THE DYNAMICS OF CROWDFUNDING: AN ENTREPRENEURIAL LEARNING PERSPECTIVE

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DECLARATION

I hereby declare that the thesis is my original work and it has been written by me in its entirety. I have duly acknowledged all the sources of information which have been used in the thesis.

This thesis has also not been submitted for any degree in any university previously.

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13 August 2017

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SUMMARY

The recently emergent phenomenon of IT-enabled crowdfunding has garnered much interest from practitioners and academics alike. Crowdfunding provides an effective alternative for financing a project or a venture by tapping into the general public. Pursuant to the popularity of this phenomenon, a growing corpus of academic work has been devoted to this domain. However, although many studies offer important insights into understanding the phenomenon of IT-enabled crowdfunding, most extant studies offer a somewhat static perspective, which is not sufficient to shed light on the development trajectories of successful entrepreneurs. This dissertation seeks to extend the boundary of the crowdfunding literature by examining the dynamics of crowdfunding with regard to two aspects: across- and within-campaign dynamics. These constitute two essays of the dissertation.

The first essay titled "The Path of Successful Entrepreneurs: A Fine-Grained Understanding of Prior Experience in Entrepreneurial Learning" investigates the role of prior experience in entrepreneurial success. Drawing on the theory of organizational learning, I theorize entrepreneurial learning effects from several fine-grained experience dimensions: direct/indirect, successful/failed, experience relatedness and richness. Using six years of panel data involving 3,521 serial entrepreneurs running fundraising campaigns on a popular IT-enabled crowdfunding platform, I find that entrepreneurs not only learn directly by creating and managing their own projects but also indirectly from backing others' projects. The results also suggest that the learning depreciation is more likely to occur in indirect learning. Surprisingly and more interestingly, the results show the prevalence of an "early success trap" phenomenon in entrepreneurial practices; successful founding experience is detrimental to subsequent success, and furthermore, earlier successful ones are even more destructive. The relatedness and richness may not always facilitate learning.

The second essay titled "Learning from Performance Feedback: The Dynamic Interplay Between Fundraising Patterns and Entrepreneur Strategies in Crowdfunding" examines how the fundraising patterns influence entrepreneurs' strategic actions during the course of the fundraising and how these actions in turn affect final funding performance. Building on the performance feedback model from organizational learning theory, I

propose hypotheses related to the effects of performance relative to the aspiration level on entrepreneurs' explorative and exploitative actions for managing a crowdfunding campaign, the effects of strategic action taking on end-of-period project performance as well as the role of time in these relationships. Based on a unique dataset encompassing daily observations from a leading reward-based crowdfunding platform, I find that there is a positive relationship between concurrent funding performance and entrepreneurs' probability of taking exploitative actions, and such relationship is strengthened when deadline draws near. Entrepreneurs are less likely to merely taking explorative actions (without exploitation), as it is usually accompanied by exploitative actions. Furthermore, entrepreneurial strategies in managing the project are shown to be effective, and those entrepreneurs who take actions at early stages tend to harvest more.

Overall, by taking a dynamic view towards the crowdfunding phenomenon, this dissertation uncovers the across- and within- campaign dynamics in crowdfunding. It suggests that learning effects are salient in *knowledge*- and *innovation*- based work (e.g., entrepreneurship) even though much of the organizational learning research has focused on repetitive / routinized work. Entrepreneurial performance can be enhanced with the enrichment of experience. And particularly, as the entrepreneurial context is manifold and volatile, it is paramount for entrepreneurs to obtain timely feedback while at the same time seek a balance between exploitation and exploration. In addition, this dissertation offers valuable contributions to the literature in organization theory and entrepreneurship.

Keywords: entrepreneurship, entrepreneurial learning, crowdfunding, innovation, dynamics, organizational learning, learning behavior, behavior theory of the firm, prior experience, fine-gained analysis, performance feedback, aspiration level, qualitative aspects, topic modelling, regression analysis, econometrics, machine learning, text mining, propensity score matching

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CHAPTER 1 INTRODUCTION AND OVERVIEW

1.1 Research Background

Innovation-oriented entrepreneurship plays a prominent role in driving the economy (Acs 2006; Van Stel et al. 2005). Entrepreneurs bring new ideas to fruition by establishing new independent businesses (Kirchhoff 1994; Mollick and Nanda 2016). Their innovations creates solutions to meet new requirements and unarticulated needs or superior solutions to meet existing marketing needs (Bayus 2013; Maranville 1992). Such micro-level individual entrepreneurial activities promote macro-level economic growth by increasing productivity and intensifying competition with new market entrants (Geroski 1989; Nickell et al. 1997; Nickell 1996) and by introducing innovative products into the market (Acs and Audretsch 1990; Wang and Hahn 2015). From this perspective, entrepreneurship plays two major roles in economic development: new entries and innovative creators (Wennekers and Thurik 1999). In both roles, entrepreneurs are acting as innovators, who "transform innovation and ideas into economically viable entities" (Baumol 1993, p.198). For example, Samila and Sorenson (2011) show that a doubling in the number of firms funded by venture capital results in a 0.22% to 1.24% expansion in the number of jobs and a 0.48% to 3.78% increase in aggregate income. Additionally, a January 2012 report from the U.S. Small Business Administration (SBA) finds that small businesses act as a vital stimulant in the economy of the United States – e.g., small businesses produced 46% of non-farm GDP in 2008. With respect to its significant influence on economic growth, entrepreneurial success is essentially important to economic society and it has garnered substantial attention in recent decades.

Pursuant to this trend, a growing number of individuals are making a transition in the labor market by considering self-employed entrepreneurship as a viable alternative to

economic self-sufficiency (Lin et al. 2000). However, despite the popularity of entrepreneurship, its success rate is quite low. As a recent investigation shows, around eight out of ten new start-ups fail within 18 months after they have been launched.[1] Recent data illuminates the situation: out of 3723 deals invested by venture capitalists occurring in 2012, there were only 49 IPOs and 449 mergers and acquisition deals (Forrest 2014). As illustrated here, entrepreneurs are facing severe situation.

The difficulty of entrepreneurial success can be attributed to several reasons. First, it is hard for start-ups to raise seed money for their entrepreneurial practices (Hsu 2004). As fresh founders of new businesses, the majority of entrepreneurs are not guaranteed stable and sufficient sources of income to sustain their businesses. During the early stage of establishment, many entrepreneurs resort to family and friends for needed capital, but that is far from enough. In such a setting, venture capital funding serves as an indispensable resource for entrepreneurs to thrive their businesses. The second difficulty arises from strict constraints of venture capitalists and their limited credits available to entrepreneurs. The process of financial application is tedious and inefficient. The requirements for the funding applicant are very stringent. There also exist geographic restrictions between entrepreneurs and financing parties. In this regard, even though there emerge prodigious financial support and favorable government policies to foster new start-ups, it is still difficult for individuals to successfully launch enterprises. Many innovative ideas are precluded from the market due to difficulties in sourcing financial capital (Mollick and Nanda 2016).

A novel model sourcing capital that leverages information and communication technologies – IT-enabled crowdfunding – has recently emerged and gained popularity to incentivize entrepreneurial activities. Crowdfunding platforms enable entrepreneurs to

[1] See: http://www.forbes.com/sites/ericwagner/2013/09/12/five-reasons-8-out-of-10-businesses-fail/#380b0db35e3c

directly reach the crowd at an unprecedented scale for needed capital at lower cost, whereby entrepreneurs' innovative ideas can be supported by a diverse and large group of individuals (Howe 2008; Kuppuswamy and Bayus 2017; Malone et al. 2010; Schwienbacher and Larralde 2010) rather than by professional investors, such as venture capitalists or banks, for necessary funding for their ventures. Contrast to traditional sourcing models, crowdfunding can be characterized by unskilled crowdfunders, collective evaluation of proposed projects, greater transparency of funding status and reduced geographical constrains (Hahn and Lee 2013; Wang et al. 2016; Yang and Hahn 2015). Specifically, on crowdfunding platforms, these indicators about projects and venture owners are recorded and published for open consumption. Entrepreneurs are exposed to less geographic constrains, as the electronic nature of online platforms facilitates transactions between and collaborations among geographically distributed parties (Agrawal et al. 2011; Agrawal et al. 2015). Besides, crowdfunding enables early assessment of market response, in that entrepreneurs are able to promote their product to the market in parallel with fundraising process. They also have ongoing and timely interactions with their supporters (Yang and Hahn 2016). Some notable crowdfunding platforms include Kickstarter, IndieGoGo, RocketHub, to name a few.[2] According to a recent crowdfunding industry report, these platforms have helped new ventures to raise billions of dollars (Massolution 2015) and the volume and amounts of transactions continue to increase.

Despite the popularity of crowdfunding, the success rate on crowdfunding platforms is still quite low. According to Kickstarter statistics[3], around 60% projects fail to reach their funding goal. These unsuccessful projects also tend to fail by large margins.

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[2] See: http://www.forbes.com/sites/chancebarnett/2013/05/08/top-10-crowdfunding-sites-for-fundraising/

[3] See: https://www.kickstarter.com/help/stats?ref=footer (visited on 07/20/2017)

The average amount of their pledges is 10% of the goal, and only 3% failed projects reach 50% of their goal (Mollick 2014). Compared to the traditional market, where about 80% of start-ups fail (Wagner 2013), entrepreneurs on crowdfunding platforms are still exposed to a grave situation and it is challenging for them to be successful (Jung et al. 2014).

However, entrepreneurial capabilities can be continuously acquired over time (Erdélyi 2010). The development of entrepreneurship is accompanied by the process of learning, where entrepreneurs learn to recognize and react to opportunities, and develop the capabilities to act differently (Guiso et al. 2015; Rae 2006). Meanwhile, the entrepreneurial process is also characterized by both constructing contextual knowledge though experience and creating new reality (Weick 1995). It is apparent that learning has become a prominent component in entrepreneurial practice and activity (Cope 2005). The process of entrepreneurial learning is the updating of accumulated subjective knowledge, and it occurs through initiating, organizing and managing ventures in social and behavioral ways (Rae 2006). Therefore, in light of the importance of learning and low success rate in entrepreneurial activities, the focus of this dissertation is to better understand the development trajectories of successful entrepreneurs in IT-enabled crowdfunding. The information transparency of crowdfunding allows the observation of entrepreneurs' behaviors and performance over time (Yang and Hahn 2015). Specifically, this dissertation consists of two essays that investigate entrepreneurial learning from macro and micro levels respectively. At the macro level, the first essay examines how serial entrepreneurs learn from their prior experiences, the focus of which is *across-campaign* performance enhancement. At the micro level, the second essay aims to uncover how entrepreneurs enact strategic actions during fundraising process in response to concurrent performance, the focus of which is *within-campaign* performance feedback effects.

1.2 Research Questions

In IT-enabled crowdfunding platforms, entrepreneurial learning occurs at both macro and micro levels. At the macro level, entrepreneurs are able to acquire experience directly by launching their own projects and indirectly by backing other entrepreneurs' projects. When they observe the performance of prior experience, they are likely to adjust their subsequent behaviors accordingly (Fiol and Lyles 1985). More specifically, the success or failure of prior experience foster their understanding about why something works and something does not. During this learning process, entrepreneurs gradually develop their skills through reflection, association and eventually translate knowledge into subsequent behaviors. Therefore, to better understand entrepreneurial success, the first research question this dissertation aims to answer is:

- *How do entrepreneurs' prior experience influence their subsequent crowdfunding performance?*

In crowdfunding, entrepreneurs are able to play roles on both sides of the market (i.e., founders and backers), and their prior experience can be associated with different outcomes (i.e., success and failures). More interestingly, their level of engagement in each experience and the content of prior and current experiences may vary. Aiming to explore the variations in learning effects for different experience dimensions, the second research question asks:

- *How do the entrepreneurial learning effects vary with different dimensions of experience?*

At the micro level, each crowdfunding campaign allows entrepreneurs to obtain ongoing and timely feedback from the market during the funding process. The entire fundraising cycle is a continuous interaction process among funders, project concurrent performance as well as entrepreneurs. The interactions among market participants provide opportunities for reflection and growth – i.e., entrepreneurs may continuously

learn to adjust their actions in response to feedback from the market. Specifically, in light of satisfactory and less than ideal funding performance, entrepreneurs tend to take actions accordingly to their projects in subsequent funding period. In order to understand how concurrent performance affects their strategies, our third research question asks:

- *How do dynamic fundraising patterns influence entrepreneurs' strategic behaviors during funding process?*

The strategies taken by entrepreneurs may in turn alter subsequent fundraising outcomes. Generally, how entrepreneurs manage the campaign process is an essential element. The primary objective of taking strategic actions is to increase project crowdfunding performance. Intending to examine this impact, our fourth research question asks:

- *How do strategic actions taken by entrepreneurs during the fundraising process affect final crowdfunding performance?*

In sum, the four research questions in this dissertation intend to investigate the entrepreneurial learning effects from both macro and micro levels. At the macro level, RQ1 and RQ2 examine how entrepreneurs learn from their prior experiences. At the micro level, RQ3 and RQ4 explore how entrepreneurs learning from concurrent performance feedback. Two levels of learning correspond to the *across*- and *within-campaign* dynamics in crowdfunding, which has yet to be fully studied. Therefore, investigating entrepreneurial learning effects also forward our understanding regarding the dynamics in crowdfunding.

1.3 Abstracts of the Two Essays

This section presents the abstracts of the two essays.

Essay I: The Path of Successful Entrepreneurs: A Fine-Grained Understanding of Prior Experience in Entrepreneurial Learning

Given the growing interest in serial entrepreneurship, studies have investigated the effect of entrepreneurs' earlier experience on subsequent entrepreneurial performance. We extend this strand of literature by examining the entrepreneurial learning from prior experiences at a fine-grained level and taking a dynamic perspective towards this phenomenon. Drawing on organizational learning theory, we theorize about the different learning effects from multiple experience dimensions: indirect vs. indirect experience, successful vs. failed experience, the relatedness, and richness of prior experience. Using six years of panel data involving 3,521 serial entrepreneurs in crowdfunding context, we empirically tested our framework. We find the positive effects of both direct and indirect learning. However, successful founding experiences have a detrimental effect on subsequent entrepreneurial performance, and such negative effect is more salient for early success. Entrepreneurs seem to learn from their own failure and other entrepreneurs' success. In addition, related and rich experience do not always facilitate learning and consequently lead to enhanced performance. Our study extends the organizational learning theory to entrepreneurship context by investigating the dynamics across multiple founding experiences.

Essay II: Learning from Performance Feedback: The Dynamic Interplay Between Fundraising Patterns and Entrepreneurial Strategies in Crowdfunding

Crowdfunding is a novel mechanism for sourcing financial capital for entrepreneurial ventures. The IT-enabled nature of crowdfunding platforms facilitates entrepreneurs to interact directly with current and prospective backers and to obtain timely and immediate feedback from the market during the fundraising process. Despite the dynamic nature of this process, there is a notable dearth of attention to it. The present study strives to fill this gap by examining the dynamic interplay between fundraising patterns and entrepreneurs' strategic behaviors for managing the project during the course of fundraising. Building on the performance feedback model from the behavioral theory of

the firm, we propose hypotheses related to the influences of concurrent funding performance on entrepreneurs' exploitative and explorative actions, and the effects of taking actions on project performance as well as the role of deadline proximity in these relationships. The proposed hypotheses are empirically tested using a unique dataset that contains daily snapshots of crowdfunding projects. Theoretical and practical contributions are also discussed.

1.4 Contributions of the Dissertation

This dissertation aspires to contribute in multiple ways to the literature and has a variety of research and managerial implications. First, this dissertation furthers the IS literature on crowdfunding by unveiling the dynamics of entrepreneurial process from *across*- and *within- campaign* perspectives. I posit that entrepreneurs not only obtain necessary knowledge with the accumulation of prior experiences, but also continuously adjust their entrepreneurial practices in light of the feedback from concurrent funding performance. Second, this dissertation extends the behavioral theory of the firm (Cyert and March 1963), in particular organizational learning theory and performance feedback theory, from typically *repeated tasks* to *innovation-based creative tasks* (e.g., entrepreneurship) where less routinization is entailed and which often requires problem solving (Boh et al. 2007). Traditional organization tasks are often repetitive and structured (Argote 2013b), whereas entrepreneurial activities are characterized to be manifold, complex and less structured (Cope 2005; Yang and Hahn 2015). Investigating learning behaviors in this new form of work can inform and provide further insights to the theory. Third, this dissertation responds to calls from prior literature by characterizing experiences at a fine-grained level in learning processes (Argote and Miron-Spektor 2011) and explicitly incorporating the role of time in the feedback-learning cycle (Lehman and Hahn 2013). Examining learning effects from multiple experience dimensions offers more nuanced

theoretical insights. Time acts as an important resource for entrepreneurs and thus shapes the learning curve. Fourth, this dissertation suggests that learning is an essential and inseparable part of entrepreneurial process. I extend the emerging field of "entrepreneurial learning" by providing empirical evidence on how entrepreneurs construct acquire knowledge via experience enrichment. Practically, the findings of this dissertation inform entrepreneurs in crowdfunding platforms of how to design experience to cultivate success. It also provides implications for platform operators on function designs to facilitate entrepreneurial learning.

1.5 Organization of the Dissertation

This dissertation focuses on the learning dynamics of crowdfunding with regards to two aspects: learning from prior experience for *across*-campaign dynamics and learning from performance feedback for *within*-campaign dynamics. The two aspects of dynamics correspond to the two essays in this dissertation, each of which is a separate study.

In order to tie the two essays together into a coherent whole, this chapter has offered an introduction including research background, motivations, research questions and contributions. The reminder of this dissertation is organized as follows. Chapter 2 provides a broad overview of the crowdfunding phenomenon in terms of its origin, development, definition, unique features and different types of crowdfunding platforms. Chapter 3 presents a comprehensive literature review of the crowdfunding research to date and identified important research gaps. At end of this Chapter, I discuss how this dissertation is able to fill the void in existing crowdfunding literature and how the theoretical foundation I adopt can provide insights for addressing these gaps. Then Chapter 4 presents the theoretical background, including organizational learning theory and performance feedback theory, both of which originate from the behavior theory of the firm (Cyert and March 1963). During the literature review for these two theories, I

cover primary constructs and main underlying mechanisms that are discussed in the theories, and importantly, before concluding each section, I also discuss how the these main constructs relate to the special features of crowdfunding (which is covered in Chapter 2), how the theories facilitate us to address the identified research gaps in crowdfunding literature (which is presented in Chapter 3), and how the theories inform the hypotheses development in the two essays (which are discussed in Chapter 5 and Chapter 6). It is worth mentioning that this chapter has some overlaps with the theoretical background section that will be shown in the two essays. The objective of the theoretical background within each essay is to offer an overview of the applied theory, whereas the aim of Chapter 4 is to provide a comprehensive review of the theoretical literature relevant to the dissertation. Chapter 5 presents the first essay which intends to uncover the dynamics across crowdfunding campaigns. This essay is a currently almost completed research paper with minor refinement remained. Chapter 6 introduces the second essay that aims to explore the within-campaign interplay between funding patterns and entrepreneurs' strategic actions. This essay is a working paper and first-round analysis has been finalized. Each essay is written so that they are self-sufficient – each essay consists of its own introduction, literature review, research hypotheses, research method, results and conclusion. Finally, I conclude this dissertation by summarizing the findings and discussing their implications in Chapter 7.

CHAPTER 2 THE CROWDFUNDING PHENOMENEON

2.1 From "Crowdsourcing" to "Crowdfunding"

The term "crowdfunding" is derived from the better known term of "crowdsourcing" (Hemer 2011; Ingram et al. 2013), which has existed far longer than crowdfunding and has recently received substantial attention. Jeff Howe first coined this concept in his 2006 *Wired Magazine* article entitled 'The Rise of Crowdsourcing'. Crowdsourcing is defined as the activity of a profit-oriented organization to outsource their ideation efforts to a large and undefined group of people (the "crowd") external to the organization rather than to a designated party (a firm, an employee, informal or formal team) (Afuah and Tucci 2012; Howe 2006; Howe 2008; Jeppesen and Lakhani 2010). Simply put, in crowdsourcing, individual volunteers from the "crowd" are considered as the source and taskforce of companies' value creation, as they are the source of ideas, feedback, and solutions to develop corporate activities.

Crowdfunding is reckoned as a subset of crowdsourcing. Within crowdfunding activities, the general public provides needed capital by making investments in companies. These funds raised may help new ventures in certain activities such as importing new technologies, acquiring assets or paying employees. The first difference from crowdsourcing is that it is financial investments that the crowd contribute rather than ideas or labor. Crowdfunding can be seen as crowdsourced funding. It goes beyond the ingredients of crowdsourcing by incorporating the inspiration of microfinance. Crowdsourcing helps corporations obtain innovative ideas, while crowdfunding targets ordinary entrepreneurs especially those unable to access financing from mainstream sources of financing (e.g., banks, venture capitalists). For example, *Kiva.org*, a lending-based crowdfunding platform aims to make it easy for marginalized populations to obtain loans to start businesses. Its approach is to raise funds through the Internet, which

facilitates tapping the crowd as a source of funding (Duncan 2014). Therefore, crowdfunding can be regarded as crowd-empowered microfinance (Marom 2013). It mobilizes a large community (i.e., the crowd) to give away small amounts of money to the ventures and initiatives they find attractive. The sum of small contributions may add up to sum that is substantial enough for starting up a new business.

Another important distinction between crowdsourcing and crowdfunding is that the crowdsourced resource (i.e., ideas generated) belongs to the community in the case of crowdsourcing, such that it allows exploitation and use by any individual without restrictions on who can use it (Belleflamme et al. 2014); yet in crowdfunding, the crowdsourced resource (i.e., funds raised) ultimately belongs to the project owner.

2.2 Information Technology Enabling the Tapping of the Crowd

The development of crowdsourcing and crowdfunding is driven by the expansion of web technology (Brabham 2008; Kleemann et al. 2008), as Web 2.0 technologies facilitate and accelerate the mobilization of the "crowd" – an essential feature for crowdsourcing and crowdfunding. The participation of the crowd is also enhanced by the increased prevalence of the Internet as well.

The popularity of crowdfunding (and thus also crowdsourcing) is inseparable from the "wisdom of the crowd" – i.e., the greater efficiency in solving entrepreneurial problems by a crowd compared to a few individuals or small teams (Howe 2008; Schwienbacher and Larralde 2010; Surowiecki 2005). That is, the inputs of individuals from the crowd trigger the crowdfunding process and influence the ultimate value of the offerings and outcome of the process. Each individual acts as an agent of the offering, selecting and promoting projects that they believe in, and disseminate information about the project they support to their online communities (e.g., Facebook connections), which generates further support for the project (Estellés-Arolas and González-Ladrón-de-

Guevara 2012). Compared to the limited financial sources in traditional fundraising, crowdfunding incorporates the power of the crowd. Entrepreneurs' innovative ideas are more likely to be supported by the general public within a short period of time. In addition, the efficiency of the crowd lies in web-enabled collective intelligence (Malone et al. 2010) whereby a diverse and large organized groups of people can work together through the Internet in surprisingly effective ways, under which crowds can do things faster, with higher quality and higher motivation.

Besides, the individuals in the crowd that participate in crowdfunding initiatives are inclined to reveal several traits (Ordanini et al. 2011; Prive 2012): innovative orientation, social identification and monetary exploitation. Innovative orientation motivates them to put forward new ideas and to give effective feedback to entrepreneurs. Social identification sparkles their desire to be part of the initiative, and inspires active participation. Monetary exploitation refers to that participants from the crowd typically have expectations of payoff from their monetary contribution. These traits not only distinguish investors in crowdfunding from those in traditional market, but also promote innovative initiatives generation from entrepreneurs and facilitate entrepreneurial success.

2.3 Definition of Crowdfunding

As mentioned previously, crowdfunding enables pitching an initiative to more than just family and friends (Ingram et al. 2013). It is "the crowd" that helps to get those innovative ideas off the ground. In simple words, crowdfunding is the financing of a project or a venture by a large group of mostly non-professional individuals instead of professional parties (like, for instance, banks, venture capitalists or business angels) (Schwienbacher and Larralde 2010). Crowdfunding bypasses these intermediaries

(Beaulieu and Sarker 2013) to raise money by directly "tapping the crowd" on Internet-based platforms, such as *Kickstarter.com*, *Indiegogo.com*, and *Spot.us*.

More generally, crowdfunding is defined by Belleflamme et al. (2014) as an "open call, essentially through the Internet, for the provision of financial resources either in form of donation or in exchange for some form of reward and/or voting rights in order to support initiatives for specific purposes"(p. 4). This definition is more comprehensive and covers several forms of crowdfunding, in which participants have different expectations of payoff from their monetary contribution.

2.4 Different Forms of Crowdfunding Platforms

To date, crowdfunding has taken several forms in terms of the method of raising money from the crowd (Zvilichovsky et al. 2013). Broadly, four kinds of business models exist: 1）loan/lending-based, 2) equity-based, 3) donation/patronage-based, and finally 4) reward/preordering-based (Mollick 2014). Table 2-1 summarizes the different types of crowdfunding models, their characteristics as well as representative websites. In essence, the various crowdfunding platform types differ with respect to whether or not funders' motivation for contribution is related to financial returns (Kuppuswamy and Bayus 2013). Therefore, based on this view, we classify these four models into two broad categories: with and without financial returns (see Table 2-1). Funders in the first two approaches (i.e., loan/lending-based and equity-based crowdfunding) participate for the purpose of financial returns. In the loan/lending-based model, funds are offered as a loan, with the expectation of some rate of return on the capital invested. In the equity-based model, funders are treated as investors that are given equity stakes in return for their funding. Alternatively, funders in the following two models (i.e., donation/patronage-based and reward/preordering-based crowdfunding) do not contribute for financial returns. Rather, in the donation-based model, funders act as philanthropists who do not expect direct

return for donations. Finally, in reward-based crowdfunding, funders receive rewards by backing the project. Many entrepreneurs provide discounted pre-ordering as a reward so that funders get the new product at a discounted price.

