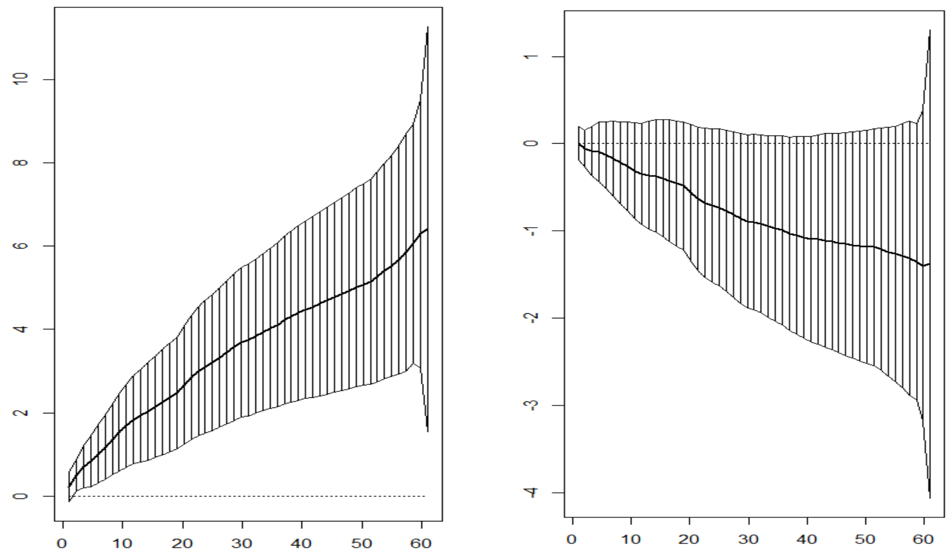

Figure 3.13 Plots of estimated beta curves with functional confidence intervals

Next, we performed pairwise comparisons of two groups using a functional permutation F-Test (1,000 replications) to check whether the two groups statistically differed from each other. Figure 3.14 show shows the permutation F-Test results and p-value curve. We found statistically a significant p-value at the time of 60% of entire duration (40days/60days). Crowd-based projects have a significant increasing pattern at that time point (pointwise 0.05 critical value). Therefore, crowd-based projects are more likely to have the late hyper-funding pattern, where the majority of funding comes from funders who have less expertise and are less sensitive to entrepreneurial innovation performance. This also provides evidence of how dynamic fundraising patterns can address the heterogeneity of crowdfunding projects and underlying funding mechanisms.