Table 2-1. Four Types of Crowdfunding Platforms

Crowdfunding Models		Descriptions and Characteristics[a]	Example
With financial return	Loan / lending-based model	**Description**: Investors are repaid for their investment plus interests. **Characteristics**: Funds are offered as a loan, which the expectation of some rate of return on capital invested. **Motivation**: Investors want to maximize their financial return as minimize the risk of default.	*Kiva.org* *Prosper.com* *Somolend.com* *Fundingcircle.com*
	Equity-based model	**Description**: Investors receive stakes in the company. **Characteristics**: Investors carry out financial investment in firms and startups. They will be endowed with equity shares in the company and earn dividends as an investment return. This model is subject to high level of regulation, and its eventual adoption is uncertain relative to other forms of crowdfunding. **Motivations:** Investors want to maximize their financial return.	*Circleup.com* *GrowVC.com* *MicroVentrue.com* *AngelList.com*
Without financial return	Donation / patronage-based model	**Description**: Givers make benevolent contributions. **Characteristics**: Funders are placed in the position of philanthropists, who expect no direct return for their donations. **Motivations:** Donors want to feel good.	*JustGiving.com* *Fundrazr.com* *GiveForward.com* *Rally.com*
	Reward / preordering-based model[b]	**Description**: Funders receive tangible items, services or other types of rewards. **Characteristics**: Funders receive a reward by backing a project, such as enjoying "pre-selling" products or services as early customers, having creative input into a product under development, or having an opportunity to meeting creators. **Motivations:** Funders want the project to be implemented.	*Kickstarter.com* *Indiegogo.com* *Rockethub.com* *Spot.us*

Notes: [a] Descriptions and characteristics are based on Beaulieu and Sarker (2013), Belleflamme et al. (2013), Kuppuswamy and Bayus (2013), Mollick (2014) and Schwienbacher and Larralde (2010). [b] The reward/preorder-based model is the most prevalent model currently in practice and is also the focus of this dissertation.

Basically, donation/patronage-based crowdfunding is aimed at charity giving. These platforms are acting as online tools and processing services to enable the collection of charitable donations (Smithers 2011). As equity-based and loan-based platforms are

more likely to be subject to many other peripheral causes, such as the regulation from the Financial Conduct Authority, entrepreneurial success would inevitably be influenced by these factors. Furthermore, equity-based crowdfunding is highly restricted by regulation (Heminway and Hoffman 2011), and up until mid-2013, it was permitted only in some countries (Mollick 2014). Hence, considering the focus of this dissertation (i.e., entrepreneurial learning) and the prevalence of reward-based crowdfunding, the reward-based model is chosen as our research focus.

2.5 Unique Features of IT-enabled Crowdfunding

Crowdfunding has some strikingly different features compared to traditional approaches to entrepreneurial financing. These features play an important role in the formulation of this dissertation, insomuch as they not only facilitate entrepreneurs to obtain immediate market responses but also enables us to observe entrepreneurs' practices during the whole entrepreneurial process more easily.

One of the most important characteristics is the large **geographic dispersion** of investors (Agrawal et al. 2011). The reduced role of spatial proximity arises from the electronic nature of online investment platforms, which enables the convenience of transactions between and collaboration among geographically distributed parties. In online crowdfunding platforms, all interactions between entrepreneur and investors occur electronically. Entrepreneurs do not need to make a deal by visiting the investors in person (Lin and Viswanathan 2014). Notwithstanding, to some degree, geographic distance does play a role to some extent in funder's decision making (Agrawal et al. 2010; Agrawal et al. 2011; Agrawal et al. 2012; Burtch et al. 2014a; Kim and Hann 2015; Lin and Viswanathan 2014). For example, in the context of online pro-social lending, Burtch et al. (2014a) find that lenders prefer geographically proximate borrowers. Even so, the influence of geography has been effectively minimized with crowdfunding. For

instance, reduced geographical constraints has also the impact of democratization of access to capital (Kim and Hann 2015) in that fundraisers (entrepreneurs) in less populated areas are more likely to get finance for their ventures from crowdfunding.

Another significant feature of the crowdfunding model is **information transparency** – information about entrepreneurs and their projects are publicly observable on crowdfunding platforms (Burtch et al. 2011; Burtch et al. 2013a). Different from information scarcity of traditional fundraising, these indicators about projects and venture owners are recorded and published on the crowdfunding platform for open consumption. For example, a summary and detailed records of entrepreneurs' founding and funding histories are typically visible on crowdfunding platforms. These indicators have implications for potential contributors' decision making, so the social aspect of crowdfunding has become prominent (Zhang and Liu 2012). For instance, prior contribution histories, including others' contribution amounts and contribution times, are influential in later contributions and may influence future contribution trends. An entrepreneur's past founding histories (e.g., quality of past project, success rate of past project) may signal his/her experience and capability, which may have an effect on crowdfunders' choice (Burtch et al. 2011; Ward and Ramachandran 2010; Zhang and Liu 2012). The quality of project descriptions is seen as a signal for entrepreneur's level of preparation – e.g., including a video pitch indicates a higher-quality project, whereas the presence of spelling errors implies the lack of preparedness and low quality (Mollick 2013; Mollick 2014). In addition, it is more difficult for investors to assess the social capital of an entrepreneur in traditional fundraising market due to limited information provided by entrepreneurs. On the contrary, crowdfunding platforms provide explicit indicators of entrepreneur's social network size, such as the number of Facebook friends and number of twitter followers. Social network size plays a role in determining the success of entrepreneurial financing efforts, as it provides endorsement of project quality

and entrepreneur's connections to likely contributors (Sørensen and Fassiotto 2011; Stam and Elfring 2008). Therefore, potential contributors may consider the social network size of entrepreneurs for identifying promising projects to fund. In addition, on the entrepreneurs' side, the information transparency enables them to improve the design of their own projects by observing others' campaigns and behaviors. In summary, information transparency in crowdfunding markets influences the decision making of crowdfunders and consequently may also impact the initiating behavior of entrepreneurs. When considering the focus of my dissertation– entrepreneurial learning, the information transparency facilitates the examination of learning effects from various forms of entrepreneurial experiences (i.e., founding and backing experiences, success and failed experiences) and the exploration of variations in the effects of different types of learning.

The third feature is that crowdfunding platforms serve as **two-sided markets** (Eisenmann et al. 2006). Traditionally, in order to get access to wealthy investors, entrepreneurs need to network through intermediaries (Beaulieu and Sarker 2013). The process is tedious and inconvenient. Usually it is only professional parties that participate as investors to entrepreneurs, so the likelihood of being an entrepreneur and an investor at the same time is low. Conversely, crowdfunding bypasses these intermediaries and brings capital-raising to the crowd in a direct way (Beaulieu and Sarker 2013). Furthermore, crowdfunding platforms facilitate information flow and transactions between project owners and potential backers (Zvilichovsky et al. 2013). Some crowdfunding platforms, such as *Kickstarter.com* and *Indiegogo.com*, are similar to commercial two-sided markets, such as eBay or the iPhone App Store, where the platform facilitates the purchase of goods and services. Besides, it is more prevalent to play both sides of the market on crowdfunding market – creating projects to raise funds and backing other projects by pledging funds. During entrepreneurial learning process, entrepreneurs' dual role enables

them to accumulate entrepreneurial experiences in various ways, which constitute multiple dimensions of experiences in my study.

Fourth, crowdfunding platforms enable **ongoing and timely interactions** between entrepreneurs and contributors. For example, on reward-based crowdfunding websites such as *Kickstarter.com* or *Indiegogo.com*, potential contributors can contact project creators directly or post comments and questions on the project page. Meanwhile, creators may receive immediate feedback from the market in terms of qualitative comments on their project ideas and the realized demand based on which they can make refinements to their projects and accordingly post updates to keep their backers informed about project progress. The strategic interactions are assisted by the IT-enabled nature of crowdfunding. It is helpful for entrepreneurs to refine their ideas during fundraising duration, which in turn promotes better outcomes. Therefore, interaction among market participants allows for reflection and growth – i.e., entrepreneurs may continuously learn and adjust their actions in response to feedback from the market.

Fifth, crowdfunding provides entrepreneurs a platform on which to pre-sell their products, through which they conduct **fundraising in parallel with marketing**. Take reward-based crowdfunding as an example, project backers typically receive the product as a compensation for their financial contribution. Thus, entrepreneurs promote their product to the market while engaging in the fundraising process, which allows them to gauge market response.[4] Probing the customer base in advance reduces the length of time required to market and promote products and helps entrepreneurs identify and address potential concerns early on. That is, say, if the market acceptance of a certain product is low, entrepreneurs may avoid devoting extra time to developing a product they thought customers might want, but only to find out that it is incredibly not the case. In other

[4] For consumers, this mode of consumption is also called "pre-tail" – i.e., consumers shop for projects and services at concept stage. See: http://trendwatching.com/trends/pretail/

words, crowdfunding allows early assessment of market response. Conversely, in the traditional market, entrepreneurs are more likely to do financing prior to developing their products, let alone promoting their products. Entrepreneurs in traditional markets only typically begin production after obtaining sufficient funding. Ultimately, they may end up with an unsuccessful product even if they are supported financially by venture capital. In this regard, crowdfunding plays a great role in reducing the acceptance risk for new products.

Last but not least, **capital requirements are low** in a crowdfunding market. To be a creator, the only thing one needs to prepare when initiating a fundraising campaign is a prototype of product or even just a conceptual idea for a product rather than a full-fledged business plan. The relative low entry of crowdfunding acts as an enzyme that encourages entrepreneurship. To be a crowdfunder, any ordinary individual has the opportunity to support ideas that they like. The dual roles of participants on crowdfunding platforms encourage direct and indirect entrepreneurial learning which promotes fundraising and entrepreneurial success. On the other hand, the traditional fundraising approach requires extensive preparations. Securing venture capital funding is increasingly difficult for entrepreneurs,[5] since a venture capitalist usually expects a serious commitment from entrepreneur to pursue ideas that are highly experimental.[6]

In sum, these unique features of crowdfunding inform my exploration of entrepreneurial learning effects (i.e., my research focus) from several aspects. First, the information transparency and dual role of entrepreneurs in crowdfunding platforms facilitate me to observe entrepreneurs' activities more easily, as entrepreneurs' prior founding and backing experiences are publicly available on crowdfunding platforms for

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[5] See: http://www.forbes.com/sites/dorieclark/2012/11/24/want-venture-capital-funding-heres-how/

[6] See: http://blog.pmarca.com/2010/03/02/angels-vs-venture-capitalists-1/

open consumption. This enables me to observe the entrepreneurial development trajectory for each entrepreneur, where they are likely to harvest knowledge with their accumulation of prior experiences and the obtained knowledge can be manifested in crowdfunding performance. Besides, these two features enable me to observe experiences from multiple dimensions – i.e., founding and backing experiences, successful and failed experiences. Exploring the variations in learning effects from different experience dimensions offers me an opportunity to develop more nuanced insights into learning theory. Second, the fundraising process is a dynamic cycle, where entrepreneurs are able to get ongoing and timely feedback from the platform and to market their product in parallel. This feature allows me to investigate the performance feedback process, in which entrepreneurs are likely to strategically adjust their subsequent activities based upon the ongoing feedback they obtain. Delving into this fundraising process, my dissertation sheds light upon the dynamic interactions between entrepreneurs and crowdfunders as well as the developmental growth of entrepreneurs in this process. Third, the geographic dispersion and low capital requirements of crowdfunding participants lower the entry barriers of entrepreneurs. It probably implies an increase in the number of entrepreneurs in crowdfunding market, especially for those who can not be guaranteed sufficient financial resources from traditional fundraising approaches. This facilitates me to observe richer entrepreneurial practices – i.e., more entrepreneurial experiences – in my dissertation.

CHAPTER 3 EXISTING LITERATURE IN CROWDFUNDING

Pursuant to the rising popularity of crowdfunding, a growing body of research has started to examine this phenomenon. In this section, I present a comprehensive and systematic literature review of this domain. Laying on the foundation of the existing literature, I identify important research gaps and present a theoretical lens to address these gaps. At end of this section, I discuss how this dissertation seeks to contribute to the crowdfunding literature.

Crowdfunding serves as a two-sided market (Eisenmann et al. 2006; Zvilichovsky et al. 2013) since users can participate not only as entrepreneurs seeking funds but also as crowdfunders contributing funds.[7] *Crowdfunding* platforms support transactions and information flow between *entrepreneurs* and *crowdfunders* via *project* campaigns. I review the emerging literature from the following three perspectives: the crowdfunder's perspective and the entrepreneur's and the project's perspective. For each perspective, the prevalent research topics and theories used are discussed.

3.1 Crowdfunders as Focus of Research

3.1.1 Contributor Decision Making

A large volume of research from this perspective examines the effects of observable indicators in crowdfunding platforms on participants' contribution decisions. Several studies have investigated the influence of prior contributions on later contribution behaviors (Burtch 2011; Burtch et al. 2011; Burtch et al. 2013a; Burtch et al. 2014b; Ward and Ramachandran 2010; Zhang and Liu 2012). Other studies have addressed the impact of geographic and cultural differences on participation decisions (Agrawal et al.

[7] According to the data I collected, 51% of project creators also act as backers on *Kickstarter.com*. It is prevalent for creators to play dual roles in crowdfunding market.

2010; Agrawal et al. 2011; Agrawal et al. 2012; Agrawal et al. 2013; Burtch et al. 2014a; Kim and Hann 2015).

Even though the crowdfunding literature is quite nascent, there are generally two inconsistent results in terms of the **effect of prior contributions**: some studies show a positive effect while others show a negative effect. For example, drawing on data from *Prosper.com*, Zhang and Liu (2012) find evidence of rational herding among lenders, such that projects exhibiting higher funding levels tend to attract more subsequent funding even after borrower and project characteristics have been controlled. They also controlled payoff externalities to avoid overestimation of herding behavior. Further, they show that rational herding dominates irrational herding, as lenders' inferences from observing others' lending decisions are moderated by publicly observable attributes related to borrowers and projects. This moderation effect suggests that lenders are rationally observing others' behaviors to make their contribution decisions rather than blindly engaging in simple mimicry. Using archival data from a music crowdfunding website *Sellaband.com*, Ward and Ramachandran (2010) find empirical evidence for peer effects where actions of other investors are taken as input in investors' funding decisions. Investors' decisions tend to be influenced by the success and failure of relevant projects. That is, they are likely to invest more when the project has been successful at raising fund. Similarly, leveraging a novel dataset comprised of web traffic statistics related to t-shirt designs projects, Burtch (2011) finds that contributors have the tendency to herd, and this behavior is strengthened with the increase in the number of decision makers in the crowdfunding market. Furthermore, he finds a negative association between herding and optimality of investors' decision-making. This phenomenon is characterized by the author as "herding behavior as a negative network externality" (p. 1), referring to the result that herding is actually related to poorer investment decisions, since the higher the frequency of investment at the completion of funding (a proxy for herding), the lower the

subsequent product sales after the project enters production. Although different perspectives (e.g., herding, peer effects, eWoM) are adopted by different studies, the observed behaviors are quite similar – crowdfunders follow the behaviors of others. However, in contrast to these positive effects, extant studies also suggest that previous contributions could negatively impact subsequent contributions especially in the context of fundraising for public goods (e.g., crowdfunding for journalism) (Hong et al. 2015), since the marginal utility contributors obtain from a particular project decreases with others' contributions (Burtch et al. 2011; Burtch et al. 2013a). Because other contributors fulfill the need for the public good; potential funders have less incentives to contribute. This finding is consistent with existing economic models of substitution. It has been argued that people contribute to public goods for the purpose of deriving utility from their own consumption of the good and aiding others' consumption. As the level of others' contribution rises, the marginal benefit an individual derives from contribution falls, even if the volume of the available public good increases.

In addition to the influence of within-platform factors (e.g., prior contributions), a set of studies have investigated how some **off-campaign factors** affect backers' contribution intention. Project creators' social media activities is a dominant factor (Hong et al. 2015; Thies et al. 2014). For example, using data from *IndieGoGo.com* and social media platforms, Thies et al. (2014) find that social buzz has positive impact on subsequent campaign support while the impact of campaign support on consecutive social buzz is negative. Further, based on the same data sources, Hong et al. (2015) suggest that the impact of social media on contribution patterns is contingent on project characteristics. Specifically, the effect of bidirectional social network, like Facebook, is more salient for public goods, whereas the effects of unidirectional social media, like Twitter, is more influential for private goods. The underlying mechanism is that Facebook primarily supports connections, and therefore facilitates the manifestation of

social norms, while Twitter is mainly utilized for gathering objective information, and is thus a better approach for sourcing information about product or service quality.

Another stream of research deals with the effect of **geographical influence** on contributors' decisions. In contrast to the noted importance of spatial proximity in traditional entrepreneurial finance, Agrawal et al. (2011) uses data of artists from *Sellaband.com* to show that the investment patterns on the crowdfunding platform are independent of geographic distances between entrepreneurs and investors, when entrepreneurs' offline social networks have been controlled. The online fundraising approach reduces economic frictions arising from physical distance, such as monitoring progress, providing input, and gathering information. However, distance still plays a role in that distant and near contributors tend to exhibit different investing behaviors: distant investors are more responsive to information about cumulative funds raised by an artist (Agrawal et al. 2012) whereas more proximal investors have higher inclination to invest more and earlier during the funding cycle (Agrawal et al. 2010). That said, some special types of investors, "friends and relatives", tend to invest early regardless of whether they are proximal or distant (Agrawal et al. 2010). On the other hand, using a natural experiment on a self-constructed platform "mini Prosper", Lin and Viswanathan (2014) show evidence of "home bias" in online financial investments – the tendency that transactions between parties within the same country or state are more likely to occur. Such home bias may be attributed to emotional reasons, and it cannot be explained by social networks or other economic factors in online financial investment. Similarly, Burtch et al. (2014a) find that lenders do prefer culturally similar and geographically proximate borrowers, in the context of peer-to-peer lending. These two effects have a substitutive relation to one another, as the increase in physical distance is associated with a decline in the effect of cultural differences.

3.1.2 Privacy and Information Hiding

The second research theme on contributors' behavior in crowdfunding platforms centers on privacy concerns and information hiding activities/preferences. Some crowdfunding platforms permit campaign contributors to conceal their identity and contribution amounts from being publicly displayed. Drawing on data from a reward-based crowdfunding platform, Burtch et al. (2013b) explores the determinants of individuals' information hiding behaviors across contribution events. They find three conditions under which individuals are more likely to conceal their information: 1) individuals are sensitive to privacy concerns, 2) the extent of project exposure is high, and 3) individuals' contribution behaviors have the potential to be construed as "extreme" or "undesirable" by others. Moreover, in light of social comparison, the behaviors of contributors exhibit an anchoring effect – prior contribution amounts are employed as the benchmark for their own contributions. This effect is attenuated if prior contributors choose to hide their contribution amounts (Burtch et al. 2013c). Furthermore, although information hiding is a prevalent in crowdfunding, the mechanisms are different across various crowdfunding platforms. For example, contributors' backing amount are not publicly visible on *Kickstarter.com*, whereas on *Indiegogo.com*, users are entitled to set their privacy options. Using a randomized experiment, Burtch et al. (2015) study the causal relationship between information privacy control mechanisms and crowdfunders' willingness to transact. They find evidence of both positive and negative causal effects – i.e., introducing the information control mechanism after payment increases crowdfunders' likelihood of completing a transaction but decreases both large and small contributions.

3.1.3 Backer Heterogeneity and Dynamics of Backing Behaviors

The third research theme centers on the different types of crowdfunders and the dynamics of their backing behaviors over the project duration. Crowdfunders consist of highly heterogeneous groups with different project choices and subsequently differential impacts on project outcomes. Using public data from *Kickstarter.com*, Hahn and Lee (2013) discover five distinct archetypes of backers (i.e., portfolio master, category enthusiast, casual wanderer, focused supporter, one-time backer) based on two dimensions of crowdfunding behavior: backing frequency and category concentration. They find that projects with different compositions of crowdfunders differ in their fund raising success. An et al. (2014) investigate the backing behaviors of two different types of investors: occasional investors who have funded fewer than four projects, and frequent investors who have funded more than 30 projects. They find that frequent investors are likely to fund projects that are well-managed, have high fundraising goals, are global, grow quickly, and match their interests. By contrast, occasional investors use a different set of criteria for their choices, exhibiting donor-like behaviors mainly on art-related projects.

As for backer dynamics in crowdfunding, the literature has already investigated typical patterns of project support. For example, Kuppuswamy and Bayus (2013) find a U-shape pattern – i.e., backers are more likely to back in the beginning and end of the fundraising cycle. Combining the two aforementioned aspects, Lin et al. (2014) also recognize four types of crowdfunders (i.e., active backers, trend followers, the altruistic and the crowd), each with their distinctive motivations and strategies. These types further exhibit different backing dynamics during fundraising. Specifically, different types of backers differ in their tendency to invest early or late in projects' funding cycle.

In summary, research from the backer perspective study the decision-making, geographical influence, privacy concerns and different types of crowdfunders. Generally,

these studies deem that backers' contribution behaviors are affected by social influence, in that crowdfunders tend to behave with higher or lower contribution intentions than they really should, because they usually take some others factors (e.g., others' contribution amounts, existing number of backers) into consideration. Accordingly, some projects that are supposed to fail may ultimately achieve fundraising success; while some others, especially in the case of public goods, may unduly fail. So how projects achieve success is quite complex.

3.2 Entrepreneurs and Projects as Focus of Research[8]

3.2.1 Motivations of Participation

Compared to the crowdfunders' side, there has been less research from the entrepreneurs' and projects' perspective. One stream has concentrated on the choices and motivations of entrepreneurs to participate in crowdfunding platforms. Between pre-ordering and profit-sharing forms of crowdfunding, Belleflamme et al. (2014) show that entrepreneurs prefer pre-ordering when the initial capital requirement is relatively small compared to market size and prefer profit sharing otherwise. Through this the authors point out the importance of aligning project attributes to the type of crowdfunding platform. Similarly, Schwienbacher and Larralde (2010) conduct interviews in a company which successfully raised money using crowdfunding to find several characteristics of entrepreneurial ventures that choose crowdfunding rather than other approaches of financing. These crowdfunded ventures are characterized by low amount of capital requirements, having interesting projects and having an entrepreneur who is willing to extend his/her skill sets. Finally, Gerber et al. (2012) studied creators and funders on three popular crowdfunding

[8] Research from these two perspectives (i.e., entrepreneurs and projects) are combined in the literature review, as these studies are tightly related to the two aspects. For example, the motivation of entrepreneurs to participate in crowdfunding platforms usually also deals with their projects' attributes.

platforms to find that people are motivated to launch and fund projects on IT-enabled platforms because of extrinsic motivations, such as securing funding (creators) and consuming products and experiences (funders), as well as social interactions and connections to a community of people with similar interests.

3.2.2 Projects' Key Success Factors

Apart from entrepreneurs' motivations to participate in crowdfunding, another stream has primarily investigated the factors influencing fundraising success. The key success factors are twofold: project features and entrepreneur characteristics. **Project features**, such as reward design (Xiao et al. 2014), product descriptions (Mollick 2014), project updates (Xu et al. 2014), pricing strategy (Hu et al. 2015), media richness (Beier and Wagner 2015), usage of stretch goals (Li and Jarvenpaa 2015; Li and Jarvenpaa 2016), backer composition (Hahn and Lee 2013; Inbar and Barzilay 2014), fundraising patterns (Jung et al. 2014), innovativeness of project ideas (Chan and Parhankangas 2017) and prefunding initiative of a project (Garimella et al. 2017) are shown to impact campaign outcomes (e.g., fundraising success, successful on-time delivery). For example, using cross-sectional data extracted from *Kickstarter.com*, Mollick's empirical studies indicate that the success of crowdfunding projects is associated with project quality and social capital of entrepreneurs, suggesting that quality signals play an important role in determining project outcomes (Mollick 2013; Mollick 2014). Drawing on signaling theory, these studies show that qualitative information, such as project description, may signal project quality and/or the entrepreneur's level of preparedness, since due to information asymmetry, crowdfunders only have limited information about entrepreneurs. Jung et al. (2014) identify four types of fundraising patterns in technology crowdfunding projects, and they found that projects that create early funding momentum are associated with positive projects' performance. On the contrary, those that experience

later hype-funding are likely to have negative performance. The underlying mechanism is that early momentum funding patterns guarantee a financial resource sufficiency and create slack resource that can be used for later product development, whereas late hype-funding without early momentum may signal entrepreneurs' lack of preparedness for executing projects, and excess resources from hype-funding involve risk to create more rewards for their backers. Further, Li and Jarvenpaa investigate the impact of using stretch goals (i.e., dynamic goal setting) during the crowdfunding process, and suggest that the positive effect of stretch goals is attenuated when the novelty of this strategy is low (Li and Jarvenpaa 2015) and is strengthened when community feedback is high (Li and Jarvenpaa 2016). Recently, some crowdfunding platforms, such as JD crowdfunding, have introduced a prefunding feature, where entrepreneurs are able to raise awareness of their incoming projects before the funding stage. Garimella et al. (2017) examine the effect of prefunding on crowdfunding outcomes. They find that using prefunding can increase crowdfunding success, and prefunding projects have higher number of backers and greater contribution size on the first day of funding.

In addition, **entrepreneur characteristics**, such as entrepreneurs' prior backing (Zvilichovsky et al. 2013) and creating (Greenberg and Gerber 2014) behaviors, are found to influence crowdfunding success. For example, by tracking the founding and funding behaviors of entrepreneurs, Zvilichovsky et al. (2013) investigate project owners who play dual roles in the crowdfunding market and find evidence for direct and indirect reciprocity. In other words, crowdfunders are more inclined to back projects created by their backers (i.e., direct reciprocity) or by frequent backers on the platform (i.e., indirect reciprocity). In addition to backing experiences, entrepreneurs founding experiences influence eventual success as well. Greenberg and Gerber (2014) conduct a mixed method study with quantitative data from *Kickstarter.com* and qualitative interviews with online entrepreneurs to show that public failure acts as a stepping stone to eventual

entrepreneurial success – a small portion of entrepreneurs relaunched their unsuccessful projects, and almost half of these relaunched projects eventually became successful.

3.3 Broader Perspective – Crowdfunding as Focus of Research

In addition to previously discussed perspectives, there is a growing corpus of research that examines the crowdfunding phenomenon from a broader perspective, including the social impacts of crowdfunding platforms (Burtch and Chan 2014), quality of crowd-based decisions (Mollick and Nanda 2016), evaluation of policy change in crowdfunding platforms (Wessel et al. 2015), types of crowdfunding intermediaries (Haas et al. 2014) and the impact of crowdfunding on innovation (Stanko and Henard 2017).

This stream of research addresses some essential but neglected issues – i.e., the **effectiveness of crowdfunding**. Particularly, drawing on a survey of a panel of national experts and data from a crowdfunding site, Mollick and Nanda (2016) find that there is a high agreement between the funding decisions of crowds and experts. When a discrepancy exists, it is more likely to be the case where a project is supported by the crowds but not by experts. This research shows the important role of crowdfunding platforms in complementing experts' decisions. Stated differently, crowdfunding provides additional and viable alternatives for entrepreneurs to source needed financial capital for their startups. Furthermore, Burtch and Chan (2014) initiate the first step to examine the societal impact of crowdfunding. Using data from *Giveforward.com*, a medical-based crowdfunding platform, and public bankruptcy filings across the US, they show that crowdfunding plays an important role in reducing incidences of personal bankruptcy fillings. In addition, Stanko and Henard (2017) seek to understand the impact of crowdfunding on innovation by regarding crowdfunding as one form of open search. Based on data from a crowdfunding platform and survey data from innovating entrepreneurs, they find that amount of funding raised during a crowdfunding campaign

does not significantly impact the later market performance of the crowdfunded project, while the number of backers attached to the campaign does.

Moreover, in light of **features of crowdfunding platform** itself, Haas et al. (2014) identified three generic types of crowdfunding intermediaries, which are different regarding their value proposition. Wessel et al. (2015) investigate the impact of relinquishing the input control on participants' behaviors. Their findings suggest that this policy change increases the number of new campaigns launched in each day and boosts platform revenue.

3.4 Classification of Crowdfunding Literature

In summary, the nascent crowdfunding literature concentrates on several research streams: backers' decisions about contribution and information hiding, geographical influence on backers' decision-making, heterogeneity in backer community, crowdfunding projects' success factors, the motivations for entrepreneurs' participations as well as the effectiveness and objective of crowdfunding. Table 3-1 provides a systematic summary of the extant literature by different research themes, whereas Table 3-2 summarizes the broader crowdfunding literature by the different crowdfunding models (i.e., loan/lending-, equity-, donation/patronage-, and reward/preordering-based models) that were the focus and context of prior research.

Table 3-1. Primary Research Themes in Crowdfunding

Research Themes	Study	Research Focus	Theoretical Lens	Data Sources/ Platform	Dependent Variable(s)	Findings
Backers' contribution behaviors	Burtch (2011); Burtch et al. (2013a)	Investigate the effects of prior contributions on later participants' contribution decisions	Public good contribution models: substitution effect	Contribution events and web traffic data of online Journalism Pitches (approximate 100 story)	Contribution amount Page visiting duration	Altruism is the key incentive to contribute in journalism crowdfunded marketplace. The amount of individuals' contributions falls as they observe others contributing more frequently. Up-front marketing effort (e.g., projects duration) is crucial to success of crowdfunding projects.
	Burtch (2011)	Evaluate the influence of network scale on prevalence of herding behavior in crowdfunding marketplace	Herding behavior Negative network effects	Proprietary web traffic statistics and firm data including 319 T-shirt designs	Number of subsequent investors	Herding behavior does manifest in crowdfunding contexts. The tendency to herd is moderated by the number of users in the marketplace, such that an increase in the number of observable decision makers within a marketplace would drive an increase in herding.
	Zhang and Liu (2012)	Explore the behavioral mechanisms underlying herding among Prosper lenders	Herding effect	*Prosper.com* Internet microloan market	Herding momentum	Lenders on Prosper engage in rational herding after controlling unobserved heterogeneity and payoff externalities. Unfavorable listing attributes, such as credit risks, amplify the herding momentum, whereas favorable listing attributes, such as friend endorsements, weaken the herd.
	(Kuppuswamy and Bayus 2017)	Examine the effect of existing contributions on new contributions	Perceived impact Goal gradient effect	*Kickstarter.com*	Daily number of new backers	Support for a crowdfunding project will significantly increase as the project funding approaches its target goal. Crowdfunding contributions will significantly decrease after the target goal is reached. The positive effect of goal proximity on project support is accentuated if the project is nearing its funding deadline.

	Ward and Ramachandran (2010)	Estimate the extent to which demand for crowdfunding projects is driven by peer effects	Peer effects	*Sellaband.com* Unsigned music artists crowdfunding platform	Demand for project shares	Investors are influenced by the success or failure of related projects and use the actions of other investors as a source of information in their funding decisions.
	Burtch et al. (2014b)	Tease apart the effects of observational learning and word-of-month among customers' contribution behaviors peer-referrals at a leading crowdfunding platform	WOM & Peer referrals	42,000+ peer referrals at a leading crowdfunding platform	WOM conversion rate	WOM and observational learning have distinct, significant effects in customer acquisition in crowdfunding. The effect of WOM is larger than that of observational learning. The effects of both WOM and OL are increasing in the degree of prior effects, on the part of the referral transmitter.
	Liu et al. (2014)	Investigate the influence of specific perspectives that are emphasized in product videos on donations and the pre-order behavior of supporters on crowdfunding platforms.	Self-determination theory Transportation theory	Lab experiment	Contribution intention	Campaign videos that put more weight on creators and product development journey tend to attract higher donations, whereas those emphasizing customers' utility and benefits tend to have higher pre-order intentions. Backers that take project creators' perspective in the decision making are more resistant to the perceived project risks than those taking a customers' view. (research-in-progress)
	Gierczak et al. (2014)	Examine the effects of perceived risks with regard to the funding object in reward-based CF	Perceived risk theory Literature of perceived risk in e-commerce	Survey	Backer's funding on revocation behavior	Three types of perceived risks (i.e., those associated with funding object, the project initiator or the intermediary) are proposed as the potential influence for backers' funding on revocation behaviors. (research-in-progress)
Backers' contribution	Thies et al. (2014); Wessel	Explore the reciprocal relationship between	Existing literature in contribution	*IndieGoGo.com (daily)*	Number of backers (daily)	There is an inversed relationship between social buzz and project support; the impact of social

behaviors *(Off-campaign influencing factors)*	et al. (2017)	social buzz (eWOM), prior contribution behavior and consumer decision making. Investigate the interplay of social buzz and project backing in different project categories.	behaviors on crowdfunding Electronic Word-of-Mouth	*Twitter.com* *Facebook.com*	Number of social media shares (daily)	buzz on subsequent campaign support is positive while the impact of campaign support on consecutive social buzz is negative. The effects are more salient in bidirectional social network Facebook than unidirectional network Twitter.
	Hong et al. (2015)	Examine the interplay between social media activity and accumulated capital	Task-technology fit theory	Daily data from *Indiegogo* (223 campaigns) Twitter, Facebook	Funding amount per day	Different impacts of social media on contribution patterns for differing campaigns. Twitter is more influential for private good campaigns, whereas Facebook is more impactful for public good campaigns.
	Tan et al. (2016)	Examine social media users' motivations (i.e., reputation incentive, peer effects and popularity effects) for charitable giving	Existing literature in crowdfunding Philanthropy literature	Weibo Philanthropy (*gongyi.weibo.com*)	Whether a user donate to a project	Higher visibility of donors' contributions may have negative impact on fundraising. Peers effects are positive. While most users crowd to popular projects, a group of users who exhibit leadership features crowd out from popular projects.
Geographical influence on contributors' decisions	Agrawal et al. (2010); Agrawal et al. (2011); Agrawal et al. (2012)	Examine the geography of early stage entrepreneurial finance in internet marketplace for new musical artist-entrepreneurs	General theories of capital markets, entrepreneurial finance, or social networks	*Sellaband.com*	Investment propensity (any investment and total investment)	Crowdfunding relaxes geographical constrains of entrepreneurial finance. Still, local investors tend to invest more and earlier in the funding cycle. Local investors are less responsive to decisions of other investors. So that crowdfunding platform eliminates distance-related frictions, not social-related frictions.
	Lin and	Address whether	Research of "home	*Prosper.com* and "*mini Prosper*":	Lender's	"Home bias" appears to be consistent across

	Viswanathan (2014)	internet help overcome home bias in online financial investments and how investors' behaviors change with moving of borrowers	bias" phenomenon	a scaled-down version of the website *Prosper.com* Quasi-experiment	decision to bid on a borrower	three scenarios: 1) *Prosper.com* generic market conditions; 2) "*mini Prosper*" a regulated-induced period on the market with investors coming from one state; 3) a quasi-experiment design in which entrepreneurs move across state boundaries.
	Burtch et al. (2014a)	Examine the dual effects of geographical distances and cultural differences on the selection of transaction partner	Research of pro-social lending and cultural differences	*Kiva.org* peer-to-peer lending website	Lending actions	Pro-social lenders prefer to contribute their funds to locally and culturally similar others. Cultural difference and geographical distances are substitutable for lenders.
Contributors' privacy decisions	Burtch et al. (2013b)	Investigate factors driving users to employ information hiding mechanisms and their economic consequences	Research of online privacy and information hiding	An anonymous reward-based crowdfunding platform	Degree of information hiding Dollar amount supplied by contributor	Individuals are more likely to conceal information 1) when they are privacy sensitive, 2) when the campaign received greater public exposure, 3) when their behaviors have the potential to be viewed as 'extreme' or undesirable by others.
	Burtch et al. (2015)	Identify and quantify the causal relationship between a crowdfunding platform's information control features and contributors' willingness to transact	Literatures dealing with privacy and reputation	Randomized field experiment	Conversion rate Average conditional contribution	Information privacy control mechanisms have both positive (e.g., comfort) and negative (e.g., privacy priming) causal effects on crowdfunder's behavior. Specifically, placing information control mechanism after payment increases willingness to engage with the platform (i.e., higher probability of contribution) and simultaneously decreases the average contribution amount.
Heterogeneity	Hahn and Lee	Identify archetypes of	Existing literature	*Kickstarter.com*	Project success	Five distinct archetypes of crowdfunders are

and Dynamics of Backers	(2013)	crowdfunders and examine how composition of different types of crowdfunders affect fundraising outcomes	in crowdfunding		Percentage raised	identified based on two dimensions of backing frequency and category concentration. Projects with different compositions of crowdfunders differed in the success of their fund raising efforts.
	Lin et al. (2014)	Identify archetypes of crowdfunders and their differences in backing behavior	Signaling theory Social influence	*Kickstarter.com*	Odds of a project being chosen	Active Backers, Trend Followers, the Altruistic, and the Crowd four types of crowdfunders are identified, each with their specific strategies and motivations when decide which and when to fund projects.
	An et al. (2014)	Characterize pledging behavior of different micro-funders	Existing literature in crowdfunding	*Kickstarter.com* (Period: three months)	Probability of investor B funds project P	Investors behave quite differently depending on whether they are very active in the community or not. Frequent investors are attracted by ambitious projects, yet they carefully diversify their investment portfolios. By contrast, occasional investors act as donors, mainly in art-related projects.
Entrepreneurs' Participation	Belleflamme et al. (2014)	Investigate entrepreneurs' choice of two forms of crowdfunding: pre-ordering and profit-sharing	Existing literature in crowdfunding	Unified model	–	Entrepreneurs prefer pre-ordering form when the initial capital requirement is relatively small, but prefer the profit-sharing mechanism otherwise.
	Gerber et al. (2012) *(Qualitative Research)*	Discover how and why crowdfunding platforms work and the impact they can have on what projects are realized	Existing literature in crowdfunding, online social communities and motivations for giving	Semi-structured interview with 11 informants	–	People participate in crowdfunding for extrinsic motivations, such as securing funding (creators) and consuming products and experiences (funders). They are also motivated to participate because of social interactions realized through crowdfunding platforms, such

		and how they are disseminated in the world				as strengthening commitment to an idea through feedback (creators) and feelings of connectedness to a community with similar interests and ideals (funders).
Projects' Success Factors	Mollick (2014)	Explore underlying mechanisms of crowdfunded ventures	Signaling theory	*Kickstarter.com*	Fundraising success	Projects generally succeed by small margins, fail by large amounts. Social capital, preparedness and geography are associated with success probability of projects. Most entrepreneurs deliver products but not timely.
	Chan and Parhankangas (2017)	Study the effect of campaign innovativeness on crowdfunding outcomes	Radical and incremental innovativeness	*334 Kickstarter campaigns and survey on Amazon Turk*	Funding amount	Campaigns with greater radical innovativeness result in less favorable funding outcomes, and such negative effect may be mitigated by incremental innovativeness, which may help crowdfunders to understand and appreciate radical innovativeness more.
	Zvilichovsky et al. (2013)	Study the impact of entrepreneurs' out-of-project actions on the successful financing of projects	Reciprocity Social networks	*Kickstarter.com*	Fundraising success	Direct and indirect reciprocity do manifest in online crowdfunding platform. Entrepreneurs with backing experiences tend to have higher success rate, higher level of pledged amount and a larger number of backers.
	Greenberg and Gerber (2014)	Study what project creators learn and change through the process of failing	Existing literature in crowdfunding about reactions to public failure	*Kickstarter.com* *Interview with 11 entrepreneurs*	–	A low percentage of entrepreneurs relaunch their projects after failure. But relaunched projects succeed 43% of the time. Failing on crowdfunding platform such as Kickstarter can be seen as largely positive experience.
	Marom and Sade (2013)	Study how the project's representation is related to fundraising outcome	Existing literature in crowdfunding; Literature of "horse versus jokey dilemma"	*Kickstarter.com*	Fundraising success (Reached funding goal; percentage pledged; number of investors)	In Kickstarter fundraising, entrepreneurs' descriptions do matter – projects which highlighted their entrepreneurs enjoyed higher rates of success, controlling for other relevant variables.

Qiu (2013)	Analysis how creators use updates relate to the success of the campaigns.	Existing literature in crowdfunding (project representation, project updates)	*Kickstarter.com (8529 campaigns)*	Campaign success	Seven types of updates are identified: social promotion, progress report, new content, reminder, answer question, new reward, appreciation. There are statistical relations between the different types of updates and the outcomes of the campaigns. How project creators communicate with potential funders during a campaign is more predictive of success than the representation of project page.
Xu et al. (2014)	Identify several types of project updates and explore their relationships with campaign success	Existing literature in crowdfunding	*Kickstarter.com*	Campaign success	Several categories of project's updates are identified: social promotion, progress report, new content, reminder, answer question, new reward and appreciation. *New reward* updates were more likely to increase the chance of success of a campaign than *new content* updates. *Update representation* is more predictive of the campaign success than *project representation*. *Social promotion* update in the initial stage, *progress report* in the middle stage and *new reward* updates in the final stage have positive correlations with the probability of campaign success.
Xiao et al. (2014)	Examine the impacts of the reward scheme related and unrelated factors on projects' crowdfundng performance.	Existing research in crowdfunding Signaling theory Choice overload theory	*Kickstarter.com* (802 projects from April 2009 to July 2012)	Total amount of money each project raised	A project creator can raise more money in the crowdfunding market if he/she sets a bit higher maximum backing price; lists relative fewer reward tiers in their reward schemes; publishes well designed project homepage; and communicates with backers as much as possible during the project's survival time.
Inbar and Barzilay (2014)	Explore the magnitude and impact of the	Online (virtual) communities	*Kickstarter.com*	Fundraising success	Platform attachment acted as a two-edged sword. Users who funded multiple campaigns of

	crowdfunding community on campaign performance (GAP) Uncover the associations of users with different communities over time.	literature	(150, 000+ projects and 6.3 million users ranges over more than 5 years)		different categories supported more campaigns than category-centered community members did. However, their support misses the *community added value* associated with the support of members of the other community types. Backing by category-based community members had a positive impact on campaign success.
Jung et al. (2014)	Investigate the existing dynamics in fundraising process (i.e., funding patterns), and how the fundraising patterns are related to crowdfunding projects performance.	Entrepreneurship theory Bandwagon effects literature	*Kickstarter.com* (daily) *Linkedin.com*	Entrepreneurs delivered promised outcomes on time or not (binary)	There exist different fundraising patterns and different impacts on entrepreneurial performance. Projects that create early momentum are associated with positive projects' performance. However, projects which do not attract early funding but have late hype-funding negatively influence projects performance.
Li and Jarvenpaa (2015); Li and Jarvenpaa (2016)	Investigate the effect of stretch goals on project funding performance	Goal-setting theory	*Kickstarter.com* (18,940 campaigns)	Funding ratio	Stretch goals (i.e., dynamic goal setting) have a positive effect on project funding performance and this effect is negatively moderated by novelty of this strategy. The positive effect of dynamic goal setting is even stronger for projects with a higher level of community feedback. Furthermore, dynamic goal setting has a negative effect on project delivery performance, as it increases a project's likelihood of delivery delay.
Liu et al. (2015); Yang et al. (2015)	Examine the impacts of blockbuster projects on crowdfunding platforms	Network effects	*Kickstarter.com*	Funding performance in certain category (category-month)	There are positive network effects within category and negative effects across categories. The presence of blockbuster projects would boost the performance of related projects but hurt the performance of

				Number of backers in each back group Performance deviation	less-related projects. Within the same category, blockbuster projects also exhibit lasting spillover effects, while across the categories, they exhibit negative lasting effects.
Beier and Wagner (2015)	Examine the determinants of fundraising success.	Media richness theory Existing research in crowdfunding	A crowdfunding platform in Switzerland (740 campaigns)	Number of donations Average amount of donations Campaign success	Those projects with high media richness in project presentation are more likely to succeed. Simple application of social media channels is not helpful.
Garimella et al. (2017)	Examine the effect of prefunding on crowdfunding outcomes	Existing research in crowdfunding	JD Crowdfunding	Campaign success Pledged amount Number of backers	Prefunding prior to fundraising significantly increases the likelihood of campaign success. Prefunded projects have a higher number of backers and greater contribution size on the first day of funding compared to non-prefunding projects.
Zheng et al. (2017)	Examine the role of lottery in crowdfunding outcomes	Existing research in crowdfunding Lottery literature	*Zhongchou.com*	Number of backers Number of rewardees Number of doners Number of non-rewardees Amount of	The lottery in reward-based crowdfunding does attract more backers to a project. However, it has a negative effect on the total money a project raises and its probability of success. In addition, the effect of lottery is highly heterogeneous, in that the lottery has a larger incentivizing and cannibalizing effect on donors than on rewardees and on frequent backers versus infrequent backers. The positive incentivizing effect of the lottery on the number of backers turns negative when the lottery price is set at high levels.

					money Crowdfunding success	
Others	Burtch and Chan (2014)	Examine the social impacts/outcomes of medical crowdfunding	Existing research in medical bankruptcy & unmet healthcare costs	*Giveforward.com* (proprietary data) Publicly available data on quarterly bankruptcy filings across the US	The average number of individual bankruptcy filings (quarterly)	Crowdfunding reduces incidence of personal bankruptcy filings. There exists a substitution effect between medical crowdfunding and public health insurance.
	Mollick and Nanda (2016)	Examine how crowds differ from experts in judging which ideas to fund.	Literature in expert judgments and crowd-based judgements	*Kickstarter.com* (Theatre projects) 180 survey responses from expert judges	Different funding thresholds Different project characteristics	This is a significant agreement between the funding decisions of the crowd and experts. The disagree comes from the projects that are funded by the crowd but not by experts. These projects are not shown to be qualitatively and quantitatively different.
	Wessel et al. (2015)	Investigate the impact of relinquishing the input control on the participants' behavior changes. Examine the changes regarding success drivers of campaign from this policy.	Governance and control in platform ecosystems Existing research in crowdfunding	*Kickstarter.com* (67,384 campaigns)	Number of campaign backers	This policy change increases the number of new campaigns launched in each day and platform revenue also follows to increase. The success rate and project quality have decreased after abolishing input control.
	Haas et al. (2014)	Explore various archetypes of crowdfunding intermediaries	Two-sided markets Financial intermediation	127 crowdfunding intermediaries	NA (cluster analysis)	Three generic archetypes of crowdfunding intermediaries are identified, which are different in their value proposition: Hedonism, Altruism, and For Profit.

		theory			
Hu et al. (2015)	Examine crowdfunding product and pricing decisions	Marketing literature of product line design Public economics literature	Analytical modeling	Extent of success Backers' surplus	In crowdfunding, high-type buyers may still choose the high-price option, even though there is little variations in product options. The incentive of high-type buyers to coordinate with other buyers is influenced by creators' pricing decisions. Crowdfunding shifts the optimal product line design, such that it diminishes product line quality gap.
Belleflamme et al. (2014)	Examine crowdfunding's effect on innovation	Open search literature	*Kickstarter.com* Survey of crowdfunding entrepreneur	Product Market Performance Radical Innovation Focus	Amount of funding raised during a crowdfunding campaign does not significantly impact the later market performance of the crowdfunded project, while the number of backers attached to the campaign does.
Ingram et al. (2013) *(Qualitative Research)*	Explore the reason why crowdfunding is not yet adopted widely in Sweden ICT entrepreneurs	Technology affordance Institutional logics and institutional entrepreneurship	Primary sources: 20 semi-structured interviews of institutional actors Secondary sources	NA	Both design platform and existing institutional logics among entrepreneurs shape perceptions of affordance and thus the adoption of this new form of start-up financing.
Beaulieu and Sarker (2013) *(Qualitative Research)*	Analyze the discourse of crowdfunding project page and the meaning it creates over the course of crowdfunding campaign	Sociomateriality	*Kickstarter.com*	NA	Crowdfunding can be conceptualized as an IS artifact. The majority of the meaning created through the comment discourse involves the relationships and the identity building task.

Table 3-2. A Summary of Research Topics in Four Crowdfunding Models

Crowdfunding Models	Research Topics	Examples
Loan/lending-based model	- The effect of existing contributions on new contributions - Herding effect and network effects - Geographical influence on contributions' decisions - Geographical distances and cultural differences - Choice of market mechanisms	Burtch (2011); Burtch et al. (2013a); Lin and Viswanathan (2014); Burtch et al. (2014a); Wei and Lin (2016)
Equity-based model	- Geographical influence on contributions' decisions - Signals in equity investments	Agrawal et al. (2010); Agrawal et al. (2011); Agrawal et al. (2012); Bapna (2018)
Donation/patronage-based model	- Peer effects in funding decisions - Reputation incentive, peer effects and popularity effects - Social impacts of crowdfunding	Ward and Ramachandran (2010); Tan et al. (2016); Bapna (2018); Burtch and Chan (2014)
Reward/preordering-based model	- The effect of existing contributions on new contributions - Perceived goal gradient effect - Effects of perceived risks on revocation behavior - The effect of social media buzz on contribution - Design mechanisms in information hiding and economics consequences - Archetypes of crowdfunders and their differences in backing behavior - Projects' success factors (e.g., signaling, innovativeness, reciprocity, project's representation, project updates, stretch goal, reward design) - Effects of fundraising patterns on delivery performance - The effect of prefunding - The effect of lottery - Crowd judgement vs. expert judgement - Crowdfunding's effect on innovation	Kuppuswamy and Bayus (2017); Gierczak et al. (2014); Wessel et al. (2017); Lin et al. (2014); Chan and Parhankangas (2017); Zvilichovsky et al. (2013); Jung et al. (2014); Li and Jarvenpaa (2016); Liu et al. (2015); Yang et al. (2015); Mollick and Nanda (2016); Belleflamme et al. (2014)

3.5 Focus of this Dissertation

This dissertation seeks to contribute to the crowdfunding literature in the sub-stream with projects and entrepreneurs as the focus of research. Although past research from this sub-stream has examined the potential drivers of successful crowdfunding campaigns, much

of it has used a somewhat reductionist, factors-oriented approach. For example, many studies typically investigate the impacts of project features, such as the project reward and project updates, or entrepreneurs' behaviors, such as their backing experience and number of friends. In general, a factors-oriented approach may shed light upon the static aspects of entrepreneurial success, but cannot reflect the development of entrepreneurial process or explain how to make entrepreneurship work, which we deem are critical in offering deep insight about the phenomenon. Importantly, entrepreneurial capabilities can be *continuously* acquired along with the feedback from their prior success and failure (Cope 2005). This dissertation therefore can offer more meaningful insights by focusing on the development trajectories of entrepreneurs. In particular, I intend to investigate the crowdfunding phenomenon by focusing on across- campaigns and within-campaign dynamics.

My first essay uncovers crowdfunding dynamics by investigating the developmental process of entrepreneurs *across-campaigns*. The core argument of this essay is that entrepreneurs develop necessary knowledge and skills *over time* to become successful. It focuses on serial entrepreneurs in crowdfunding to explore whether and how entrepreneurs' prior experiences facilitate subsequent entrepreneurial endeavors. More specifically, I posit that serial entrepreneurs accumulate experience-based knowledge which can be an important resource for subsequent performance improvements. This process appears to naturally fit the basic theoretical mechanisms of organizational learning which views organizations as extracting inferences from prior experience and in turn utilize these inferences to guide present and future behaviors (Argote 2013b; Argote and Miron-Spektor 2011; Levinthal and March 1993; Levitt and March 1988). Hence, organizational learning is adopted as the theoretical lens to conceptualize this process.

The second essay intends to discover the *within-campaign* dynamics in crowdfunding by examining the entrepreneurs' learning and adaptation that occurs during fundraising process. Since the first essay identifies the important role of prior experience in determining current performance, what is still lacking is an understanding of what entrepreneurs do *during* the entrepreneurial process, which is essentially the primary source of learning. Furthermore, the entire fundraising cycle is a continuous interaction process among funders, project concurrent performance as well as entrepreneurs and their actions. In fact, how entrepreneurs manage the campaign process is an essential element. My second essay therefore investigates how concurrent funding performance influences entrepreneurs' adaptation behaviors and how these strategy alterations in turn impact ultimate entrepreneurial performance. The performance feedback model from organizational learning serves as the theoretical foundation to conceptualize this feedback cycle.

In sum, this dissertation consists of two studies that inform the IS literature on crowdfunding by uncovering the across- and within- campaign dynamics. Organizational learning and performance feedback theory serve as the theoretical foundation for the conceptualizations. The next section presents a review of the theoretical background.

CHAPTER 4 THEORETICAL BACKGROUND

As aforementioned, the focus of this dissertation is to uncover the *across*- and *within*-campaign dynamics in crowdfunding. The organizational learning theory is adopted to conceptualize the developmental process of entrepreneurs with their accumulation of prior experience (i.e., across-campaign). The performance feedback theory is used to conceptualize dynamic interaction cycle between concurrent performance and entrepreneurial strategies (i.e., within-campaign). In this chapter, I present a theoretical background for my dissertation by reviewing the basic mechanisms and major components of the two theories.