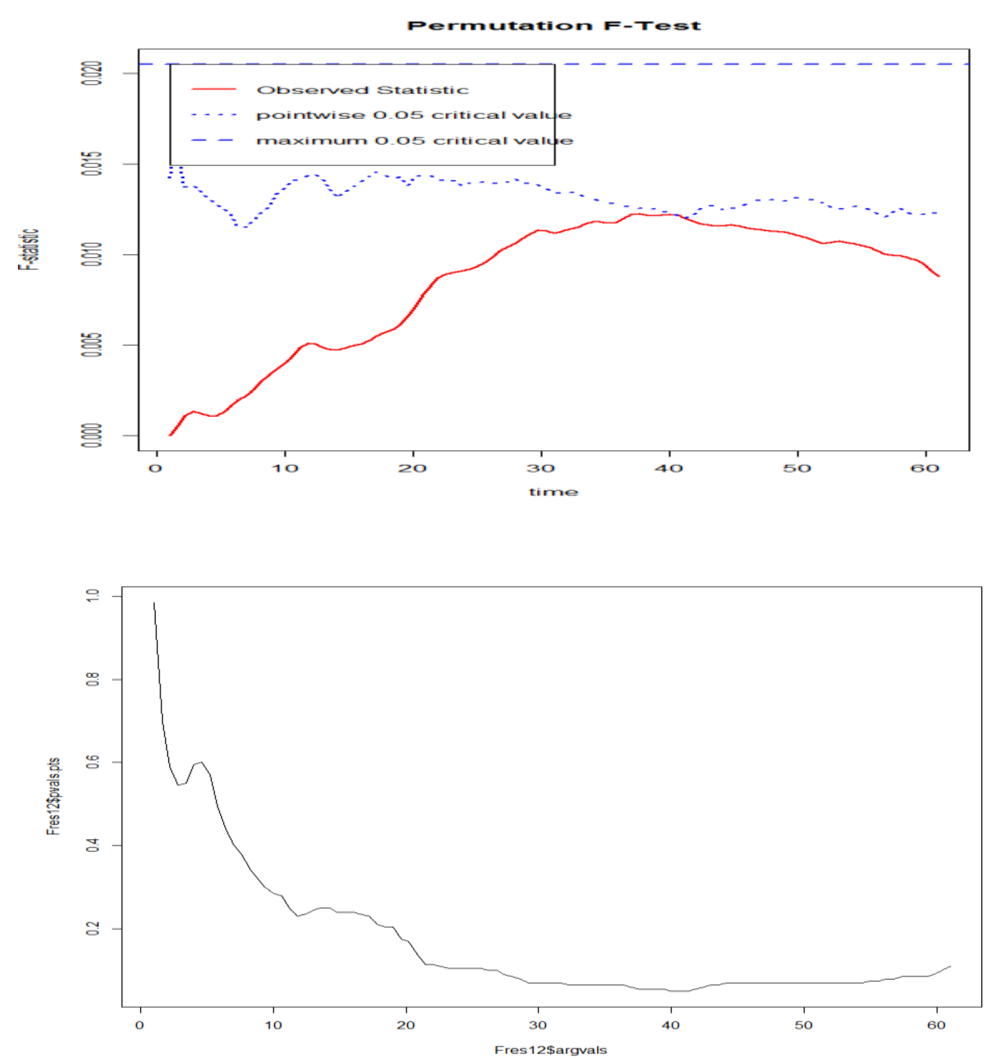

Figure 3.14 Plots of Permutation F-Test and P-Value

3.6 CONCLUSION AND IMPLICATIONS

This study investigated the dynamics of fundraising patterns and their impact on crowdfunding project performance. Using the entrepreneurship theory and bandwagon effects as a theoretical lens, we examined which fundraising dynamics (incorporating projects, investors, entrepreneurs' characteristics, and contingent entrepreneurial behaviors) enhanced or hindered entrepreneurs' project performance in IT-enabled funding platforms.

Employing functional data analysis (FDA) methods, we identified different fundraising dynamics across crowdfunding projects. FDA provides a set of techniques that can improve the prediction of empirical models (Sood et al., 2009). A functional principal component analysis (FPCA) helped us to identify the patterns of shapes in the fundraising. FPCA provides a parsimonious, finite-dimensional representation for each curve, which helps us understand the variations among the curves. Additionally, this allows us to perform functional regression by treating the functional principal component scores as independent variables. Prior studies show that a functional data analysis approach provides a more accurate prediction than a traditional approach of using information from only one curve (Sood et al., 2009).

Our empirical analysis results show different fundraising patterns that had yet to be explained. The results also show that the performance of projects with late funding infusion was negatively influenced, because of the entrepreneurs' lack of preparation for unexpected demands for outcomes resulting from slack resources. Additionally, projects that failed to create early momentum and were underfunded for most of the fundraising period, but had a late infusion, showed negative performances. This sheds light on the process by which entrepreneurs generate heterogeneous value, and their ability to execute projects given ostensibly similar circumstances (in the sense of fulfilling the original funding goals). To improve performance, entrepreneurs need to prepare for project execution early in their innovation process, and be equipped with the capability to cope with extreme hyper-attention, so they do not “make the pleasure of today become the sorrow of tomorrow.”

Online communities can provide available resources, as well as community knowledge and ideas about projects that enhance entrepreneurs’ performance. Entrepreneurs might try to complete projects through their own will, and from the pressure of online communities. In crowdfunding platforms, online crowds can work as information regulators because they can easily post their opinions and questions about project performance, and share them with other participants. Entrepreneurs in crowdfunding platforms cannot ignore these actions because doing so would hurt their legitimacy. In addition, their ability to obtain funds in crowdfunding platforms can signal their legitimacy to financial institutions and future investors. Failing to deliver their outcomes to online funders on time is a negative signal to future investors. Thus, for the survival of their business and future funding, it is critical for sound entrepreneurs to deliver promised outcomes on time.

Our study also supports the long-lasting argument of “legitimacy and resource acquisition.” Entrepreneurs who have prior visibility have a better chance of gaining early momentum than others. We have emphasized that in order for entrepreneurs to achieve better performance they need to gain legitimacy and access to resources early in the fundraising stage. By doing this, they can reduce the burden of resource dependency and focus on the execution of projects. Projects in crowdfunding platforms need to overcome the inherent difficulty in obtaining early funding in crowdfunding platforms by using other intermediaries such as online social media and establishing good track records. Along with this, crowdfunding platform providers need to implement design tools that enhance the visibility of new projects. Otherwise, crowdfunding becomes a place where project creators are able to raise funds without ever delivering outcomes to their funders. In addition, funders need to consider fundraising trajectories to avoid the risk of not having outcomes on time, and of investing in projects of low quality or entrepreneurs with low potential. We also found that entrepreneurs' prior experience plays an important role in their performance. Prior project experience positively influences project performance.

This study has some limitations that could be addressed in future research. First, in many cases, delays are caused by unexpected external elements such as shipping problems, legal screenings, and so on. In a future study, it would be valuable to consider how entrepreneurs cope with these issues. While our findings are limited to one technology category and platform, it would be interesting to investigate whether a different category has different dynamic patterns, and how they are associated with entrepreneurial performance.

Despite the limitations, this study provides managerial implications for both start-ups who want to raise funds and investors who contribute to projects and are seeking sound projects in crowdfunding platforms. Entrepreneurs should emphasize their prior performance. If they have none, they should increase their visibility to obtain early resources. Investors should look at the dynamics of fundraising patterns and review the indicators of projects' and entrepreneurs' quality. Our findings offer novel and important implications for the theory and practice of project performance in crowdfunding platforms. We expect that our work will contribute to and promote future research that enhances our understanding of crowdfunding participation and performance regarding resource access and new firm creation.

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