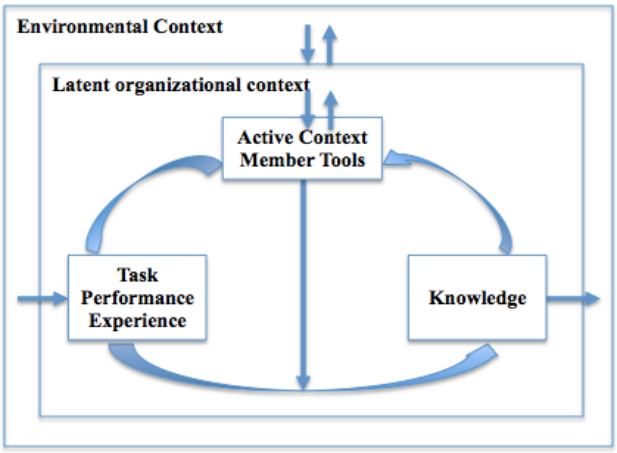
4.1 Organizational Learning Theory

Organizational learning has been central to organizational theory, as the capability to learn and adapt is essential to the long-term success of organizations (Argote and Miron-Spektor 2011). This section presents the key elements in this theory and the three sub-process of learning.

4.1.1 Elements of the Learning Process

Organizational learning refers to the change of organizational knowledge along with experience. Learning occurs over time in a feedback cycle where past experience interact with the organizational and environmental context to reinforce existing knowledge and create new knowledge, which in turn guides subsequent actions (Argote and Miron-Spektor 2011; Fiol and Lyles 1985). The review paper by Argote and Miron-Spektor (2011) presents a framework for understanding organizational learning (see Figure 4-1). This figure depicts the process through which task performance experience can be converted into knowledge, which in turn guides subsequent behaviors.

Figure 4-1. Organizational Learning Framework from Argote and Miro-Spektor (2011)



As displayed in the organizational learning model (see Figure 4-1), there are three major components in the ongoing learning cycle: experience, context and knowledge. **Experience** is the beginning of the organizational learning process and it represents inferences transpired from history. Organizations accumulate experience as they perform tasks (Argote 2013a). Typically, experience is measured by the number of tasks performances, which can be incomplete, complete but unsuccessful, or complete and successful (Argote and Miron-Spektor 2011). For example, in software development teams, experience can be measured by cumulative number of projects completed (Boh et al. 2007). In the entrepreneurship context, experience can be measured as the number of founding initiatives. Going beyond the number of experience, there is an emerging stream that analyze organizational experience at fine-grained levels from several dimensions. Argote and Todorova (2007) are the first to characterize experience within organization in terms of several dimensions: organizational, content, spatial and temporal ones. The basic dimension of experience is whether the experience is acquired directly through focal organizational task performance or indirectly from observation of others' task performance (Argote 2013b). The process of indirect learning has been termed as

vicarious learning (Bandura and McClelland 1977) or knowledge transfer (Argote et al. 2000). In terms of experience content, an important characterization of experience includes successful vs. unsuccessful experiences (Kim et al. 2009). Some tasks entail heterogeneous experience, while others entail homogeneous experience. The spatial dimension concerns the degree of geographical distance for history experience – e.g., experiences could be geographically concentrated or geographically dispersed (Cummings 2004). Lastly, the temporal dimension deals with frequency and timing of experience. For example, a prior experience could have happened a long time ago or very recently. In line with prior studies, my research also studies the learning effects at fine-grained levels, in terms of the experience obtained from several dimensions. Specifically, I investigate the impact of experience from the dimensions of direct/indirect, successful/unsuccessful and degree of relatedness, richness and diversity of experiences. The fine-grained analysis of experience enables us to uncover possible differential impacts on entrepreneurial activities and outcomes, as well as to explore possible interactions among different types of experience dimensions (e.g., direct/indirect experience interacting with successful/unsuccessful experience). Furthermore, according to organizational learning research, most of research are still concentrating on the number of experience, such as the number of new products introduced (Katila and Ahuja 2002) or the number of aircraft accidents (Haunschild and Sullivan 2002) when examining learning effects. I deem it is not enough to understand its impact only through the number of trials, since it fails to consider the richness aspect of experience. It is highly possible that people would distill more lessons from experience where they have active and high levels of engagement compared to where their involvement was passive with low levels of engagement. Thus, in the current dissertation, I incorporate the effect of depth dimension of experience (i.e., richness of experience) on learning effects as well.

Pursuant to the unique feature of IT-enabled entrepreneurship, the information transparency aspect of crowdfunding platforms empowers and facilitates this exploration.

Context is the second essential component of the organizational learning process because experience interacts with context to create knowledge. Context is defined as the "contingency that affects learning processes and moderates the relationship between experience and outcomes" (Argote and Miron-Spektor 2011, p. 1127). A number of studies highlight the importance of the context. The core argument is that cognition can only be understood given a specific context, which is referred to as "situated cognition" (Brown and Duguid 1991). Therefore, context influences the process through which experience is converted into knowledge. Different organizational contexts may lead to differential learning outcomes. For instance, Ingram and Baum (1997) find that generalists are less influenced by learning effects from one's own experience compared to specialists. A culture of psychological safety (Edmondson 1999) or where members trust each other (Levin and Cross 2004) has been found to facilitate learning. As indicated in Figure 4-1, organizational context is composed of latent and active components, both of which influence the learning process through its effects on organizations' active members, tools, and tasks (Argote 2013a). More specifically, the organizational context determines the tasks and the tools available affecting focal organization's accomplishment. The context also affects members' motivations, emotions as well as activities. In entrepreneurial learning, the context can refer to economic and social context, etc. Entrepreneurial growth is a learning process that is an important element of macro social development. The development process is influenced by situational factors, such as gender, geographical location and social context. Furthermore, the context can also be conceptualized as different market timing (Gompers et al. 2010) and various industrial environments (e.g., competition).

Third component, **knowledge,** is the outcome of the learning process, which resides in multiple knowledge reservoirs (or stocks) within organizations: in individuals, in the organization's culture and structure, etc. (Levitt and March 1988). The knowledge reservoir serves as a basis for later task performance; since activities are conducted with reference to knowledge in the knowledge reservoir (Argote and Miron-Spektor 2011). Knowledge is contextualized to address the specific situation at hand. Having a preeminent knowledge reservoir is the principal source of advantage and increased performance (Argote and Ingram 2000). In organizational learning research, knowledge is conceptualized at the individual level, which refers to the members, tools or tasks where organization knowledge is embedded, and at the organizational level, which represents organization memory (members, routines and transactive memory systems). When applied to entrepreneurship, our study adopts the view that knowledge is at the individual level to represent entrepreneurs' autonomy of knowledge gained from experience and to understand how entrepreneurs' performance is influenced by individual level knowledge reservoir. The reservoir is the outcome of the learning process. The knowledge in the reservoir can manifest itself in the entrepreneurs' thinking and initiatives.

In summary, I adopt the three-component model of organizational learning – experience, context and knowledge – to conceptualize entrepreneurs' learning process in online crowdfunding. Specifically, on crowdfunding platforms, entrepreneurs acquire experience by directly initiating or indirectly backing projects. Meanwhile, they interact with and receive timely feedback from the online platform (context)[9]. For example, when

[9] In crowdfunding, context here may also refer to the diverse market conditions in different categories. Specifically, the combinations of different types of entrepreneurs and success rates in various categories may be different. These contextual factors may moderate the learning effects. I do not give detailed conceptualization of "context" here because this element – context in organizational learning, is not my main research focus. My primary focus of this dissertation is on "experience" and "knowledge". The experience represents entrepreneurs' prior entrepreneurship-

an entrepreneur creates a project, (potential) crowdfunders may leave messages on the project page, from which the entrepreneur may receive market response about her current project. Gradually, these experiences and context feedback would be instilled into knowledge, which in turn guides entrepreneurs' subsequent activities.

4.1.2 Learning Sub-processes

The overall organizational learning process can be decomposed into three sub-processes: knowledge creation, retention and transfer (Argote and Miron-Spektor 2011). In the beginning, organizations create knowledge from experience. Then the knowledge will be stored in the active components of organizations: members, tools and tasks, and this is how knowledge is retained within the organization. Meanwhile or afterwards, knowledge may flow from one component to another. This knowledge transfer process happens within and outside organizations. When organizations conduct ensuing activities, elements within the context interrelate with existing experience to create new knowledge. The three learning sub-processes are inter-related. For example, when organizations absorb experience from other units, meanwhile, they utilize knowledge obtained from this process to guide new activities. Here knowledge transfer is also one part of knowledge creation process.

Knowledge creation refers to the process through which a unit or an organization generates new knowledge from its own experience. As a result, the nature of the experiences in terms of consistency vs. diversity should have an influence on the efficacy with which new knowledge is created. With regard to the influence of experience diversity in knowledge creation, there are seemingly inconsistent findings in the extant literature. Some studies find that larger and more diverse experiences increase the

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related experience, such as founding and funding experience. The knowledge will manifest itself in entrepreneurial outcomes: the successful and failure fundraising.

potential paths that organizations or entrepreneurs can act on, laying the foundation for more creative activities. For example, Shane (2000) discovers that differences in prior information promote entrepreneurs to discover new opportunities and to exploit new technologies. In contrast, other studies posit that prior experiences induces organizations to develop heuristics that continually adopt similar strategies, and therefore, impede creative behaviors. For example, analyzing patenting in the hard disk industry, Audia and Goncalo (2007) find successful individuals tend to generate increasingly incremental ideas, because they favor exploiting familiar knowledge at the expense of exploring new knowledge. However, they also find that this tendency may be attenuated by collaboration with other investors or organizational norms. The possible explanation underlying these apparently contradictory findings is that perhaps experience itself is heterogeneous. This dissertation attempts to reconcile these inconsistencies by distinguishing the effects among different types of experience, and aims to explore when, how, and to what extent previous experience influence the knowledge creation process.

Research in **knowledge retention** primarily focuses on the stock of knowledge in organization memory (Majchrzak et al. 2004; Moorman and Miner 1997) and knowledge depreciation in organizations (Besanko et al. 2010; Holan and Phillips 2004). Specifically, extant research has investigated whether knowledge – the outcome of organizational learning – depreciates or perseveres over time. Generally, a bulk of research discovers the evidence for knowledge decay, but this happens to different extents (Argote and Miron-Spektor 2011).

The third sub-process of organizational learning is **knowledge transfer**. This transferring occurs when organizations learn indirectly from the experience of others (Argote and Ingram 2000). This process is also called vicarious learning (Bandura and McClelland 1977). Knowledge transfer occurs among different units within an organization and also across organizations. It has been posited that organizations need to

facilitate internal transferring and meanwhile prevent leakage or spillover to outside organizations and managing this tension has become an important focus of inquiry (Argote and Ingram 2000; Kogut and Zander 1992). Furthermore, prior research sought to identify the factors that facilitate or inhibit knowledge transfer. These factors primarily arise from three aspects: characteristics of the knowledge, characteristics of parties involved in the transfer, and characteristics of the relationships among the units (Argote and Miron-Spektor 2011). As an example, Szulanski (1996) shows that the major barriers of internal knowledge transfer are the recipient's lack of absorptive capacity, causal ambiguity of the knowledge and an arduous relationship between the source and the recipient of the knowledge transfer.

Fundamentally, the learning itself represents skill acquisition. Through the three learning sub-processes, there are several learning stages that could be achieved: novice, advanced beginner, competent and eventually expert (Dreyfus and Dreyfus 1986). The learning begins at the novice stage, in which leaners are beginning to apply rules by determining actions on the basis of features in each of the rules. But they have not benefited from experience. After the novice gains experience, they learn to practice and recognize the rules in coping with real situations, whereby they are transferred to the advanced beginner stage. At the competence stage, learners start to choose analytical rule-guided actions. They consciously assess the rules that are salient with respect to the situation. They may adopt or discard rules depending on the situations. Lastly, at expert stage, learners are proficient performers. Their sufficient experience with a variety of situations allows an immediate intuitive response to each situation. Dreyfus and Dreyfus (1986) argue that at different learning stages, learners exhibit differing common patterns.

4.2 Performance Feedback Theory

Building on the assumption of bounded rationality, organizational theory traditionally posits that decision makers make an attempt to maximize the positive outcomes for organizations but meanwhile are constrained by their cognitive limits (DiMaggio and Powell 1983; Jordan and Audia 2012; Ocasio 1997). In line with this reasoning, a primary mechanism for decision makers to deal with their cognitive limitation is learning from performance feedback (Audia et al. 2000; Greve 1998; Jordan and Audia 2012). Two essential aspects of this theory are aspiration levels and decision makers' behaviors in response to them (Greve 2003c), which constitute the two parts of this section.

4.2.1 Origins of Aspiration Levels

Performance feedback theory, originating out of behavioral theory of the firm (Cyert and March 1963), holds that decision makers set target levels of performance that they intend to achieve, which is termed as aspiration level, and in turn evaluate their current performance relative to this aspiration level (Greve 2003c). If performance falls below the aspiration level, decision markers strive to identify barriers to performances and work to improve it, whereas if performance is above aspirations, decision makers are less inclined to take corrective actions with the aim of increasing performance (Jordan and Audia 2012). The aspiration level is an essential component of this theory, as it naturally categories performance levels to success or failure which provide simplifying heuristics to boundedly rational decision makers. The origins of aspiration levels come from three aspects: learning from the performance of oneself, learning from the performance of others, and direct learning of the aspirations of others (Greve 2003c).

A particularly thorny issue in the theory of performance feedback is the determination of aspiration levels (Argote and Greve 2007). When decision makers are informed of what aspiration level is suitable and why certain aspiration levels are

favorable than others, it is common for them to naturally choose this given aspiration level as their own, leading to **natural aspiration levels**. The formation of natural aspiration level requires less information (than historical and social aspiration levels that are introduced later) and is thus cognitively easier to process. But it is only present when there are strong clues in the environment showing what aspiration level is preferable than others. In such situation, the natural aspiration level is temporally stable, such that different decision makers choose the same aspiration level (Greve 2003c). Despite its simplicity, natural aspiration levels are most likely rare in organizations considering possible variations in performance targets across organizations.

In most cases, decision makers need to form their own aspiration levels from existing information. An important source of information is the historical experience of organization itself, resulting in **historical aspiration levels**. The rationale of historical aspiration level is that past performance acts as an indicator of how well the organization can perform and in turn it can become a benchmark for how well organization should perform in the future (Greve 2003c). Simply put, a historical aspiration level is generated by taking into account the organization's past performance. Organizations' aspiration levels are typically measured in terms of the metrics that are salient to organizational decision makers (Baum and Dahlin 2007). For example, in the radio broadcasting industry, Greve (1998) uses the radio station's prior audience shares to measure the historical aspiration levels. In the shipbuilding industry, Greve (2003b) specifies the historical aspiration as shipbuilders' previous year's return on assets (ROA).

In general, a historical aspiration level would be most useful in the absence of available, reliable and relevant external information sources, so it is prevalently used in organizations whose business is unique so that it is not easy to draw a comparison across organizations. Because it is dependent on the organizations' own past performances, historical aspirations are also greatly useful in forecasting organizations' subsequent

performance (Greve 2003c). The reason behind this is that it incorporates some relatively stable information of the firm, such as resource base and knowledge (Barney 1991). Nevertheless, it is worth mentioning that accurate forecasting is not necessarily a good criteria for an aspiration level (Greve 2003c).

Alternatively, decision makers could use information of other organizations that are comparable to their own organization to set the desired level of performance, resulting in a **social aspiration level**. In order to form a social aspiration level, a decision maker need to select a suitable reference group and observe its performance (Greve 2003c). In empirical studies, the social aspiration level is usually operationalized as the average performance metrics of other firms in the same industry. For example, Greve (1998) uses the average market share of all radio stations in the market to capture the social aspiration level. In the railroad industry, Baum and Dahlin (2007) define it as the average number of accidents of other railroads. Generally, social aspiration level is more valuable for organizations in turbulent environments, in that in rapidly changing environments, the historical performance of organizations is less diagnostic for evaluating its performance than the concurrent performance of comparable organizations. However, social aspiration has the demerit that it cannot take into account organizational heterogeneity in capabilities or niches (Greve 2003c), or how organizations form their reference group.

In addition to historical and social aspiration levels, organizations can directly learn from others about their aspirations (Lewin et al. 1944). In this case, instead of using others' performance to make desired level of performance for themselves, decision makers obtain direct information about others' aspirations to set their own. This is called direct learning of the aspirations of others.

The existence of multiple sources of aspiration levels makes it hard for their estimations, there are several ways to address this issue. First, it is suggested in

organizational formulation of aspiration levels that historical and social aspirations can be combined to one aspiration level where different aspirations are given certain weights (Cyert and March 1963). A second approach posits that behaviors are jointly and simultaneously affected by multiple aspiration levels. In this case, the performance relative to each aspiration level would be entered as an independent factor in determining decision makers' behaviors. A third approach argues that the focus of attention of decision makers would be shifted among different aspiration levels depending on the concurrent performance (March and Shapira 1992).

Overall, different aspiration levels involve their own specific adaptation rules of target performance. Some studies tend to combine all existing aspirations into one in their empirical models, while others may use separate aspiration levels to allow for separate estimations of their respective effects. The accurate estimation of aspiration levels is a difficult and inconclusive issue in the literature. In this dissertation, when applying performance feedback theory to the crowdfunding context, I argue that the fundraising period occurs as a feedback cycle, entrepreneurs use the aspiration level to evaluate their concurrent funding performance and in turn to inform their subsequent practices. Here the aspiration level is unambiguous because entrepreneurs launch their project hoping to achieve their pre-determined funding goal. The funding goal is typically constructed by considering entrepreneurs' prior experience as well as the performance of other projects. It has been deemed as the borderline between success and failure (Greve 2003c). Therefore, it can be conceptualized as a natural aspiration level for entrepreneurs.

4.2.2 Behavioral Consequences of Aspiration Levels

Based on a variety of related research, Greve (2003c) identifies three predictions in terms of the effects of performance relative to the aspiration level (Jordan and Audia 2012): search, risk taking and organizational change.

Search

Search plays a central role in the behavioral theory of the firm (Cyert and March 1963). Relative performances with respect to aspiration levels can induce search behavior. Search generates alternatives to current set of practices, therefore provides potential for organizational change. Basically, there are multiple processes driving search behavior: slack search, institutional search and problemistic search (Greve 2003c). **Slack search** stems from extra resources and time that allow decision makers to experiment (Jordan and Audia 2012). However, it is usually not deliberately managed. Conversely, **institutionalized search** results from search activities initiated by organization units, such as Research and Development and Strategic Planning. This kind of search is typically planned in terms of organizational structure and resource allocation. **Problemistic search** is done as a response to subpar organizational performance. It is governed by performance relative to aspirations and therefore it is the most relevant type of search in the performance feedback theory. When performance falls short of the aspiration level, decision makers conduct problemistic search and enact changes if decent solutions can be found (Cyert and March 1963). Problemistic search is regarded as goal-oriented behavior because of its primary aim to remedy performance shortfalls. In addition, problemistic search is myopic (Argote and Greve 2007; Levinthal and March 1993), in that it is initially conducted around the current activities or near the problem symptom, even though it may expand over time.

Risk Taking

Organizations conduct slack search, institutionalized search and problemistic search, all three forms of which are likely to generate organizational change, and problemistic search is particularly likely to do so (Greve 2003c). When evaluating proposals to change the organizations, decision makers tend to weight the costs and benefits of enacting

changes, wherein risk is the central consideration. Thus, performance relative to the aspiration level may also influence decision makers' risk taking behaviors (Lehman and Hahn 2013; Lehman et al. 2011), such that decision makers' propensity to choose solutions that entail greater risk is higher when the organization is under-performing and is lower when it is out-performing (Jordan and Audia 2012). Stated differently, risky alternatives are more likely to be enacted when decision makers are in the loss domain. It is therefore reasonable to expect that managers regard major organizational changes as more acceptable when performance is below the aspiration level.

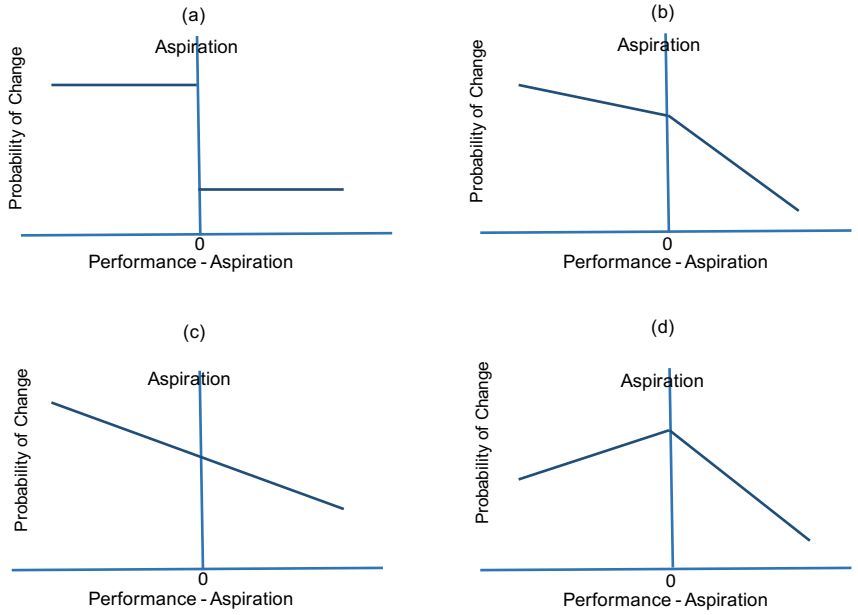
Organization Change

The combined effects of performance feedback on both organizational search and managerial risk-taking propensity yields the effect on conducting organizational change. The organizational decision-making process can be conceptualized as a flow of solutions arising from search, within which problemistic search is more responsive to performance feedback, whereas slack search and institutionalized search are less likely to be. The three search behaviors my generate solutions that induce organizational change –actions that entail risk (Greve 1998). For solutions that involve risk, whether they would be implemented is determined by whether the solutions can be attached to organization problems and whether their organizational and financial risks are tolerable for decision makers (Greve 2003c). In general, changes are more likely to occur when the performance is below the aspiration level. It is probably because in such condition, problemistic search is more salient as more problems are existing and waiting to be resolved. Furthermore, the managers tend to be risk averse and undertake less risky behaviors (i.e., less organizational change) when they are outperforming (Baum et al. 2005; Greve 2003c). Nevertheless, organizational change still exists because slack and

institutionalized search may also produce solutions that involve risk, even though such risk tends to be more acceptable from decision makers' point of view.

Several different functional forms of the proposed relationship between performance relative to aspiration level and the probability of organizational change are shown in Figure 4-2. In Figure 4-2a, decision makers simply classify performance to failure or success, and the probability of changing is higher in the failure category (March and Simon 1958). Figure 4-2b-d show continuous adjustments of organizational change. Specifically, in Figure 4-2b, the probability of change is declining as performance increases on both sides of the aspiration level (Cyert and March 1963), but the decline in the probability of change is greater above the aspiration level. The lower sensitivity when performance is relatively lower than aspiration is due to organizational inertia in the face of failure (Audia and Greve 2006; Hannan and Freeman 1977; Milliken and Lant 1990; Staw et al. 1981). Inertial factors slow down decision makers' rate of choosing organizationally risky actions.

Figure 4-2. Proposed Functional Forms for Relationships between Relative Performance and Organizational Change from Greve (1998)



In Figure 4-2c, these inertial factors vanish, resulting in a constant decrease in the probability of adopting organization change, and the aspiration level has no effect here. Finally, Figure 4-2d shows that changes are more likely to occur when the performance is near the aspiration level, while this propensity decreases as performance moves away from it. This relationship happens when low performance is interpreted as a threat to organization, under which managers may fall prey to learned helplessness (Abramson et al. 1980), responding with greater rigidity as they are unable to generate feasible alternatives (Lehman et al. 2011; Staw et al. 1981). In such conditions, threat rigidity reduces decision makers' likelihood of conducting organizational change (Staw and Ross 1987; Staw et al. 1981). It is worth noting that the threat rigidity differs from performance feedback, in that managers' focus of attention has been shifted from aspiration level to the fear of failure performance (March and Shapira 1992). Generally, problemistic search (as a result of performance feedback) occurs more frequently for performance just below the aspiration level, while threat rigidity typically happens for very low level of performance (Lant and Hurley 1999). In sum, relative performance with respect to aspiration levels exert influence on decision makers' search, risk taking behaviors, their propensity to adopt organizational change as well as illegitimate behaviors.[10] Some other specific actions that are investigated in this stream of literature include interfirm collaborations (Baum et al. 2005), research and development (Bolton

[10] Traditional behavioral theory of the firm implicitly assumes that relative performance only produces ethical, legitimate organizational actions. Recently, some studies have emerged to challenge this assumption by investigating how organizational performance relative to aspiration levels influence outcomes that are undesirable and unanticipated, such as financial misrepresentation (Harris and Bromiley 2007) and illegal staff violation action (Desai 2013). They posit that decision makers' illegitimate behavior constitutes risk. Firms whose performance is close to their aspirations may hope to achieve their standard via legitimate approaches, whereas firms perform far below may end up with no legitimate solutions. In such conditions, their probability of misconduct increases.

1993; Fleming and Bromiley 2002), capital investment (Greve 2003b), innovation (Greve 2003a; Levinthal and March 1981) and illegitimate actions (Desai 2013) to name a few.

4.3 How the Reviewed Literature Relates to this Dissertation

In this dissertation, building upon the organizational learning theory, the first essay proposes that entrepreneurs learn directly from their own founding experiences and indirectly from participating in other entrepreneurs' initiatives. Therefore, the learning occurs through a dual-process of knowledge creation and knowledge transfer, each process driven by specific types of experience. Based on the arguments of knowledge retention, the influences of different experiences may also vary along with time, as some experience may be more likely to suffer from depreciation. Such knowledge depreciation (or forgetting) can be moderated by the industrial environment under specific contexts. Therefore, taking into account the special characteristics of the IT-enabled entrepreneurship context (i.e., information transparency), the first essay aims to explore the dynamics of learning through the entrepreneurial process at a fine-grained level from several experience dimensions (i.e., direct vs. indirect, successful vs. unsuccessful as well as varying degrees of experience relatedness and richness), and the three sub-processes (i.e., creation, retention and transfer) and three components of organizational learning (i.e., experience, context and knowledge) guide our exploration of the process. I also propose that different aspects of learning may result in differing learning stages. Hence, the learning outcome varies across various types of experience.

The second essay draws upon the performance feedback theory. The core argument of this essay is that entrepreneurs take strategic actions with reference to the performance feedback they obtain during crowdfunding process, and the primary aim of taking actions is to attract more prospective backers and in turn to increase fundraising success. We use the performance feedback model as theoretical foundation to

conceptualize this fundraising feedback cycle. In the beginning, entrepreneurs set a fundraising goal, which we conceptualize as a natural aspiration level, that is deemed obtainable by the project deadline. During the fundraising process, entrepreneurs use the funding goal to evaluate their current funding performance and their subsequent actions are influenced by this evaluation. Specifically, this influence is related to whether the performance is a) above or below aspiration level and b) distant from or near aspiration level (Baum and Dahlin 2007; March and Shapira 1992). We propose the effects on two types of actions: *explorative* actions, characterized by discovering new approaches and changing status quo to achieve their goals, and *exploitative* actions, characterized by extension and refinement of existing competency. Further, following calls from the organization theory literature (Ancona et al. 2001; Gavetti and Levinthal 2000; Mitchell and James 2001; Zaheer et al. 1999), I examine the moderating role of time in the relationship between relative performance and entrepreneurs' strategic actions.

Taken together, organizational learning theory and performance feedback theory, both of which originate from behavioral theory of the firm (Cyert and March 1963), lay the theoretical foundation for my dissertation. Specifically, they guide my conceptualization of the entrepreneurial learning processes from macro and micro perspectives, and in turn allow me to uncover *across*- and *within-campaign dynamics* in crowdfunding. Furthermore, the unique features of crowdfunding context facilitate me to respond calls from the organization theory, which pave the way for providing nuanced insights to the theory. The following two chapters discuss the two essays in this dissertation.

CHAPTER 5 ESSAY I – THE PATH OF SUCCESSFUL ENTREPRENEURS: A FINE-GRAINED UNDERSTANDING OF PRIOR EXPERIENCE IN ENTREPRENEURIAL LEARNING

5.1 Introduction

Entrepreneurship plays a prominent role in driving the economy. Entrepreneurial innovators bring new ideas to fruition by establishing new independent businesses (Kirchhoff 1994; Mollick and Nanda 2016). Their innovation creates solutions to meet new requirements and unarticulated needs, or superior solutions to meet existing market needs (Bayus 2013). Such micro-level individual entrepreneurial activities promote macro-level economic growth by increasing productivity and introducing new products and services (Wong et al. 2005). With respect to its significant influence on economic growth, entrepreneurial success is economically important to society and has received considerable attention in recent decades.

Despite the fast-growing group of entrepreneurs, a recent investigation reveals that nine out of ten startups fail.[11] It appears that failure is quite common. Entrepreneurs are exposed to a grave situation and it is challenging for them to be successful. The reasons behind entrepreneurial success can be attributed to innate talent or the accumulation of entrepreneurial experience (Eesley and Roberts 2012). The "innate talent" arguments state that there is a high probability for talented entrepreneurs to succeed due to their superior innate ability, as such ability helps them generate greater entrepreneurial earnings (Evans and Jovanovic 1989) or better meet customer needs (Amit et al. 1990) out of a given amount of capital invested. However, the innate talent is

[11] See: http://www.forbes.com/sites/neilpatel/2015/01/16/90-of-startups-will-fail-heres-what-you-need-to-know-about-the-10

less likely to be controlled by entrepreneurs themselves, and thus this perspective received relatively little attention.

A more recent and dominant strand of research emphasizes the "learning-by-doing" aspect in entrepreneurial success arising from prior entrepreneurial experience. For example, as Shepherd (2003) posits, the most common reason for business failure is insufficient experience. It appears that entrepreneurial capabilities can be acquired over time with the accumulation of experience. A commonly discussed topic in this field is *serial entrepreneurship* (MacMillan 1986) – entrepreneurs found multiple firms and operate them in a sequential way. Serial entrepreneurs are more likely to develop routines that can be reproduced in subsequent ventures instead of developing them from scratch. They are in a position to learn from prior experience (Gruber et al. 2008; Lazear 2005) and the learning results in adaptive actions and improved performance. During the learning process, entrepreneurs gradually develop their skills through reflection and this eventually translates knowledge into subsequent behaviors. Specifically, through engaging in multiple founding experience, entrepreneurs gain a richer understanding of the tasks needed to successfully launch a new business such as identifying the market opportunities (Baron and Ensley 2006; Ucbasaran et al. 2009), evaluating customer preferences (Eesley and Roberts 2012), gaining financial resources (Hsu 2007; Zhang 2011) and choosing appropriate industries (Eggers and Song 2015; Gompers et al. 2010), etc.

Even though prior research offers valuable insights into the benefits serial entrepreneurs gain from prior founding experience, studies have largely focused on one out of a series of businesses founded by serial entrepreneurs (Parker 2013; Ucbasaran et al. 2006). Ostensibly, entrepreneurial activities are not independent from each other, and entrepreneurs improve their stock of knowledge over the process of experimentation on different strategies. That is, what is learned in one stage is dependent on the outcomes of

earlier stages (Minniti and Bygrave 2001). Considering the path-dependent nature of knowledge, the current view (i.e., focusing on one attempt) makes it difficult to continuously observe the capabilities entrepreneurs develop in the process of founding multiple ventures and the changes they make to subsequent entrepreneurial attempts after experiencing different outcomes. Recently, Parker (2013) advances this stream to a dynamic field of literature (Gompers et al. 2010) by analyzing the performance trajectories of serial entrepreneurs. He finds that serial entrepreneurs obtain a rising trajectory over successive venturing experiences but such benefits eventually fade away.

Nevertheless, existing research implicitly assumes that each venturing experience is homogeneous, and entrepreneurs repeat similar strategies in each attempt. However, it is important to note that entrepreneurial experiences vary along various dimensions and are heterogeneous in nature (Argote and Todorova 2007), in terms of the source (i.e., how the experience is acquired) of and content (i.e., what happens within the experience) in each experience. A fundamental dimension of entrepreneurial experience is whether it is acquired directly from focal entrepreneurs through "learning by doing" or indirectly from others through "learning by observation" (Levitt and March 1988). In addition to their own founding experiences (as the primary focus of the existing literature), entrepreneurs are very likely to benefit from indirectly engaging in other entrepreneurial initiatives (Guiso et al. 2015). Such indirect learning has become another important approach that serial entrepreneurs accumulate knowledge; when observing others' founding practices, entrepreneurs may develop their own interpretations of the outcome through association and refection. Regarding the content of experience, each entrepreneurial founding activities can produce promising or failed outcomes, following which entrepreneurs' knowledge is updated accordingly (Minniti and Bygrave 2001). Furthermore, each experience resides in some domain context and varies in content, so that different entrepreneurial activities may be related to unrelated to each other. Entrepreneurs may

exert different levels of engagement in each entrepreneurial endeavor. Considering the multiple experience dimensions, it still remains unclear how entrepreneurial learning is shaped with different sources and contents of experience. Thus, to better understand entrepreneurial learning and success, we attempt to close this literature gap by *investigating entrepreneurial learning from fine-grained dimensions of experience and examine their influences on subsequent entrepreneurial performance.*

In this study, we use the theoretical lens of organizational learning (Argote and Miron-Spektor 2011) to conceptualize the entrepreneurial learning process. Its basic argument is that organizations (or individuals within organizations) are seen to extract inferences from prior experience and in turn use these inferences to guide their present or subsequent behaviors. Based on this theory, we argue that entrepreneurial learning occurs in a feedback cycle, where entrepreneurs observe the performance of concurrent experiences and alter their subsequent behaviors accordingly (Fiol and Lyles 1985). We focus particularly on serial entrepreneurs. Considering the complex and manifold nature of entrepreneurial activities, we propose hypotheses related to the effects of multiple dimensions of prior experience. Entrepreneurs are expected to learn directly from their own founding experience and indirectly from engaging in other entrepreneurs' initiatives. Each entrepreneurial experience varies along various dimensions in terms of its source, outcome, domain context and the extent of entrepreneurs' involvement. Our hypotheses deal with how the heterogeneity of experience (i.e., different experience dimensions) influences the learning effectiveness.

We empirically test our proposed framework in the context of online crowdfunding – a novel business model where entrepreneurs acquire financial resources and meanwhile market their new products by posting their entrepreneurial initiatives through crowdfunding projects (Kuppuswamy and Bayus 2017; Kuppuswamy and Mollick 2016). The crowdfunding performance in an indication of not only an

entrepreneurial initiative's funding performance but also its market response, as better fundraising performance also suggests that the current product is well-received among potential customers. One advantage of this context is that crowdfunding is characterized by its information transparency, where entrepreneurs' activities and activities are recorded and published for open consumption. It gives a better observation of what happens within each founding experience. Moreover, entrepreneurs accumulate their experiences in two ways: founding their own business by launching a crowdfunding project and supporting other entrepreneurs' business by backing a project.

To uncover the dynamics of entrepreneurial learning, we employ a panel-level analysis approach based on the records from 3,521 serial entrepreneurs. Consistent with our expectations, the results show that serial entrepreneurs learn directly via launching their own projects and indirectly by funding others' projects. The combined effects are greater than the sum of their individual effects. Importantly, in contracts to our predictions, we find that successful experiences do not always lead to beneficial outcomes. Entrepreneurs seem to learn from their own failure and other entrepreneurs' successes. Specifically, we find evidence of a "success trap" (Kim and Rhee 2009; Rhee and Kim 2015) from earlier founding success, as entrepreneurial success as early stages is more likely to be detrimental than later ones. By analyzing the changes across founding experiences, we find that success may stimulate entrepreneurs to pursue risker choices but they may not be sufficiently prepared in the next venture. Regarding the characteristics of experience, the relatedness of direct founding experience facilitates learning, but that of indirect backing experience does not result in enhanced performance. In addition, timely efforts in direct experience are shown to be beneficial, whereas such positive effect does not show in indirect experience.

This study makes several contributions to the literature of entrepreneurship, organizational learning and crowdfunding. To begin with, following Parker (2013), we

step beyond one out of a series businesses and enrich the literature that takes a dynamic perspective towards the developmental process of serial entrepreneurs. Our focus on multiple founding experiences of entrepreneurs allows us to observe entrepreneurial performance as a function of experience and entrepreneurs' adaptation actions across businesses. Second, we investigate entrepreneurial learning from multiple experience dimensions by unearthing how different characteristics of entrepreneurial experience influence performance. We also identify indirect experience is an important source of entrepreneurial learning. It generates different implications from direct learning, particularly in the presence of success. Third, we extend organizational learning theory from repeated tasks to knowledge- and innovation-based tasks where less routinizations are involved. Furthermore, we generate nuanced insights for organizational learning literature by characterizing experience at a fine-grained level. Last but not least, we add to the crowdfunding literature by emphasizing that entrepreneurs develop competencies across multiple projects.

5.2 Theory and Hypotheses

5.2.1 Serial Entrepreneurship and Entrepreneurial Learning

Entrepreneurial activities are characterized by the development of the capability to organize, develop and manage business ventures against potential risks. This development is inseparable from the process of learning (Gruber et al. 2008; Minniti and Bygrave 2001). Learning has gained broad acceptance and has become a prominent aspect of academic study of entrepreneurship and practical development of entrepreneurs (Cope 2005; Rae 2006; Zhang 2011).

In this area, the fundamental research focus is on the relationship between entrepreneurs' earlier experience and subsequent entrepreneurial practice and venture performance (Paik 2014). Particularly relevant, a corpus of academic work has been

devoted to understanding how experienced entrepreneurial founders (i.e., repeat entrepreneurs) differ from novice (first-time) entrepreneurs (Eggers and Song 2015). Serial entrepreneurs, as a major sub-type of experienced entrepreneurs, are those who have founded firms multiple times and operated them sequentially (MacMillan 1986; Paik 2014; Ucbasaran et al. 2010; Westhead and Wright 1998).[12] They distinguished from novice entrepreneurs in that they are in the position of learning from earlier experience (Gruber et al. 2008; Lazear 2005) and such learning are conducive to superior entrepreneurial performance in their subsequent ventures (Eesley and Roberts 2012; Paik 2014; Parker 2013). In general, there is consensus that serial entrepreneurs acquire knowledge and capabilities with the enrichment of prior experience, and the gained knowledge serves as an impetus for the performance improvement of subsequent ventures.

While a body of literature examines the role of prior experience in entrepreneurship, a wide range of behavioral responses and entrepreneurial outcomes are considered, including opportunity recognition (Baron and Ensley 2006; Ucbasaran et al. 2009), comparative optimism (Ucbasaran et al. 2010), grief recovery (Shepherd 2003), venture survival (Paik 2014), choice of entrepreneurial strategies (Minniti and Bygrave 2001), industry selection (Eggers and Song 2015), receiving VC funding (Hsu 2007) and more generally, entrepreneurial performance (Gompers et al. 2010; Parker 2013) to name a few. For instance, Baron and Ensley (2006) suggest that entrepreneurial experience facilitates entrepreneurs to clearly recognize business opportunities and develop a richer model of ventures. Ucbasaran et al. (2010) found that entrepreneurs are less likely to report overconfidence and comparative optimism (i.e., over-optimism) after experiencing business failure.

[12] Another sub-type of experienced entrepreneurs is portfolio entrepreneurs, referring to those who have founded multiple firms and operate them *in parallel* (Westhead and Wright, 1998).

More pertinent to the current study, among the recent studies examining the link between prior experience and entrepreneurial performance, much attention has been focused on the influence of success and failure of prior business ownership experience. Gompers et al. (2010) assert that entrepreneurs benefit from prior successful experiences in that successful entrepreneurs acquire better market timing skills and exhibit persistence in selecting the right industry and time to start a new business. This finding is echoed by Parker (2013), who finds that serial entrepreneurs benefit from prior successful experience, but importantly, his findings also show that such benefits are temporary and will eventually disappear. In other words, the valuable lessons from prior successful entrepreneurial experience may depreciate when transferred to their next venture, especially when industry changing behavior occurs. In addition, while failure is not an inherently desired outcome, some research posits that failed experience can be more beneficial compared to success in the next venture creation, since entrepreneurs who experienced failure are shown to be more prepared for the next trial (Cope 2011). This view is in line with the conceptual framework of Shepherd (2003), asserting that overcoming the loss of a venture, entrepreneurs are able to benefit from failure.

By and large, existing research perspectives suggest serial entrepreneurs are inclined to learn from prior experience, whereby their knowledge gained will enlighten their following entrepreneurial behaviors and influence subsequent outcomes, even though the learning mechanisms may be complex. In order to obtain a nuanced understanding of entrepreneurial learning, the current study aims to examine the effect of prior experience at a fine-grained level, involving multiple dimensions of experience. We posit that serial entrepreneurs learn not only directly from their own entrepreneurial founding experiences but also indirectly from the entrepreneurial activities of others, and each experience varies along multiple dimensions. We attempt to study entrepreneurial learning by analyzing how entrepreneurs assimilate various kinds of experience and

opportunities and learn from past successes and mistakes. This also echoes calls from the literature on how different forms of prior experience relates to one another to shape entrepreneurial behaviors and outcomes (Cope 2005). Furthermore, this research is one of the first (e.g., Parker 2013) that takes a dynamic and longitudinal perspective towards the development of entrepreneurship.

5.2.2 Organizational Learning

Entrepreneurial learning enables entrepreneurs to accumulate experience-based knowledge that serves as the basis for subsequent performance improvements (Cope 2005; Hsu 2007). During this process, entrepreneurs, while experimenting different alternatives, seek to attribute results to causes and formulate an understanding of how alternatives are combined together to achieve outcomes (Kirzner 1979). This process naturally fits the basic theoretical mechanisms of organizational learning, where the core argument is that organizations and individuals within organizations are seen as extracting inferences from prior experience and in turn utilize these inferences to guide present and future behaviors (Argote 2013b; Argote and Miron-Spektor 2011; Levinthal and March 1993). Specifically, there are three key components in the ongoing learning cycle: experience, context and knowledge (Argote 2013a; Argote and Miron-Spektor 2011). *Experience* is the beginning of the learning process and it represents inferences transpired from prior tasks. *Context* refers to the contingency that affects learning processes by moderating the relationship between experience and outcomes (Argote and Miron-Spektor 2011). The third component, *knowledge*, is the outcome of the learning process, which resides in various reservoirs (or stocks) (Levitt and March 1988). The knowledge reservoir serves as a basis for later task execution and performance since activities are conducted with reference to knowledge in the knowledge reservoir. Hence, having a preeminent knowledge reservoir is seen as the principal source of advantage and increased performance (Argote and Ingram 2000). In entrepreneurship, serial

entrepreneurs acquire *experience* via "learning by doing" in starting their own businesses or "learning by observation" on the founding initiatives of other entrepreneurs. During the process, they receive feedback from the market (*context*).[13] Gradually, these experiences and feedback are instilled into *knowledge*, which in turn guides entrepreneurs' subsequent activities.

5.2.3 Direct and Indirect Experience

The organizational learning literature characterizes experience along various dimensions. An essential dimension distinguishes between two types of experiences: direct vs. indirect. Direct experience is acquired through a process of "learning by doing" from one's own experience (March et al. 1991; Schilling et al. 2003) whereas indirect experience is obtained by observing others' activities (Argote and Todorova 2007; Darr et al. 1995; Szulanski 1996). Learning from direct experience, also called "experiential learning," is a rudimentary form of learning that occurs via two mechanisms of knowledge creation: *trial-and-error* and *search* (Levitt and March 1988). The two mechanisms follow the logics of *appropriateness* and *consequences* whereby a series of action-outcome associations are formed in the knowledge reservoir to map each action previously taken to specific outcomes. Organizations' (and individuals') knowledge reservoirs are updated accordingly after they experience various outcomes. Consequently, in dealing with a new task, they adopt a feasible alternative with expectation of a desirable outcome using existing knowledge in their knowledge reservoirs. The

[13] In entrepreneurship, the context here may also refer to the market environment in different industries. For example, the composition of entrepreneurs and the turbulence of market in various industries may be different. These contextual factors may moderate the learning effects. In the present study, we do not elaborate on the notion of *context* as it is not our primary research focus. Our primary focus here is on *experience* and *knowledge*.

By conceptualizing these two components, we argue that our rationale for applying organizational learning theory to entrepreneurship is based on its focus of *entity task*, which we deem pertinent to the business ownership experience in the entrepreneurship context. Therefore, when applying this theory, our focus is not on organization itself, but on the *learning process* of entrepreneurs, which is based upon the task they performed – i.e., the business they started.

efficiency of this direct learning process depends on the history of experiences (Radner 1975). The rate of discovering appropriate courses of action is proportional to the abundance (i.e., quantity) and reliability (i.e., accuracy) of action-outcome associations in the knowledge reservoir (Levitt and March 1988).

Serial entrepreneurs may obtain direct experience by starting their own new ventures and indirect experience by observing the entrepreneurial initiatives of others. First, with respect to direct experiences, entrepreneurs observe the outcomes accompanying their prior founding experiences, and develop intuitions about the types of strategies most likely to contribute to better entrepreneurial performance (Minniti and Bygrave 2001; Parker 2006). Entrepreneurs with a larger number of prior founding experiences tend to have a more abundant knowledge reservoir, which provides a search pool of greater quantity – a larger number of potential alternatives with various outcomes. In addition, they are more inclined to develop reliable knowledge which entails more workable courses of actions under various circumstances. For instance, entrepreneurs who have several founding experiences, where they have been involved in negotiations with venture capitalists, are more likely to form a better sense of the types of traits and capabilities that are deemed to be favorable to (potential) investors (Zhang 2011). Their past experiences also help them horn better skills in recognizing new business opportunities from shifts in market and advances in technology (Baron and Ensley 2006). Therefore, those entrepreneurs with more founding experiences will tend to have a more accurate awareness of why certain actions result in the outcomes they seek or want to avoid. Hence, entrepreneurs with prior founding experiences have a higher likelihood of founding high-performing ventures (Paik 2014), and this likelihood increases with the number of founding experience. Based on these arguments, we hypothesize:

> ***Hypothesis 1a****: The number of serial entrepreneurs' prior direct experience is positively associated with the performance of a subsequent entrepreneurial activity.*

Second, organizations learn not only from their own direct experiences but also *indirectly* from others' experiences (Huber 1991; Levitt and March 1988). This form of learning is also referred to as knowledge transfer (Argote and Ingram 2000) or vicarious learning (Bandura 1969; Bandura and McClelland 1977). Organizations benefit from the experience of others through the transfer of experience in the form of procedures, similar routines or simulated experience (Dutton and Starbuck 1979). Basically, indirect learning is the process of diffusion of experience (Levitt and March 1988) involving the spread of experience through contact between members who possess the knowledge and those who do not, mediated by a "host carrier".

Vicarious learning from other entrepreneurs' has become another important approach that serial entrepreneurs acquire knowledge (Kim and Miner 2007). Apart from their own founding experience, entrepreneurial firms are exposed to a variety of indirect learning opportunities arising from entrepreneurial activities in one's environment (Guiso et al. 2015). For example, for high-tech entrepreneurship, it is common for entrepreneurs to obtain technological skills and innovation techniques by participating in the R&D process of another firm. When entrepreneurs acts an active participant (e.g., consumers, investors or technology experts) in others' entrepreneurial activities, it is generally easier for them to envisage how the venture can be created and what necessary knowledge and circumstances are expected (Rae 2006), compared to those who do not. By engaging in their own entrepreneurial initiatives and those in the environment, entrepreneurs' knowledge reservoirs can be enriched through direct as well as indirect learning.[14]

In a similar vein, in indirect learning, entrepreneurs observe others' entrepreneurial activities and their associated consequences and link these observations to

[14] In this paper, we consider as indirect learning when entrepreneurs are involved in entrepreneurial activities in the environment. Due to their limited attentional capabilities (Ocasio 1997), entrepreneurs would selectively focus their attention on a group of rather than all entrepreneurs in their environment.

the possible occasions with certain outcomes (Bandura and McClelland 1977). For example, software entrepreneurial firms regularly use consumer product testing for their developed software prior to market introduction (Dolan and Matthews 1993). When entrepreneurs act as early adopters of certain product, as observers, they will develop their own interpretations of the entrepreneurial experience from their individual inference. More specifically, when they observe the company include certain techniques or functions in the software product, such as the sleep tracking technology in a mobile app. They may attribute the market performance of the product to the activities they observe from the company. Thus, with an increase in the number of indirect experiences, the number of potential action-outcome associations they store in their knowledge reservoir will also increases, so does the reliability of the knowledge. The knowledge obtained through such indirect experience may serve as guidance for future founding behaviors. We therefore hypothesize:

> ***Hypothesis 1b****: The number of serial entrepreneurs' prior indirect experience is positively associated with the performance of a subsequent entrepreneurial activity.*

Although both direct and indirect learning may occur, the strengths of their effects may differ. Learning effectiveness can be assessed based on what is learnt and what is executed (Bandura and McClelland 1977). To date, the learning literature has shown inconsistent results with respect to the relative strengths of direct vs. indirect learning effects. Especially with respect to procedural behaviors, indirect learners are considered to learn faster than direct learners (Berger 1961; Rosenbaum and Hewitt 1966). However, other studies find the opposite. For example, Gino et al. (2010) find that direct task experience leads to higher performance in creativity than indirect experience in a product-development task, since adopting others' strategy (i.e., indirect learning) does not necessarily assist acquiring the tacit knowledge required. In our context, we argue that entrepreneurial activities are diversified and complex rather than merely

procedural (Cope 2005). They are also tacit and causally ambiguous (i.e., the same activity may lead to different consequences) (Lippman and Rumelt 1982). For instance, on the surface, when observing other entrepreneurial practices, an entrepreneur may perceive a product function to be effective; but the reason underlying its effective may be due to other factors in addition to the product function itself (e.g., customized services by the entrepreneurs). Therefore, without knowing the underlying mechanisms that lead to success, it would be difficult for indirect learners to develop a clear mapping of actions to outcomes. The indirect learning effectiveness tend to be weakened by uncertainties in the environment (Kim and Miner 2007). However, with direct founding experiences, they are more likely to form a clearer understanding of the mapping of actions to outcomes. With an increase in stock of direct experience, they will have a greater chance of harvesting value from prior experiences (Kim et al. 2009). Hence, we hypothesize:

> ***Hypothesis 1c****: The effect of direct learning is stronger than that of indirect learning.*

In addition to these main effects, we also consider whether the effects of direct and indirect learning may in fact be complementary. The learning literature posits that when different types of experience exist, their interactive effect depends on how they are related to each other. If one type helps the learner identify and retrieve the other type, it may increase learners' absorptive capacity and create a positive interaction (Cohen and Levinthal 1990; Kang et al. 2017). In our settings, entrepreneurs accumulate direct experience by establishing their own businesses, during which they start to formulate their own interpretations between courses of actions and potential outcomes. Such interpretations help them better comprehend others' entrepreneurial practices, whereby the uncertainties in the knowledge transfer and the formation of action-outcome associations in indirect learning will be reduced. Similarly, the knowledge gained in the indirect learning provides new insights into the interpretations of entrepreneurs' own

experiences and in turn enhance the effectiveness of direct learning (Bresman 2010). For example, starting their own businesses gives entrepreneurs better understanding about the market timing and industry selection for a certain product. The obtained knowledge facilitates them to figure out the causes of other entrepreneurs' consequences. Further, Bandura and McClelland (1977) also propose that when direct and indirect learning occur together, their combined effect on performance is greater than the sum of their independent effects. We expect entrepreneurs to be able to continuously adjust their knowledge reservoirs when they are reinforced by their own or others' entrepreneurial activities. We predict direct and indirect learning relate positively to each other. Thus, we propose:

> ***Hypothesis 1d****: The effects of direct and indirect learning will be supplementary, resulting in a positive moderating (strengthening) effect, such that, as direct experience increases, the effect of indirect experience will increase (and vice versa).*

5.2.4 Successful vs. Failed Experience

A second dimension of experience relates to outcomes of trial or experience. Success is an indication that the strategy or action was effective (Kim et al. 2009). It triggers reinforcing the association between the strategy/action and success (Audia et al. 2000; Greve 1998), which subsequently improves organizational performance and efficiency (Greve 2003a; Levinthal and March 1993).

The success and failure of entrepreneurs' prior experience may have differential effects (Ucbasaran et al. 2010). In direct learning, serial entrepreneurs receive feedback from their prior founding experiences. When they receive positive performance feedback (i.e., achieve venture success), they would attribute success to they have performed in the prior business(es) and develop and inclination to repeat such strategies (Bingham and Davis 2012). Otherwise, when they receive negative performance feedback (i.e., fail to achieve success), they may be more inclined to attribute failure to their activities within

that founding experience. Likewise, in indirect learning, by observing others' successful (unsuccessful) initiatives, entrepreneurs infer behaviors that may lead to positive (negative) results and may replicate (avoid) similar actions in their own initiatives in the future.

In both cases (i.e., direct and indirect learning), successful experiences give entrepreneurs a better understanding of favorable characteristics and features of business, since success enlightens them what seems to perform well, whereas failure only informs them what does not lead to satisfactory outcome but not what leads to successful ones. Those favorable characteristics are likely to be pursued when they are associated with success and less likely when they are associated with failure (Cyert and March 1963; Minniti and Bygrave 2001). There may exist many possible unworkable routes, but failed experience merely exposes entrepreneurs to some of them. A larger proportion of successful experiences facilitates the formation of a better appreciation of valuable lessons, which in turn leads to higher performance in subsequent entrepreneurial practices. In addition, the success history of entrepreneurs also increases the search efficiency, as it guides them searching in the right direction (Radner 1975) in the knowledge reservoir for better solutions. Taken together, we propose:

> ***Hypothesis 2a:*** *The number of successful direct experience is positively associated with the performance of a subsequent entrepreneurial activity.*
>
> ***Hypothesis 2b:*** *The number of successful indirect experience is positively associated with the performance of a subsequent entrepreneurial activity.*

5.2.5 Relatedness and Richness of Prior Experience

In addition to the number and the outcomes, we argue that the relevance of prior experience plays an important role in learning given complexity of entrepreneurship activities (Eggers and Song 2015). Entrepreneurs may start their businesses or get involved in other entrepreneurial activities in a variety of domains. Participating entrepreneurial activities in differing domains exposes them to different industrial

markets, technologies from distinctive field as well as opportunities to interact with consumers from diverse background, etc. Components in one domain can be related or unrelated to those from another.

As discussed earlier, the knowledge reservoir, which is the result of learning process, acts as a guide for subsequent behaviors. There are two major mechanisms that facilitate learning from experiences: *simplification* and *specialization* (Levinthal and March 1993) – learning processes seek to *simplify* experience before it flows into knowledge reservoir, and contextualize it into specific contexts through *specialization* during the execution of subsequent behaviors. More specifically, learning is fundamentally based on interpretation of experiences (Argote 2013b). People tend to encode the learning outcomes and meanwhile develop explanations for possible causes for the observed outcomes (Levinthal and March 1993). Simplification helps to disentangle the causes from the complexities of the context, whereas specialization involves adaptation of experience to current situations.

If there is high level of similarity between the current business and prior business ownership experience (e.g., two companies are in the same industry or are developing similar products), less cognitive efforts are required in simplification and specialization processes. Similarity expedites the search process in direct learning by increasing the number of potentially related paths in the knowledge reservoir. Otherwise, more efforts are needed to specialize obtained knowledge to certain (different) contexts. This reasoning is also consistent what Eggers and Song (2015) recently argues – changing industries in entrepreneurship is costly as it may invalidate potentially valuable industry experience so that it is likely to undermine subsequent ventures. For instance, it is highly possible that the knowledge extracted from founding a card game company would be more beneficial to starting a video game business compared to starting a hardware business.

Indirect learning, as noted earlier, is essentially a process of knowledge transfer – i.e., transferring knowledge from others' activities to one's own. It also refers to transferring knowledge gained from prior experiences to current tasks. The literature proposes many factors that may affect the efficacy of transfer. One of the most important factor is the relatedness (or similarity) between previous experience and current tasks (Argote and Ingram 2000; Darr and Kurtzberg 2000). As observers, entrepreneurs are more likely to extract reliable knowledge (i.e., action-outcome associations) from others' entrepreneurial activities when the observed tasks reside in a relevant context to their current task. Hence, if previous direct and indirect experiences are in a related (or similar) domain with the subsequent entrepreneurial initiative, learning effectiveness will be improved. Thus, we hypothesize:

> ***Hypothesis 3****: The relatedness of serial entrepreneurs' prior experience (i.e., direct and indirect) is positive associated with the performance of a subsequent entrepreneurial activity.*

Apart from experience relatedness, the quality of knowledge extracted from prior experience is also dependent on the extent of entrepreneurs' involvement and engagement in each experience. The learning literature documents that the content of prior experience matters in performing subsequent tasks (Argote and Todorova 2007). Considering experience content, each experience can be acquired by a variety of tasks or different levels of commitment. Moreover, the entrepreneurship literature finds that the levels of involvement in different management roles entrepreneurs played in their previous entrepreneurial initiatives affect the performance of their new business (Stuart and Abetti 1990). The different management roles played signifies the extent of job involvement (i.e., some roles require more involvement in certain work), and can be conceptualized as *richness of prior experience*. Richness of experience indicates one's extent of engagement in the relevant activities –the more they are engaged, the more accurate and deeper understanding of preferable consumers' taste or feasible management

styles. For example, entrepreneurs who vigorously engaged in the customer services in prior businesses are able to obtain an enhanced appreciation of customers' requirements compared to those who did not. We propose that, compared to those whose extent of involvement was low, entrepreneurs who actively committed in previous experience are more likely to distill potentially useful knowledge from the experience, and consequently, the knowledge obtained in the learning process is more reliable. Hence, we hypothesize:

> ***Hypothesis 4****: The richness of serial entrepreneurs' prior experience (i.e., direct and indirect) is positive associated with the performance of a subsequent entrepreneurial activity.*

5.3 Data and Methods

5.3.1 Study Context

We test the proposed hypotheses by using data from a crowdfunding platform. Crowdfunding is a relatively novel approach for sourcing financial resources for innovations (Burtch et al. 2015; Kuppuswamy and Mollick 2016). It allows entrepreneurs to request funding from many individual funding backers, often in return for future products, equity, or some form of recognition (Mollick 2013). Typically, crowdfunding is implemented on an online platform. Crowdfunding has taken several forms in terms of the method of raising money from the crowd: reward-based, equity-based, lending-based and donation-based crowdfunding platforms.

Our data is collected from the largest reward-based crowdfunding platform – Kickstarter (www.kickstarter.com). On this platform, entrepreneurs, known as creators, initiate creative projects and seek funds from other people, known as backers. Kickstarter categorizes projects into 15 broad category domains: art, comics, journalism, photography, publishing, crafts, dance, film, music, theater, fashion, food, games, technology and design. Each project posted on Kickstarter is independently created, gives the creator full control over, responsibility for and full ownership of his/her project.

Project creators set a fundraising goal and deadline. If people have interest in a project, they can pledge money and become a "backer". However, since Kickstarter adopts a "all-or-nothing" funding model, projects must reach their original funding goal by the predetermined deadline in order to receive funds pledged by backers. Usually, the success of a crowdfunding project involve entrepreneurs' investment of time, money, and social capital (Kuppuswamy and Mollick 2016). To date, 36% projects have achieved their fundraising success.[15]

There are several reasons why crowdfunding provides an ideal context to test our hypotheses. First, crowdfunding, especially for reward-based crowdfunding, provides entrepreneurs with a platform to pre-sell their products through which they conduct fundraising in parallel with marketing. That is, entrepreneurs promote their product to the market while engaging in the fundraising process, which allows them to gauge market response. As noted above, similar to offline traditional market, entrepreneurs need to invest effort, time and resources to manage a crowdfunding project and to interact with the potential customers. Thus, the crowdfunding success can be used a proxy for entrepreneurial success to some extent; the funding performance of a crowdfunding project also captures whether the proposed initiative (or developed new product) is well-received by potential customers (backers). Therefore, the crowdfunding performance offers an objective measure of performance of entrepreneurial activities, and that is, the outcome of entrepreneurial learning we consider.

Second, one of the significant features of the crowdfunding model is *information transparency* – information about venture owners and their projects are recorded and observable on the crowdfunding platform for researchers. For example, a summary and detailed records of entrepreneurs' founding histories are typically visible on the platform. For each launched project, we are able to observe the detailed content of the

[15] See: https://www.kickstarter.com/help/stats (visited in May 2017).

entrepreneurial initiative (through the project description) and how entrepreneurs interact with potential customers (through comments and updates posted by entrepreneurs) (Yang and Hahn 2016). Furthermore, the information transparency of crowdfunding allows us to take a longitudinal perspective towards the process of entrepreneurial learning. Moving beyond one of a serial of businesses, we have the continuous observation of entrepreneurs' behaviors in each business and performance over time across multiple entrepreneurial initiatives.

Third, learning from other entrepreneurs has become an important form of entrepreneurial learning (Guiso et al. 2015), but such indirect learning is inherently difficult to capture. In the crowdfunding context, entrepreneurs are able to accumulate their business ownership experience not only by launching their projects, but also by investing in (backing) other entrepreneurs' projects; entrepreneurs may take the role of backers in addition to the role of founders. We regard this backing behavior as a channel for indirect learning. We posit that, through such backing behavior, entrepreneurs observe others successful and unsuccessful initiatives and infer actions that may lead to superior entrepreneurial performance. Another reason for using backing behavior as a proxy for indirect experience is that only backers are allowed to post comments to a project and some project updates are only accessible to them, through which they are able to have frequent interactions with other entrepreneurs. Therefore, taking the role of backers, entrepreneurs selectively focus their attention (Ocasio 1997) on the close engagement of certain projects instead of all the projects on the platform. Based on these reasons, we see the appropriateness of using backing experience as a proxy for indirect learning in the crowdfunding context.

5.3.2 Data

We collected our data from Kickstarter. We collected relevant information on all crowdfunding projects that ended before December 8, 2014. Our data covers all projects

since the inception of Kickstarter. These projects collectively received a total amount of USD $1.4M from over 7M unique backers.

Given our research focus on *entrepreneurial* learning, we focus our analysis on three categories related to entrepreneurship: *games*, *technology* and *design*. These three categories are chosen because nearly all the projects in the categories are related to entrepreneurial activities. Entrepreneurs post their innovative projects mostly in these categories. Typical examples include a creative portable cooler, an instant iPhone camera and a novel card game, etc. However, in other categories, many (if not most) projects are not entrepreneurially-oriented. For example, some projects aim to raise money for organizing a performance or refurnishing a studio.

In total, there are 32,658 projects within these three entrepreneurship-related categories and the overall success rate is 33%, which is relatively lower compared to the overall success rate of 40% across all categories. These projects were launched by 26,961 unique entrepreneurs (or entrepreneurial teams). We define *serial entrepreneurs* here as those who launched at least two projects *within these three entrepreneurship-related categories*. We focus on serial entrepreneurs and turn to regression analysis to obtain a nuanced observation of entrepreneurial learning. The proposed hypotheses will be formally tested. An unbalanced panel data set was constructed with the *entrepreneur-project* as the unit of analysis. Ultimately, our analysis data consists of 3,521 serial entrepreneurs, with a total of 8,825 launched entrepreneurial projects.[16]

[16] Since entrepreneurship literature suggests the learning mechanisms of serial entrepreneurs and portfolio entrepreneurs might be different (e.g., Ucbasaran et al., 2010), we checked our data and found that only 5 entrepreneurs are portfolio entrepreneurs. It shows Kickstarter barely allows entrepreneurs to running multiple projects in a parallel fashion. Therefore, portfolio entrepreneurship is a not prevalent phenomenon in our context. The regression results (presented later) are consistent with and without these portfolio entrepreneurs.

5.3.3 Measures

5.3.3.1 Dependent Variable

In the learning literature, measuring performance is a common approach to assess to obtained knowledge. It has the merit of capturing tacit as well as explicit knowledge (Argote and Miron-Spektor 2011) – the learning outcome. In our context, the successful attainment (i.e., funding performance) of the crowdfunding project fundraising goal is used as a proxy for entrepreneurial performance.[17] To better capture the extent of success, rather than using a simple indicator (i.e., success vs. failure), we use the percentage pledged ($PledgedPercentage_{ij}$) as the dependent variable, where $PledgedPercentage_{ij} = PledgedAmount_{ij}/FundingGoal_{ij}$, where j is the jth project entrepreneur i launched in the entrepreneurship-related categories.[18] When the pledged percentage is equal to or larger than one, the project has been successfully funded. We take the log form to account for its skewed distribution.

5.3.3.2 Independent Variables

Direct/Indirect Experiences. The direct experience captures serial entrepreneur's learning from their own founding activities, while the indirect experience represents learning from others' entrepreneurial activities. Accordingly, the measure of past direct/indirect experiences is based on the cumulative number of launched/backed projects by entrepreneur i before the launch of the focal project j ($NumCreatedProjects_{ij}$ and $NumBackedProjects_{ij}$). It is worth noting that, when operationalizing direct and indirect experiences, we include *all prior projects in all fifteen categories* as entrepreneurs may also learn from launched/backed experiences in non-entrepreneurship-

[17] In the context of crowdfunding, a project is deemed successfully funded when its pledged amount is great than its predetermined funding goal.

[18] We add 0.01 to *PledgedPercentage* when taking the log transformation considering the cases when *PledgedPercentage* is 0.

related categories. For Hypotheses 1a, 1b and 1c, we expect significantly positive coefficients for both experience variables, and that the coefficient for $NumCreatedProjects_{ij}$ will be significantly greater than that for $NumBackedProjects_{ij}$. For Hypothesis 1d, we expect a positively significant interaction term ($Created_{ij} \times Backed_{ij}$).

Successful/Failed Experiences. Success and failure concern the outcomes of serial entrepreneurs' prior experience. In "all-or-nothing" funding model, a crowdfunding project is successful only after it reaches its predetermined fundraising goal, so each experience can be unambiguously classified as successful or failed projects. We measure successful direct and indirect experiences based on the proportion of successful projects launched/backed by entrepreneur *i* before the launch of focal project *j* ($CreatedSuccessRatio_{ij}$ and $BackedSuccessRatio_{ij}$). To generate further insights, we also computed the total number of successful and failed projects launched/backed by entrepreneur *i* before focal project *j*: ($NumCreatedSuccess_{ij}$, $NumCreatedFailure_{ij}$, $NumBackedSuccess_{ij}$ and $NumBackedFailure_{ij}$). Consistent with the operationalization of direct/indirect experiences, we calculated these variables using all projects in all fifteen categories. For Hypotheses 2a and 2b, we expect significantly positive coefficients for $CreatedSuccessRatio_{ij}$ and $BackedSuccessRatio_{ij}$.

Experience Relatedness. The relatedness of experience concerns how serial entrepreneur's prior experience is related (or similar) to current founding activities. In our setting, entrepreneurs on Kickstarter need to post descriptions that depict their entrepreneurial initiative or idea when they launch projects. The content (i.e., descriptions) of projects belonging to the same category may vary a great deal.[19] Therefore, in order to obtain a nuanced measure of experience similarity, we utilize the text information provided in each entrepreneurial initiative to construct a measure of

[19] For instance, projects in the Games category may be related to card games, mobile games or live games etc.

experience relatedness. Specifically, we build topic models with project descriptions using Latent Dirichlet Allocation (LDA), a natural language topic classification technique (Griffiths and Steyvers 2004).[20] The outputs of LDA is a topic distribution vector for each document, which represents the weights associated all of the identified topics.[21] Given two projects' descriptions (one for prior created/backed project, one for focal project), a pairwise proximity value can be calculated by cosine similarity (= $\frac{PRJ_a \bullet PRJ_b}{\|PRJ_a\|\|PRJ_b\|}$) of the topic vectors ($PRJ_a$) from projects' textual information. Similar approach was recently used in the management literature to construct similarity between two businesses using their textual documents (e.g., Shi et al. 2016) and to measure knowledge distance using patent descriptions (e.g., Kaplan and Vakili 2015). After this, we calculate the relatedness between focal projects and prior created/backed projects by taking the average across all the pairwise cosine similarities for created/backed experience pairs. Two variables are respectively generated for the direct/indirect experience relatedness: $CreatedRelatedness_{ij}$ and $BackedRelatedness_{ij}$. For Hypothesis 3, we expect significantly positive coefficients for both direct and indirect relatedness (variables).

Experience Richness. The richness of experience characterizes the extent of serial entrepreneurs' involvement in each prior experience. During crowdfunding campaigns, entrepreneurs may use project updates to inform their backers of the progress of the project. Entrepreneurs have the option to notify all of their backers about updates or only backers in selected reward tiers. Project comments can be used to answer questions from

[20] LDA is a bag-of-words model, which assumes each document (i.e., corpus of project description text) as a mixture of topics (Griffiths and Steyvers 2004). By tracing the words that appear in the documents, LDA identifies the topics for each document by associating words to those topics. The topic vector generated by LDA represents the distribution of topics in the document.

[21] It worth noting that we used all the projects that are created or backed by entrepreneurs (56,833 projects) as the input of topic modelling. Before that, we conducted pre-processing for the text documents for each text document (i.e., project description), including tokenization, lemmatization, removing stop words and removing common used words for Kickstarter projects (e.g., "Kickstarter").

backers.[22] Similarly, when they act as backers, they can communicate with project creators by posting comments in the projects they backed and in the creators' updates. These observable updates and comments is an indication of entrepreneurs' level of engagement in their past launched or backed projects. We deem that entrepreneurs have a richer experience by interacting more intensively with the backing community (i.e., by posting updates and/or comments to their own projects). The direct richness is thus operationalized by the sum of such posting activities by the focal entrepreneur (i.e., *NumUpdates* + *NumComments*) in his/her launched projects. We take the average across all of entrepreneur *i*'s prior launched projects in all domain categories as the measure of prior experience richness for focal project *j* ($AvgCreatedRichness_{ij}$). Similarly, the indirect experience richness is operationalized by the number of comments the focal entrepreneur posts on projects they are backing.[23] Again, the average across all backed projects by entrepreneur *i* in all domain categories prior to the focal project *j* is used as the measure of indirect experience richness for focal project *j* ($AvgBackedRichness_{ij}$). For Hypothesis 4, we expect significantly positive coefficients for both direct and indirect richness variables.

5.3.3.3 Control Variables

Several variables are included in the analysis to control for possible effects due to project specific factors (Wessel et al. 2017) – the number of images in the focal project (*ImageCount*), whether or not the project has a Video (*HasVideo*=1 if the project has video; 0 otherwise), the project duration (days) set by the entrepreneur (*CampaignDuration*), the length of general project description (*DescriptionLength*), the

[22] See: https://www.kickstarter.com/help/faq/creator+questions?#WhilYourProjIsLive

[23] Updates (from creators) and comments (from creators and backers) can be posted before and after the campaign deadline. The richness measures are calculated using postings before campaign deadline, since the after-deadline postings largely depends on the outcome of project. If a project is successfully funded, many after-deadline postings are related to product development or delivery issues; otherwise, there will be much less postings after project deadline.

funding goal of the project (*Goal*),[24] the number of reward levels (*NumProjectRewards*), and project domain (*Category* dummies). Moreover, we control for project quality using two variables: an indicator variable *QuickUpdate* which is coded as 1 when the entrepreneur posted updates within three days of launch (Mollick 2013) and a project description readability index (*Readability*) which captures how difficult a product description is to understand. For the readability index, we use Flesch reading ease test, where higher score indicates the material is easier to read and lower number marks it is more difficult to understand (Chan and Parhankangas 2017; Parhankangas and Renko 2017).[25] Furthermore, the year and month controls are included to account for platform-level shocks over time and the influence of product market timing (Gompers et al. 2010). Descriptive statistics and correlations of all variables are presented in Table 5-1 and Table 5-2 respectively.

[24] For projects in foreign (i.e., non-USD) currency, this was converted to USD using the currency rate for the month when the project was launched.

[25] The formula for the Flesch reading-ease score test is: $206.835 - 1.015\left(\frac{total\ words}{total\ sentences}\right) - 84.6\left(\frac{total\ syllables}{total\ words}\right)$.

Table 5-1. Summary Statistics for Estimation Sample

	Variables	Mean	Std. Dev.	Min	Max
Outcome	*PledgedPercentage*	2.705	13.70	0	631.7
Experience	*NumCreatedProjects*	1.129	1.451	0	17
	NumBackedProjects	8.109	22.08	0	735
	NumCreatedSuccess	0.550	1.143	0	17
	NumCreatedFailure	0.579	0.880	0	10
	NumBackedSuccess	6.496	17.21	0	552
	NumBackedFailure	1.613	6.454	0	198
	CreatedSuccessRatio	0.254	0.407	0	1
	BackedSuccessRatio	0.536	0.435	0	1
Relatedness	*CreatedRelatedness*	0.370	0.393	0	1
	BackedRelatedness	0.182	0.220	0	0.998
Richness	*CreatedRichness*	28.55	111.7	0	3,392
	BackedRichness	7.342	139.1	0	8,873
Controls	*ImageCount*	12.79	13.73	0	167
	HasVideo	0.631	0.483	0	1
	CampaignDuration	33.99	11.62	1	91
	DescriptionLength	5,333	4,415	1	30,573
	Goal	30,987	338,418	0.931	2.856e+07
	QuickUpdate	0.553	0.497	0	1
	NumRewards	9.636	6.465	0	137
	Readability	59.15	24.27	-1,595	205.8

Notes: Number of observations: 8,825; Number of serial entrepreneurs: 3,521. We exclude those serial entrepreneurs (20) with more than ten launched entrepreneurial projects as these observations are likely to be operated by mature corporations rather than entrepreneurial firms. The sample also excludes 7 outliers (for 7 projects) whose *PledgedPercentage* values exceeded three standard deviations above the mean. The regression results (presented later) are consistent with or without these outliers.

Table 5-2. Correlation Matrix (*N*=8,825)

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) PledgedPercentage	1.000							
(2) NumCreatedProjects	0.055***	1.000						
(3) NumBackedProjects	0.044***	0.245***	1.000					
(4) CreatedSuccessRatio	0.084***	0.445***	0.262***	1.000				
(5) BackedSuccessRatio	0.082***	0.165***	0.224***	0.273***	1.000			
(6) CreatedRelatedness	0.051***	0.413***	0.104***	0.358***	0.103***	1.000		
(7) BackedRelatedness	0.044***	0.129***	0.179***	0.208***	0.533***	0.150***	1.000	
(8) CreatedRichness	0.084***	0.151***	0.154***	0.273***	0.096***	0.162***	0.127***	1.000
(9) BackedRichness	0.068***	0.174***	0.036***	0.199***	0.148***	0.116***	0.175***	0.182***
(10) ImageCount	0.074***	0.101***	0.131***	0.155***	0.174***	0.133***	0.196***	0.064***
(11) HasVideo	0.012	0.086***	0.103***	0.119***	0.120***	0.136***	0.099***	-0.006
(12) CampaignDuration	-0.003	-0.094***	0.056***	-0.099***	-0.036***	-0.042***	-0.028**	0.111***
(13) DescriptionLength	0.065***	0.005	0.139***	0.097***	0.170***	0.097***	0.200***	0.075***
(14) Goal	-0.013	-0.029**	0.007	-0.024*	-0.022*	-0.029**	-0.018	0.014
(15) QuickUpdate	0.094***	0.080***	0.169***	0.136***	0.230***	0.043***	0.213***	0.182***
(16) NumProjectRewards	0.069***	-0.000	0.087***	0.075***	0.164***	0.011	0.173***	0.055***
(17) Readability	0.021*	0.029**	0.025*	0.015	0.047***	-0.002	0.041***	-0.028**

	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
(9) BackedRichness	1.000								
(10) ImageCount	0.314***	1.000							
(11) HasVideo	-0.002	0.314***	1.000						
(12) CampaignDuration	0.503***	-0.002	-0.093***	1.000					
(13) DescriptionLength	0.008	0.503***	0.236***	0.031**	1.000				
(14) Goal	0.275***	0.008	0.008	0.048***	0.017	1.000			
(15) QuickUpdate	0.376***	0.275***	0.130***	-0.075***	0.267***	-0.008	1.000		
(16) NumProjectRewards	0.052***	0.376***	0.106***	0.045***	0.360***	0.003	0.265***	1.000	
(17) Readability	0.314***	0.052***	0.031**	-0.033**	0.010	-0.012	0.048***	0.028**	1.000

Significance Levels: $^{***}p<0.01$, $^{**}p<0.05$, $^{*}p<0.1$.

5.3.4 Data Analysis Model

Panel Ordinary Least Squares (OLS) models are used to estimate the effects of the explanatory variables with ln*(PledgedPercentage)* as the dependent variable. The basic econometric model specification is:

$$\ln(PledgedPercentage_{ij}) = \beta \times ExperienceRelatedVars_{ij} + CONTROL_{ij} + \alpha_i + \mu_{ij}$$

where the $ExperienceRelatedVars_{ij}$ represents our focal variables that vary over each entrepreneurs and projects, and α_i captures individual entrepreneurs' unobserved heterogeneity (e.g., entrepreneur's gender, individual ability and prior industry experience before becoming an entrepreneurs, etc) that are stable over time. Since most of the explanatory variables (except for success ratios, relatedness, and the dummy variables) are highly skewed, their log transformations are used in the estimations. The

Hausman test (Allison 2005; Wooldridge 2012) suggests that fixed-effects models are preferred over random effects models for this data set, where time-invariant entrepreneurs fixed-effects α_i was eliminated in our estimation. Importantly, the fixed-effects model removes any unobserved, time-invariant heterogeneity across entrepreneurs. This approach allows the individual specific effects (e.g., entrepreneurs' innate talent) to be correlated with the focal variables. Heteroskedasticity robust standard errors are used in estimations. Variance Inflation Factors (VIF) were checked for potential multicollinearity problems and were below the recommended thresholds (Belsley et al. 2005; Cohen et al. 2013). Among all the estimation models, the maximum VIF value is 4.84 and the mean of VIF is below 2.

5.4 Results and Discussions

5.4.1 Direct and Indirect Experience

Table 5-3 shows the estimation results for direct and indirect learning. We estimate our parameters progressively by first estimating a model with control variables only (Model 1) and then adding the independent variables of interest in Models 2 and 3. As shown in Model 1, *ImageCount* is positive and significant (β=0. 019, p<0.01), which suggests that including more images to highlight information about the project increases the likelihood of project success. It is not surprising that longer campaign duration lends to higher pledged percentage (*CampaignDuration*: β=0.010, p<0.01). Consistent with our expectation, the coefficient of *DescriptionLength*, *QuickUpdate* and *NumRewards* are positive and significant (ln(*DescriptionLength*): β=0.217, p<0.01; *QuickUpdate*: β=0.674, p<0.01; *NumRewards*: β=0.033, p<0.01). Longer descriptions, quick update of project progress and a greater number of reward levels signal better preparedness of entrepreneurs, in turn resulting in higher likelihood of success. *HasVideo* and *Readability*

are not significant (*HasVideo*: β=0.053, ns; *Readability*: β=-0.000, ns). Using campaign video and increasing the textual readability for projects seem to be not significantly beneficial in improving performance. Finally, the more ambitious (i.e., greater) the fundraising goal, the less likely the project was to succeed (ln(*Goal*): β=-0.743, p<0.01).

Model 2 adds the main effects of direct and indirect experiences. The increased explanatory power between Models 1 and 2 shows that the experience variables are significant predictors of extent of success of a new crowdfunding project. The coefficients and significance of the control variables remain consistent after we add in the focal variables. The positive and significant coefficients for ln(*NumCreatedProjects*) (β=0.277, p<0.01) and ln(*NumBackedProjects*) (β=0.067, p<0.1) support H1a and H1b. Serial entrepreneurs are more likely to succeed in their crowdfunding campaigns not only when direct (founding) experience is greater but also when indirect (backing) experience is greater. To find out the relative strength of direct and indirect learning, we compare the magnitude of coefficients in Model 2. The result suggests the coefficient of direct experience is significantly higher than that of indirect experience (F=10.53, p<0.01), which lends support for H1c. This means that direct learning has significantly greater effect compared to indirect learning whereby entrepreneurs seem to be able to benefit more by launching a project than by backing a project. With the increase of both direct and indirect experience, those serial entrepreneurs who have more abundant founding experience are more likely to benefit more, which give rise to higher likelihood of entrepreneurial success.

In Model 3, we include the interaction terms of created and backed experiences and find a positive interaction effect (*Created*×*Backed*: β=0.046, p<0.05), supporting H1d. But the estimated coefficient for backed experience becomes insignificant (ln(*NumBackedProjects*): β=0.028, ns). This suggests that before entrepreneurs launch a project by themselves (i.e., without direct experience), their backing experience does not

provide benefits for their subsequent entrepreneurial efforts. But only when they have founded their own projects, their backing experiences reinforce their direct learning effects. Thus, H1d is partially supported.

Table 5-3. Panel OLS Fixed-effects Regression Results for Learning from Direct/Indirect Experiences

	DV: ln(*PledgedPercentage*)		
Variables	Model 1	Model 2	Model 3
Exploratory Variables			
ln(*NumCreatedProjects*)		**0.277*****	**0.278*****
		(0.0445)	(0.0445)
ln(*NumBackedProjects*)		**0.067***	**0.028**
		(0.0363)	(0.0409)
Created×Backed			**0.046****
			(0.0219)
Controls			
ImageCount	0.019***	0.018***	0.018***
	(0.0019)	(0.0019)	(0.0019)
HasVideo	0.053	0.064	0.069
	(0.0562)	(0.0558)	(0.0558)
CampaignDuration	0.010***	0.009***	0.009***
	(0.0016)	(0.0016)	(0.0016)
ln(*DescriptionLength*)	0.217***	0.211***	0.211***
	(0.0299)	(0.0298)	(0.0298)
ln*(Goal*)	-0.743***	-0.717***	-0.719***
	(0.0206)	(0.0210)	(0.0210)
QuickUpdate	0.674***	0.681***	0.681***
	(0.0386)	(0.0385)	(0.0385)
NumRewards	0.033***	0.034***	0.034***
	(0.0044)	(0.0044)	(0.0044)
Readability	-0.000	-0.000	-0.000
	(0.0007)	(0.0007)	(0.0007)
Constant	2.722***	2.071***	2.094***
	(0.267)	(0.279)	(0.280)
R^2	0.445	0.451	0.451
Observations	8,825	8,825	8,825
Number of entrepreneurs	3,521	3,521	3,521

Note: Category, month and year dummies along with campaign-level controls are included; Cluster-robust standard errors are reported in parentheses.
Significance Levels: $^{***}p<0.01$, $^{**}p<0.05$, $^{*}p<0.1$.

5.4.2 Successful vs. Failed Experience

We now consider the learning effects from successful and failed experiences. The estimation results are shown in Table 5-4.[26] The explanatory power of the estimation models increases significantly when we include the focal variables for successful (and failed) experiences. H2 proposed higher number of successful experiences would lead to higher likelihood of success, given the total number of direct/indirect experiences. In Table 5-4, Model 4 therefore introduces the two success ratio variables that donate the proportions of successful direct/indirect experiences. In contrast to our hypotheses, we find a negative and significant coefficient estimate for *CreatedSuccessRatio* (β=-1.036, p<0.01). This suggests that having a greater proportion of successful founding experience is negatively associated with the success of subsequent projects. One possible reason may be that entrepreneurial activities are much more complex compared to simple procedural behaviors (Cope 2005) and/or that the context is volatile. Even though each entrepreneurial campaign may be inherently unique, upon success, entrepreneurs may be replicating their prior strategies rather than exploring new actions specific to their immediate situation, ultimately leading to negative outcomes. In any case H2a is *not* supported. However, we obtained support for H2b (*BackedSuccessRatio*: β=0.130, p<0.1). The higher the proportion of successful indirect (backing) experience, the more likely entrepreneurs are to be successful in a subsequent project. To gain additional insights, we estimate a model using the *number* of successful and failed experiences as explanatory variables (in lieu of ratios). The results show that entrepreneurs' prior successful founding experiences negatively influence subsequent success (ln(*NumCreatedSuccess*): β=-0.646, p<0.01) but they can benefit from their own (i.e.,

[26] From Table 5-4 onwards, the estimation results for control variables are all consistent with those of Table 5-3. To conserve space, we no longer display them.

direct) failures (ln(*NumCreatedFailure*)*: β*=0.260 , p<0.01) and others' (i.e., indirect) successes (ln(*NumBackedSuccess*)*: β*=0.718, p<0.01). Interestingly, the positive support from previous direct (founding) experiences (ln(*NumCreatedProjects*) in Table 5-3) comes primarily from one's failed direct (founding) experiences; and the positive indirect (funding) experience (ln(*NumBackedProjects*) in Table 5-3) is only from successful indirect (funding) experiences.

Table 5-4. Regression Results for Learning from Success/Failure and Experience Relatedness and Richness

	DV: ln(*PledgedPercentage*)				
Variables	Model 4	Model 5	Model 6	Model 7	Model 8
Explanatory Variables					
ln(*NumCreatedProjects*)	**0.538*****		0.293***	0.322***	0.205***
	(0.0445)		(0.0573)	(0.0507)	(0.0583)
ln(*NumBackedProjects*)	**0.140*****		0.171***	0.104***	0.133***
	(0.0355)		(0.0359)	(0.0351)	(0.0357)
CreatedSuccessRatio	**-1.036*****		-1.119***	-1.340***	-1.330***
	(0.0498)		(0.0513)	(0.0602)	(0.0601)
BackedSuccessRatio	**0.130***		0.131*	0.144**	0.133*
	(0.0715)		(0.0752)	(0.0721)	(0.0760)
ln(*NumCreatedSuccess*)		**-0.646*****			
		(0.0610)			
ln(*NumCreatedFailure*)		**0.260*****			
		(0.0438)			
ln(*NumBackedSuccess*)		**0.718*****			
		(0.0431)			
ln(*NumBackedFailure*)		**-0.011**			
		(0.0442)			
CreatedRelatedness			**0.404*****		**0.270*****
			(0.0514)		(0.0552)
BackedRelatedness			**-0.082**		**-0.055**
			(0.1250)		(0.1250)
ln(*CreatedRichness*)				**0.170*****	**0.130*****
				(0.0180)	(0.0192)
ln(*BackedRichness*)				**-0.046**	**-0.0123**
				(0.0398)	(0.0400)
Controls	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Constant	1.981***	1.746***	1.924***	1.771***	1.780***
	(0.268)	(0.266)	(0.267)	(0.270)	(0.270)
R^2	0.493	0.499	0.500	0.502	0.505
Observations	8,825	8,825	8,825	8,825	8,825
Number of Entrepreneurs	3,521	3,521	3,521	3,521	3,521

Note: Category, month and year dummies along with campaign-level controls are included; Cluster-robust standard errors are reported in parentheses.
Significance Levels: $^{***}p<0.01$, $^{**}p<0.05$, $^{*}p<0.1$.

5.4.3 Relatedness and Richness of Experience

We now turn to experience relatedness, the results of which are also presented in Table 5-4. Hypothesis 3 proposed that the more related prior experiences are to the current initiative, the higher the performance that entrepreneurs will achieve. Two relatedness variables are introduced in Model 6 to test this hypothesis. The increased explanatory power suggests that experience relatedness variables are significant predictors of crowdfunding success. As indicated in Model 6, the positively significant coefficient for *CreatedRelatedness* (β=0.404, p<0.01) and insignificant coefficient for *BackedRelatedness* (β=0.082, *ns*) do not show full support for H3. This result suggests that relatedness between focal project and previous founded project(s) benefits the current crowdfunding performance, while it may not be the case for funding experience.[27] It seems that founding their own projects facilitates learning by enabling entrepreneurs to form a clearer mapping of actions to outcomes compared to backing projects. Related founding experience helps to develop a better understanding of the project attributes that are attractive to backers in similar contexts, and therefore such relatedness can enhance the effectiveness of direct learning. The possible reason for insignificance of backing relatedness is that it is more arduous to recognize the key underlying mechanisms that lead to success through backing a project, especially for such inherently uncertain entrepreneurial activities (McMullen and Shepherd 2006). As previously discussed, entrepreneurs as indirect learners are more likely to be challenged by causal ambiguity (Reed and DeFillippi 1990), since having only observations without knowing what was executed exactly by other actors is not sufficient to develop clear ideas about how the outcomes transpire. Thus, the relatedness in backing projects is less likely to be useful.

[27] Since the relatedness measures are coded as 0 for the observations where the created projects or backed projects are equal to 0, we wonder if this coding would affect the result. Hence, we conduct the same estimation by excluding these observations, and find consistent results with Model 6.

H3 is partially supported. Only the relatedness of direct experience facilitates learning and thereby resulting in higher fundraising performance.

Model 7 presents the results for experience richness. The explanatory power of the estimation model has significantly increased after we include the focal variables for experience richness. Hypothesis 4 proposed that richer prior experience leads to better entrepreneurial performance. The results of Model 7 show that high involvement in prior founding experience exhibits positive effect on the learning outcome (ln(*CreatedRichness*): β=0.170, p<0.01), while the engagement in backing experience does not (ln(*BackedRichness*): β=-0.046., *ns*). These results suggest that as an entrepreneur, having more timely interactions with backers during the project timeline facilitates deeper understanding of the preferable project attributes, which positively impacts subsequent success. However, richer indirect experience does not show to be helpful. From our observation, we conjecture that when entrepreneurs act as backers, they mainly use the comments to express their opinions or seek clarifications for the project they support, and such activities do not facilitate them to learn from other entrepreneurs' on how to operate their founded project. Therefore, H4 received partial support. Furthermore, we incorporate the focal variables for the relatedness and richness of experience together in Model 8, and find similar results.

5.4.4 Supplementary Analysis

5.4.4.1 Learning Dynamics

In addition to the cumulative number of direct/indirect experience, we also computed the marginal number of direct and indirect experience for different learning stages to explore more nuanced dynamic insight. More specifically, for direct learning, instead of using ln*(NumCreatedProjects)* as the independent variable (Model 2), three separate variables ln(*NumCreatedLast1*), ln(*NumCreatedLast2*) and ln(*NumCreatedLast3*) are included,

where *NumCreatedLastN* captures the number of projects created by the entrepreneur within the year that is *N* year(s) before the launch date of the focal project (*N*=1,…,3). In order to make sure that all experiences on the platform are captured, we use a subsample that includes the entrepreneurial projects that were launched after 2012. Thus, the projects before 2012 are captured in our experience variables.[28] Table 5-5 reports the results for learning dynamics, which are again presented in a hierarchical manner to understand whether the impact is sensitive to the experience in previous year(s). In Model 11, the positive coefficients of ln(*NumCreatedLast1*) (β=0.291, p<0.01) and ln(*NumCreatedLast2*) (β=0.235, p<0.1) shows that direct learning effect persist over certain period of time (2 years), but then fade away (ln(*NumCreatedLast3*): β=0.067, *ns*). However, the results for Model 8 also illustrate the indirect learning effects may be short-lived – they are significant for one year (ln(*NumBackedLast1*): β=0.065, p<0.1), but depreciate for longer lags (ln(*NumBackedLast2*): β=-0.003, *ns;* ln(*NumBackedLast3*): β=0.069, *ns*). The results suggest that learning depreciation (Argote et al. 1990; Darr et al. 1995; Parker 2013) occurs for both direct and indirect learning effects but the learning effects persist longer with direct learning. This also provides further explanation for H1c. Without clear mappings of actions to outcomes, indirect learners are more likely to suffer from knowledge depreciation. In sum, the overall effect of direct experience can be said to be stronger in terms of extent and persistence than that of indirect experience.

[28] Since our dataset time span is 6 years (2009-2014), using the second three-year's window for estimation ensures the corresponding experience variables capture the three-year's experiences on the platform.

Table 5-5. Learning Dynamics Results for Direct/Indirect Experiences

	DV: ln(*PledgedPercentage*)		
Variables	Model 9	Model 10	Model 11
ln(*NumCreatedLast1*)	**0.234*****	**0.272*****	**0.291*****
	(0.0394)	(0.0423)	(0.0440)
ln(*NumCreatedLast2*)		**0.200*****	**0.235*****
		(0.0765)	(0.0835)
ln(*NumCreatedLast3*)			**0.067**
			(0.128)
ln(*NumBackedLast1*)	**0.060***	**0.060***	**0.065***
	(0.0333)	(0.0333)	(0.0333)
ln(*NumBackedLast2*)		**0.004**	**0.003**
		(0.0299)	(0.0298)
ln(*NumBackedLast3*)			**0.069**
			(0.0449)
Constant	2.577***	2.456***	2.383***
	(0.286)	(0.289)	(0.292)
R^2	0.459	0.460	0.460
Observations	7,945	7,945	7,945
Number of entrepreneurs	3,347	3,347	3,347

Note: Category, month and year dummies along with campaign-level controls are included; Cluster-robust standard errors are reported in parentheses.
Significance Levels: $^{***}p<0.01$, $^{**}p<0.05$, $^{*}p<0.1$.

5.4.4.2 Early Success Trap

The organizational learning literature states that prior success may induce further success by virtue of the learning curve (e.g., Argote et al. 1990). However, the timing of success also matters (Kim and Rhee 2009; Rhee and Kim 2015). Success at early stages can exhibit a detrimental effect, since early success restricts the development of competencies via exploration of alternative strategies over the long run. We wonder whether such an "early success trap" exists in our context, so in Model 12 (see Table 5-6), we introduce a binary variable *EarlySuccess*, which indicates whether the focal entrepreneur was successful in the first project (1= yes; 0 otherwise). We interact this indicator with the number of prior founding experience (*NumCreatedSuccess*) and find the interaction term is negatively significant (ln(*NumCreatedSuccess*)×*EarlySuccess:* β=-0.318, $p<0.01$). It suggests the occurrence of an "early success trap" in entrepreneurship, whereby the impact of earlier successful experience is more destructive than later ones. Figure 5-2 presents the plot of the interaction effect in Model 12. We calculate and plot the

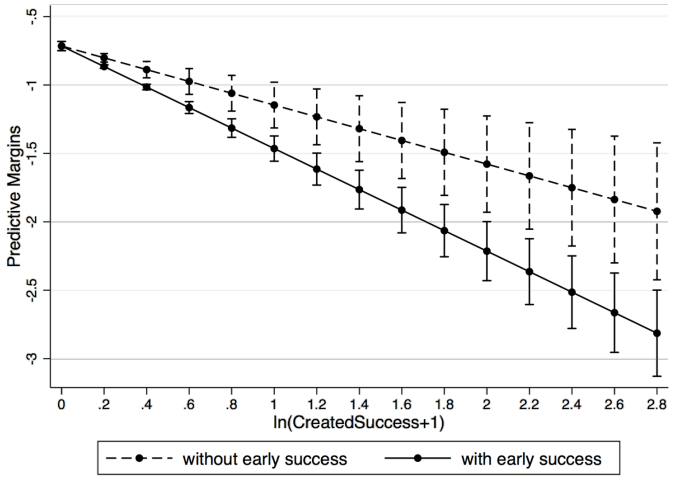
predictive margins of serial entrepreneurs with versus without early success over the range of the number of successful direct experience. From this plot, we observe that the two groups of serial entrepreneurs are exposed to the negative effects of successful direct experience, but evidently, the negative effect is much stronger for those with early successful direct experience. In Model 13, we only include entrepreneurial-related experiences and find similar results with Model 12.

Table 5-6. Regression Results for Early Success Trap

	DV: ln(*PledgedPercentage*)	
Variables	Model 12	Model 13
ln(*NumCreatedSuccess*)	**-0.432*****	**-0.384*****
	(0.0949)	(0.0990)
ln(*NumCreatedSuccess*)×*EarlySuccess*	**-0.318*****	**-0.388*****
	(0.0941)	(0.0989)
ln(*NumCreatedFailure*)	0.269***	0.307***
	(0.0434)	(0.0437)
ln(*NumBackedSuccess*)	0.680***	0.703***
	(0.0437)	(0.0434)
ln(*NumBackedFailure*)	-0.012	-0.008
	(0.0440)	(0.0453)
Constant	1.792***	1.802***
	(0.267)	(0.264)
R^2	0.501	0.505
Observations	8,825	8,825
Number of Entrepreneurs	3,521	3,521

Note: Category, month and year dummies along with campaign-level controls are included; Cluster-robust standard errors are reported in parentheses.
Significance Levels: $^{***}p<0.01$, $^{**}p<0.05$, $^{*}p<0.1$.

Figure 5-1. Comparison of Learning Effects with and without Early Success



5.4.4.3 Behavioral Changes after Success/Failure

Aiming to obtain further insights into how serial entrepreneurs manage their project after successful or unsuccessful experiences, we conduct further analysis to show how changes in various project attributes relate to project outcomes (see Table 5-7). The results suggest that for those entrepreneurs who first succeed then failed (see Panel 1; Success→Failure), they tend to dramatically increase their funding goals (from $15,188 to $34,410), however, other project properties (i.e., the length of project description, the number of rewards, whether they are quick to update) have significantly decreased or do not show significant changes. On the other hand, entrepreneurs who sustain success (see Panel 2; Success→Success) tend to increase their funding goal more cautiously (from $13,948 to $17,707). The means of *DescLength*, *NumRewards* and *QuickUpdate* do not show significant changes, but they still remain relatively high (*DescLength*: from 6,217 to 6,271; *NumRewards*: from 11.36 to 11.02; *QuickUpdate*: from 0.70 to 0.71) especially compared to that in Panel 1 ((*DescLength*: from 5,310 to 5,243; *NumRewards*: from 10.75 to 9.04; *QuickUpdate*: from 0.67 to 0.42)), which suggest that they are still well-prepared for subsequent projects. Furthermore, even though *ImageCount* and *Richenss* are significantly increased in both Panel 1 and Panel 2, the average values are much higher than in Panel 2.[29] These results are consistent with our previous arguments that "early success trap" occurs when successful entrepreneurs following previous successful (but inferior) strategies (i.e., relatively low means of attributes of first campaign in Panel 1) without additional exploration but with an expectation of further success. In fact, they are more prone to failures. The lack of preparedness and responsiveness (i.e., slow response to update and lack of involvment) may have resulted in the subsequent failed

[29] We notice that *ImageCount* and *Richness* significantly increased in all the panels. It suggests that later projects on the platform tend to have more updates and comments – a change along with the maturity of the platform. Also, entrepreneurs tend to involve more in their second project compared to the first one, but the extent of changes vary a great deal.

outcomes. This is also consistent with the commonly observed characteristic of overconfidence of entrepreneurs (Hayward et al. 2006; Moore and Cain 2007). Based on the hubris theory of entrepreneurship, entrepreneurs are inclined to overestimate their likelihood of success and erroneously expect success for themselves. A successful founding experience, especially early success, provides them with the bravado to seek new and greater challenges to launch more ambitious projects (e.g., higher funding goals), which leads to higher likelihood of failure (Hayward et al. 2006).

Additionally, the comparison between those entrepreneurs who achieve success after failure (see Panel 3; Failure→Success) and those who remain unsuccessful (see Panel 4; Failure→Failure) shows that entrepreneurs who initially experience failure seem to make certain efforts to be better-prepared for their subsequent projects (c.f., significant increase of *ImageCount* and *Richness* in both panels). The reason for consecutive failure seems to be that those projects do not have a high enough quality and they did not actively engage with the backer community (c.f., significant decrease of *NumRewards* and relatively low value of *QuickUpdate* and *Richness* in Panel 4).

Table 5-7. Mean Comparisons of Project Attributes Changes

	1st Campaign	**2nd Campaign**	***t*-value**	**1st Campaign**	**2nd Campaign**	***t*-value**
	Panel 1: Success → Failure (*N*=350)			Panel 3: Failure → Success (*N*=877)		
Goal	15188	34410	**5.34*****	32715	11041	**-12.03*****
ImageCount	11.66	12.94	**2.03****	11.64	15.82	**11.24*****
DescLength	5310	5243	**-0.32**	5603	6121	**3.79*****
NumRewards	10.75	9.41	**-3.54*****	10.51	10.62	**0.47**
QuickUpdate	0.67	0.42	**-7.56*****	0.56	0.72	**8.24*****
Richness	1.35	38.54	**7.22*****	1.53	16.18	**15.39*****
	Panel 2: Success → Success (*N*=824)			Panel 4: Failure → Failure (*N*=1470)		
Goal	13948	17707	**2.55****	75351	39504	**-1.76***
ImageCount	13.55	16.94	**6.26*****	8.57	9.79	**4.95*****
DescLength	6217	6271	**0.35**	4303	4397	**1.05**
NumRewards	11.36	11.02	**-1.23**	8.26	7.82	**-3.33*****
QuickUpdate	0.70	0.71	**0.46**	0.38	0.36	**-1.35**
Richness	2.16	51.74	**10.29*****	0.47	6.40	**7.46*****

Note. 1) *Richness* donates the sum of entrepreneurs' posting activities (updates and comments) during the project timeline. 2) The results of paired t-test between the first and second campaign of serial entrepreneurs are shown in the table.
Significance Levels: $^{***}p<0.01$, $^{**}p<0.05$, $^{*}p<0.1$.

5.5 Conclusion and Implications

The development of entrepreneurship is accompanied by a process of learning (Gruber et al. 2008; Minniti and Bygrave 2001), during which entrepreneurs' subjective stock of knowledge accumulates on the basis of prior experience (Cope 2005). This study proposes and empirically examines the effects of entrepreneurs' prior experience on the performance of subsequent entrepreneurial activities. Specifically, we focus on serial entrepreneurs and take a dynamic perspective by investigating how entrepreneurs change their activities. The entrepreneurial learning effects are examined at a fine-grained level. Drawing upon the theory of organizational learning, we conceptualize the entrepreneurial learning from multiple dimensions of experience. We propose that entrepreneurs not only learn directly from their own founding experience but also indirectly from engaging in other entrepreneurs' initiatives. The influence of prior experience is heterogeneous and depends on the content of the experience; the sources and outcomes of experience, as well as experience relatedness and richness also have an effect on subsequent entrepreneurial performance.

Using six years of panel data involving 3,521 serial entrepreneurs from a crowdfunding platform, we empirically test our hypotheses. Consistent with our predictions, when entrepreneurs accumulate their experience through directly creating their own and indirectly backing others' projects, both types of experiences resulted in enhanced performance. The effect of direct learning is relatively higher than that of indirect learning. Indirect learning is also more susceptible to suffer from learning depreciation. When both of direct and indirect experiences exist, their interactive effect on subsequent performance is of much greater significance than the sum of their independent effects. Further, we find that successful founding experience may have a detrimental effect on subsequent success, whereas successful backing experience has positive impacts. Thus, serial entrepreneurs seem to learn from their own failures and

others' successes. Those who have past success founding experiences are more likely to follow similar strategies without sufficient preparation for next initiatives but with an expectation of continued success, but instead they end up with less than ideal outcomes. The negative effect of success is more salient in early successful direct experience. In addition, relatedness and richness of experience are found to not always to be beneficial. Only the related and rich prior direct experience increases learning outcome.

5.5.1 Contributions

Our study advances knowledge in several areas. First, we add to the growing literature about serial entrepreneurship by taking a dynamic perspective towards its development. Following Parker (2013), we answered the call of Ucbasaran et al. (2008) for more research on habitual entrepreneurship (i.e., entrepreneurs with prior experience) that investigates the performance of serial entrepreneurs with a large, representative and longitudinal dataset. This contrasts with much prior work which has often focused on one of a series of businesses by serial entrepreneurs, which we deem insufficient to uncover *across*-business dynamics. Our focus on multiple entrepreneurial initiatives of entrepreneurs through a continuous observation of whether and how entrepreneurs performance improves with the accumulation of different types of experience as well as what entrepreneurs change to their subsequent business after success or failure. This focus emphasizes the essential role of entrepreneurs (through their experience) rather than firms (through firm characteristics) in the process of entrepreneurship (Ucbasaran et al. 2008). Furthermore, the dynamic perspective enables us to generate insights on how entrepreneurial effects change over time. Particularly, consistent with the notion of knowledge depreciation (Argote et al. 1990; Darr et al. 1995), although serial entrepreneurs are in a position of benefiting from prior experience, our results also

suggest that the positive influence of founding businesses decays as time passes (Parker 2013).

In addition, this study identifies indirect experience as an important source of entrepreneurial learning. Researchers increasingly argue that entrepreneurs acquire knowledge and capabilities through entrepreneurial activities in the environment (Guiso et al. 2015). Apart from founding their own ventures, entrepreneurs benefit indirectly by engaging in the innovation process of other entrepreneurs (Rae 2006). Despite the importance of indirect learning, past literature on entrepreneurial learning has been salient in this aspect. Using backing activity in crowdfunding as a proxy for indirect learning, we examine the effect of indirect experience and how it occurs in the presence of direct learning. Our findings acknowledge the benefit of indirect entrepreneurial activities, as entrepreneurial performance can be improved through both direct and indirect experience. Importantly, due to the complex nature of entrepreneurship, entrepreneurs may not extract as much lessons from indirect experience as direct experience, as indirect learning effect is shown to be weaker and to depreciate faster than direct learning. This study therefore contributes to the research on entrepreneurial learning that seeks to understand the potential approaches through which entrepreneurs can achieve performance enhancement.

Third, our work contributes to the literature on organizational learning. Prior studies investigating learning effects have been primarily situated in traditional industries, such as manufacturing (e.g., Argote et al. 1990) and service industries (e.g., Reagans et al. 2005), where organization typically deal with *repeated* tasks. We extend the learning literature to *knowledge-based* and *innovation-oriented work* (e.g., entrepreneurship) where less routinization (Boh et al. 2007; Cope 2011) and more creative works are entailed. Some of our findings are in stark contrast to the existing results in organizational learning literature, which predominantly documents positive

impacts of successful experiences (e.g., Greve 2003c; Kim et al. 2009). Specifically, prior research argues that organizations (and individuals within organization) can learn fruitfully from their successful experiences, since success helps them develop a more comprehensive and richer repertoire of appropriate strategies (March 1991). Similar strategies will be embraced for future tasks. Nevertheless, for entrepreneurial ventures, where entrepreneurs need to develop fledging and innovative ideas every time, this may not be the case. Instead, this study shows a strong evidence that past successful direct founding experience is *negatively* associated with subsequent entrepreneurial performance. Entrepreneurs are likely to fixate their strategies on previously successful ones, rather than exploring situational actions given the complex and dynamic context. Unfortunately, the naturally-occurring experiential learning-based strategy (i.e., repeating what seems to produce success and avoiding what seems to produce failures) does not ensure continued success in entrepreneurial activities, since every entrepreneurial initiative is inherently a new task. Further analysis suggests that "early success traps" (Kim and Rhee 2009; Rhee and Kim 2015) are also prevalent in our context. The impediment for learning from successful founding experience is stronger when the success occurs at early stages or when only limited experience is accumulated (Denrell and March 2001). Our investigation of learning effects in entrepreneurship context informs and contributes further understanding the learning theory.

This study also contributes to the organizational learning literature by characterizing experience at a fine-grained level, which enables us to develop more nuanced insights into the learning effects (Argote et al. 2003; Argote and Todorova 2007). Specifically, we examine learning from several dimensions: direct vs. indirect, successful vs. failed as well as relatedness and richness of experience. Consistent with prior research, we find empirical evidence of both *experiential* (Schilling et al. 2003) and *vicarious* learning (Bandura 1969; Bandura and McClelland 1977) in entrepreneurial

activities. However, in contrast to prior learning literature, where routinized tasks were typically investigated (Boh et al. 2007), entrepreneurs, who mainly deal with problem solving and novel activities, seem to benefit from their own failure and others' success. Their own successful experiences may confine them into "early success traps" (Kim and Rhee 2009; Rhee and Kim 2015). When entrepreneurs have the tendency to reproduce actions that have been successful, it may result in a bias against alternatives that seem to be new and risky but more pertinent to their subsequent initiatives (Denrell and March 2001). Further, this finding is consistent with the entrepreneurship literature which states that entrepreneurs tend to be overconfident (Hayward et al. 2006; Moore and Cain 2007), meaning that they are inclined to overestimate the occurrence of positive events and erroneously expect success without sufficient preparation. We believe that such over-confidence may not be a personality trait (i.e., innate trait or nature) but a consequence of experiential learning and competency traps (i.e., learned behavior or nurture). Moreover, the positive influence of failed founding experiences aligns with previous arguments that after experiencing failure, entrepreneurs are less likely to report over-confidence (Ucbasaran et al. 2010) and therefore tend to be better prepared for next venture (Cope 2011). Additionally, the complexity of entrepreneurial tasks facilitates our examination of the effect of experience relatedness and richness. Our study suggests that it is not only the number of experiences that matters (as has been the predominant view in the existing literature), but also the content of experience and the extent of involvement in each of the experience that is also important, as timely and deep involvement in related domains seems to improve learning effectiveness.

Finally, this research contributes to crowdfunding literature. Existing studies have largely devoted to exploring the potential drivers of successful crowdfunding projects. For example, the influence of some drivers such as project quality (Mollick 2014), project updates (Xu et al. 2014) and returns provided by the project (Xiao et al.

2014) have been examined. Generally, existing attention has paid to the characteristics of projects, neglecting the notion that entrepreneurs develop competencies over time. We add to this strand of literature by emphasizing the role of entrepreneurs in launching a successful project. We use a panel-level analysis approach and find that serial entrepreneurs accumulate experience-based knowledge, which in turn can be leveraged to facilitate performance improvements.

From the practitioner perspective, we provide guidance to entrepreneurs on how to design experiences to promote learning that may help to ultimately lead to entrepreneurial success. In particular, entrepreneurs should avoid overconfidence, especially when they experience early success. Rather than fixating themselves to existing seemingly successful strategies, they are recommended to explore new strategies that fit well with their new innovative ideas. When they found their new business, they will benefit more if they have deep involvement in the experience. Moreover, entrepreneurs should not be discouraged in the presence of failure. Failure does not mean the adopted strategies are not feasible and should be discarded. Some strategies may not initially show to be reliable and effective, as they require practice to achieve their potential. It also typical that one alternative not working well in one context is actually shown to be effective in other domains. Our findings imply that entrepreneurs with failed experience are less susceptible to cognitive bias and more rationally treat success. Failure stimulates entrepreneurs to be well prepared for their next venture which increases the likelihood of superior future performance.

In addition, our findings provide implications for entrepreneurship and innovation centers. Since the learning from other successful entrepreneurs is beneficial, interactive entrepreneurial communication forums can be regularly organized to facilitate experience sharing among entrepreneurs. Entrepreneur mentoring program needs to be provided to deliver crucial advice and real-world experience to novice and experienced

entrepreneurs. Advisors are encouraged to tailor their suggestions based not only on the venture itself but also considering the past experience of entrepreneurs.

5.5.2 Limitations and Future Research

This study has a few limitations that suggest directions for future research. First, the study context might be specific and the crowdfunding platform represents one type of entrepreneurial activities that may not be generalizable to other forms of entrepreneurship. The entrepreneurial actions in crowdfunding are characterized by innovativeness and advanced technologies, which might be distinct from other industries such as transportation and real estate. However, there is evidence showing that a great number of crowdfunding projects have turned out to be ongoing ventures afterwards (Kuppuswamy and Mollick 2016; Mollick and Kuppuswamy 2016). We posit that our findings could be generalized to innovation-based entrepreneurship, typically including small business ventures that are characterized by high-tech and new product development. Also, one avenue for future research would be to investigate how the entrepreneurial learning effects occur in other traditional industries and whether the specific characteristics of each industry lead to different outcomes. Second, a strength in this paper is that we are able to observe multiple founding attempts for each entrepreneur, but the majority of entrepreneurs in our sample have two entrepreneurial-related experience, even though we code experience that are related and less-related to entrepreneurship. Following this point, it would be very interesting to examine the lasting effect of entrepreneurial learning with a dataset that captures the long-term activities for serial entrepreneurs. Due to our data limitations, future research can also examine how the success trap evolves with the accumulation of experience using dataset that keeps track of a large amount of successful and failed entrepreneurial experience.

In conclusion, serial entrepreneurship has become an important topic and has garnered an increasing amount of attention from academics and practitioners. This study

investigates the learning effects of serial entrepreneurs using a large and longitudinal dataset. By examining the entrepreneurial learning at a fine-grained level involving multiple dimensions of experience, we offer nuanced insights surrounding the entrepreneurship and learning literature. Our study highlights the importance of understanding the developmental process of entrepreneurship. It is hoped that this study provides a fertile ground for future work.

CHAPTER 6 ESSAY II – LEARNING FROM PERFORMANCE FEEDBACK: THE DYNAMIC INTERPLAY BETWEEN FUNDRAISING PATTERNS AND ENTREPRENEURIAL STRATEGIES IN CROWDFUNDING

6.1 Introduction

Crowdfunding has been recognized as a novel mechanism for fundraising and has recently garnered substantial attention from both researchers and practitioners (Burtch et al. 2013a; Hong et al. 2015; Lin et al. 2014; Mollick and Nanda 2016). It supports the financing of an initiative, usually in the form of a project or a venture, by a large group of mostly unprofessional individuals, called crowdfunders or backers, instead of professional parties (e.g., venture capitalists, business angels) (Hahn and Lee 2013; Schwienbacher and Larralde 2010). Some notable crowdfunding platforms include Kickstarter, IndieGoGo, RocketHub, to name a few. Since their inception, these crowdfunding platforms have helped new ventures to raise billions of dollars (Massolution 2015) and the volumes and amounts of transactions continue to increase (Liu et al. 2015; Yang et al. 2015).

One distinguishing feature of crowdfunding arises from its enablement of ongoing and timely interactions between entrepreneurs and contributors (i.e., backers) (Yang and Hahn 2015). The IT-enabled crowdfunding platforms facilitate entrepreneurs to interact directly with potential (and committed) contributors to obtain timely and immediate feedback once their campaign is under way. The feedback could be reflected as realized demand (i.e., amount of pledges) or qualitative comments on the projects. Based upon the feedback, entrepreneurs are able to gauge the market response for their projects (i.e., products) and at the same time enact strategic actions for managing the crowdfunding campaign. For instance, they can make refinements to their projects by revising the project description or by posting project updates accordingly in light of

concurrent fundraising progress. Facilitated by the IT-enabled nature of crowdfunding, this dynamic process allows entrepreneurs to refine their initiatives along the way, the aim of which is to achieve successful fundraising goals.

Despite the inherent dynamic nature of the fundraising process, there is a notable dearth of attention on this aspect of crowdfunding. A growing body of IS research in crowdfunding has focused on the potential drivers of successful campaigns. Some factors, such as creators' backing history (Koch and Siering 2015; Zvilichovsky et al. 2013), project quality (Mollick 2014) and design of project rewards (Xiao et al. 2014) are found to be influential in project funding performance. By and large, extant research has taken a static view of crowdfunding success, where they implicitly assume project attributes, such as project rewards, even though they could be dynamically adjusted within the funding period, to be unchanged throughout the campaign. However, how entrepreneurs manage their projects plays an essential role in their crowdfunding success. Therefore, in order to better understand what works and what doesn't work in crowdfunding, we first need to understand how entrepreneurs are actually dynamically taking actions over the fundraising process to manage their projects.

The void of studies taking a dynamic perspective is possibly attributed to the difficulty of data collection. Crowdfunding platforms usually display the final state of completed projects (except for those are still on-going) rather than the dynamic changes.[30] Nevertheless, as previously discussed, the crowdfunding cycle is a dynamic process; a project's contemporaneous changing status (e.g., a sudden surge in backers / pledges) may influence the entrepreneur's behaviors in managing the project, and the strategies taken by the entrepreneur may in turn alter subsequent fundraising outcomes.

[30] For example, the number of backers and the funding amount within each day across the whole funding period are not available. We are only shown the final state of projects once they are completed.

In other words, the entire fundraising cycle is a continuous interaction process among backers, project concurrent performance as well as entrepreneurs.

The present study therefore aims to fill this void by uncovering the dynamics of *how fundraising patterns affect subsequent entrepreneurial strategies in managing the project during the funding process* and *how entrepreneurs' actions during the course influence final funding performance*. Exploring this dynamic fundraising process enables us to understand what entrepreneurs do and change and how these behaviors are influenced by their concurrent project performance. More specifically, we use the theoretical lens of the performance feedback model (Greve 2003c) – a dominant framework for understanding managerial decision making – to conceptualize this dynamic fundraising process. The performance feedback model states that decision makers receive feedback on their performance, with respect to their aspiration level, and such feedback informs their following strategies. Based upon this theory, we posit that entrepreneurs evaluate their concurrent performance relative to their pre-defined funding goal and in turn adjust their subsequent activities based on this evaluation. In particular, we intend to identify two types of strategic behaviors from the potential courses of actions: *exploitative actions*, characterized by incremental adjustments of existing competency, and *explorative actions*, characterized by discovering new approaches for the project. We propose hypotheses regarding the influences of concurrent performance on entrepreneurs' explorative and exploitative actions, the effects of taking actions on crowdfunding outcome as well as the moderating role of time in this feedback cycle.

The proposed hypotheses are empirically examined based on a unique dynamic dataset of daily observations we collected from a leading reward-based crowdfunding platform. We find that there is a positive relationship between concurrent funding performance and probability of taking exploitative actions. In general, entrepreneurs are less likely to take only explorative actions when the performance increases, as it is

usually conducted together with exploitative actions. Entrepreneurs are more sensitive to performance changes when campaign deadline draws near. In addition, entrepreneurial strategic actions are shown to have positive effects on eventual crowdfunding performance, and early actions turn out to be more helpful.

This study makes several contributions to existing literature. First, we extend crowdfunding literature by focusing on the dynamics of entrepreneurial strategies within fundraising duration. Second, we add to the performance feedback theory by examining more nuanced dimensions about strategic actions induced by concurrent performance. Third, this study enriches the stream of literature that emphasize the role of time in the process of learning from performance feedback. Finally, practical implications are yielded to entrepreneurs on how to respond high/low funding performance relative to their funding goals.

6.2 Theoretical Background and Framework

Building on the performance feedback model of organizational learning, we posit that entrepreneurs take strategic actions on their campaigns with reference to the contemporaneous feedback they obtain *during* the fundraising process, where the objective of these actions is to attain fundraising success. The aspiration-performance feedback model, originating from Cyert and March's (1963) behavioral theory of the firm, has emerged as one of the dominant frameworks for understanding managerial decision making (Argote and Greve 2007; Greve 2003c). According to this model, decision makers use an aspiration level – an acceptable level of accomplishment – to evaluate current performance and subsequent actions are informed by the performance relative to this aspiration level. The *aspiration level* refers to the "smallest outcome that would be deemed satisfactory by the decision maker" (Schneider 1992, p. 1053) or the borderline between perceived success and failure (Greve 2003c). The aspiration level

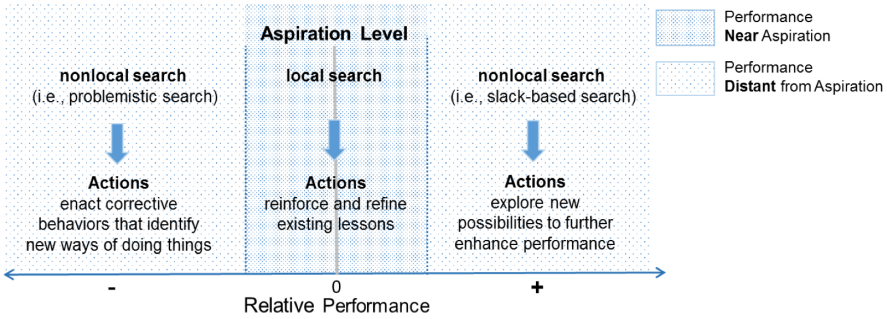
categorizes performance to contemporaneous success and failure, which in turn influences not only the decision marker's willingness to take actions but also the type of action she will consider. In particular, this influence depends on whether performance is a) distant from or near the aspiration level and b) below or above the aspiration level (Baum and Dahlin 2007; March and Shapira 1992).

As to the first dimension – i.e., distant or near, when an organization is performing near the aspiration level, the decision maker's focus of attention is on the aspiration level (i.e., attaining aspiration level if performance is below aspiration, or maintaining above aspiration performance), whereby current efforts would be reinforced by exploitation (Lehman et al. 2011; March and Shapira 1987). In such a situation, decision makers are inclined to maintain the status quo or at best refine or conduct minor/incremental adjustments to existing strategies in the form of local search, the purpose of which is to reduce uncertainty in the quality and efficiency of task performance. Exploration-oriented actions would be avoided as they are associated with risks and hence might be detrimental to current efforts (Baum and Dahlin 2007). Alternatively, when the performance is far below or far above the aspiration level, nonlocal search becomes dominant, which would be reflected as explorative actions that seek identifying new ways to do things or new things to do (Baum and Dahlin 2007; Baum et al. 2005).

As to the second dimension – i.e., below or above aspiration, organizations performing far below aspiration levels engage in problemistic search and conduct goal-directed adaptation, such as undertaking changes if acceptable solutions to problems can be found (Cyert and March 1963; Greve 1998), making risky choices (Lehman and Hahn 2013), taking exploration actions (March 1991), enacting innovation (Bolton 1993) or even financial misrepresentations (Harris and Bromiley 2007). These actions are in the form of nonlocal search (Baum and Dahlin 2007), whose aim is to seek new alternatives

and courses of actions and in turn to remedy the performance shortfall (Singh 1986). The extent of problemistic search and actions is typically related to how far performance is below the aspiration point. The performance just below aspiration levels leads to local search that reinforces old certainties and targets for aspiration attainment. Alternatively, organizations with performance just above aspirations are also inclined to engage in local search and try to avoid any action that could cause performance to fall below aspirations (March and Shapira 1987). But when the performance is far above the aspiration level, decision makers may engage in more exploratory actions in the form of slack-driven search. This arises from the idea that overperforming generates extra resources for and instills confidence in organizations, so it induces decision makers to pursue new approaches (Lant 1992; Levinthal and March 1981; March and Shapira 1992) (see Figure 6-1).

Figure 6-1. An Illustration of the Relationship Between Relative Performance and Strategic Behaviors



6.2.1 Behavioral Antecedent: Relative Performance

The performance feedback model posits that, organizational decision makers are more likely to conduct local search, which is akin to exploitative actions that refine existing efforts, when organization performs near the aspiration level, while the probability declines when performance departs away from it. On the contrary, nonlocal search that explores new possibilities to correct performance shortfalls or further enhance

performance surpluses is less likely to occur when concurrent performance is around the aspiration level (Baum and Dahlin 2007).

For crowdfunding campaign, entrepreneurs need to set a fundraising goal to achieve by project deadline. It can be conceptualized as a natural aspiration level for entrepreneurs, as it denotes the borderline between project success and failure (Greve 2003c).[31] Given the dynamic fundraising process, both entrepreneurs and backers are allowed to make changes to their previous decisions; entrepreneurs are able to change the approach they present the project or post updates to inform backers about new product information, and backers are able to cancel their pledge as long as it occurs before the campaign deadline.[32] It is therefore reasonable to expect that entrepreneurs are exposed to a higher level of uncertainty when the pledged level of a project is around its funding goal (i.e., aspiration level). When it is slightly under- or over-performing, entrepreneurs are more concerned with their concurrent performance, as even minor changes may lead to disparate funding outcomes. In such a situation, the high level of uncertainty over funding goal attainment induces entrepreneurs to choose less risky and exploitative alternatives (Lehman et al. 2011; March and Shapira 1987). The exploitation is characterized by *extension and refinement of existing competency*, whose returns are positive and proximate (Greve 2007; March 1991). Since the project has already achieved a certain amount of funding, existing efforts have shown to be feasible and therefore are more likely to be refined in this condition. Hence, it is reasonable to expect a higher probability of taking exploitative actions in light of performance around the fundraising goal. Exploitative actions can exhibit as posting project updates for progress

[31] When constructing the funding goal, entrepreneurs are likely to take into consideration of their experiences in prior projects (creating/backed projects if they have) as well as their observation of other related projects on the platform. For example, if their prior launched project has a goal that has been achieved and the prior project has similar content to current one, they tend to rationally increase their goal in the current project.

[32] Cancelling pledges is quite common in crowdfunding platforms. The average cancellation rate is 5%. For details, see: http://stonemaiergames.com/kickstarter-lesson-79-cancellations/.

report, posting responses to frequently asked questions (FAQ), as such actions are marked by strengthening and refining the status quo. For example, posting project progress report signals the feasibility and developmental progress of proposed product functions. Posting frequently asked questions demystifies doubts raised by current backers.

When the pledged level is far below the pledging goal, it would seem that existing strategies will not be able to produce satisfactory outcomes. When the pledged level is far above it, current efforts have shown to be highly effective. In these two cases – i.e., when there is high discrepancy between performance and aspiration level, entrepreneurs have less incentive to make incremental refinement to existing competency, resulting in lower probability of exploitative actions. Hence, we propose:

> ***Hypothesis 1****: During crowdfunding process, the likelihood that entrepreneurs will take exploitative actions is associated with the distance between pledged level and funding goal, such that the nearer the distance, they are more likely to take exploitative actions.*

As mentioned above, performance discrepancy from aspiration level stimulates decision makers to conduct nonlocal problem- or slack-driven search for new ways to enhance existing strategies or new challenges to achieve (Baum and Dahlin 2007). This suggests that when performing near aspiration, decision makers are less likely to enact explorative actions as it is associated with risks that may cause performance to drop, while when failing to achieve or far exceeding aspiration levels, more explorative actions are expected to uncover new approaches to remedy performance shortfall or further enhance the performance.

In crowdfunding, the higher level of uncertainty around funding goal reduces entrepreneurs' likelihood of performing explorative actions, which are characterized *by discovering new approaches and changing the status quo to achieve their goals* (Greve 2007). Entrepreneurs' explorative actions include major changes in project presentations,

posting updates about new product features and adding new reward tiers, to name a few. Such actions may dissatisfy current backers and result in cancelled pledges, or increase the risk of losing prospective backers.

When fundraising performance is low, existing efforts may not be shown to be effective enough in attracting backers. In such a situation, entrepreneurs are likely to search for new strategies of showcasing their project or to propose new product features that may be better received by backers. Alternatively, when the pledged funding is higher than funding goal by a large margin, entrepreneurs may experiment with slack resource (i.e., surplus financial resources) rather than to focus merely on maintaining aspiration attainment. This slack-based search is likely to produce explorative actions, such as stretch goals, which may involve high risks for entrepreneurs (Greve 2003c).[33] Hence, a higher likelihood of explorative actions is expected when entrepreneurs under- or over-perform to a great extent. Based on these arguments, we hypothesize:

> ***Hypothesis 2:*** *During crowdfunding process, the likelihood that entrepreneurs will take explorative actions is associated with the distance between pledged level and funding goal, such that the nearer the distance, they are less likely to take explorative actions.*

6.2.2 The Role of Time in Strategic Behaviors

The organization theory literature suggest that *time* plays a central role in organization processes (Ancona et al. 2001; Gavetti and Levinthal 2000; Mitchell and James 2001; Zaheer et al. 1999). Managerial behaviors are frequently associated with an explicit deadline (Jewell 2003). Performance feedback also typically occurs within a pre-determined duration for attaining desired levels of performance (Lehman et al. 2011). For

[33] In the "stretch goal" case, it involves risks because stretch goal typically comes with promises of new rewards or other incentives, which may put the project at risk. It has been shown that stretch goals leave some projects overwhelmed, over-budget and behind schedule.
Furthermore, some backers may support the project for some stretch-goal related reward. If the "stretched" goal cannot be met, it leads to bad experiences for backers. See: https://www.kickstarter.com/blog/think-before-you-stretch

example, project groups often face a specified completion date/time when they are about to finish a designated task (Labianca et al. 2005; Waller et al. 2002), and sales teams are usually required to meet certain sales goals in a timeframe of a quarter or a year (Mezias et al. 2002). Research in this subject has shown that managerial decisions are different in the presence of deadlines (Jewell 2003). It posits that time – a form of temporal resource – plays an important role in managerial decision making, in that it shapes decision makers' perceptions of current performance (Humphrey et al. 2004; Lehman et al. 2011) as well as their motivations (Waller et al. 2002), which in turn influences the behaviors they conduct (Labianca et al. 2005). It has been argued that an imminent deadline stimulates decision makers' to pay more attention to time (Waller et al. 2002). It also acts as a temporal goal that may elicit greater motivations from managers for target accomplishment (Seers and Woodruff 1997). Based on these arguments and the variation of performance within a period, time availability can be expected to shape the influence of performance on decision makers' strategic behaviors.

In the case of crowdfunding, the role of time is even more salient. Entrepreneurs need to raise in excess of the predefined funding goal by the end of a project deadline. If the current pledged level is around the funding goal, as the deadline draws near, their perceived uncertainty of achieving the goal is heightened. The rationale is that the depletion of time leaves them with less chances to reach a funding level that can be deemed to exceed the goal by some "safe" margin. For example, if the current pledged level is slightly higher than funding goal and time resources wane, entrepreneurs are left with less time to attract additional subsequent backers. They are aware of the risk that existing backers may choose to cancel their pledges. This results in higher perceived uncertainty in eventual funding success. While if this occurs in the mid of fundraising process, they tend to be more confident that the time remaining is sufficient to attract

more backers so that final success would be attainable. The distant deadline involves lower uncertainty as the risk of losing existing backers is less salient.

Furthermore, the management literature suggests that decisions typically involve both positive and negative outlooks. Individuals tend to avoid thinking with a negative outlook (i.e., less pessimistic) when deadlines are distal, while they are more likely to be pessimistic and critical as deadlines approach (Loewenstein and Prelec 1991). Following this line of reasoning, the concern about losing existing backers becomes more salient when less time remains in the fundraising process. Based on the two mechanisms, we argue that, when the funding performance is near the aspiration level, the more proximal the deadline, the more uncertainty entrepreneurs would perceive. Hence, an imminent deadline drives them to predict end-of-period performance with less confidence, which leads to more exploitative actions as those actions involves incremental refinement of existing strategies where more positive outcomes and less risks are entailed.

But when the pledged level is far below or above the fundraising goal, entrepreneurs are less inclined to enact exploitative actions to refine existing strategies, as they are shown to be unattractive or highly effective. The approaching deadline even reduces their probability of taking exploitative actions in such conditions. Overall, the proximal deadline strengthens the relationship between performance and aspiration level (see Figure 6-2a). Hence, we propose:

> ***Hypothesis 3****: The effect of H1 is moderated by the proximity of crowdfunding deadline, such that when the project is <u>underperforming</u> or <u>outperforming</u>, the relationship between relative performance and likelihood of taking <u>exploitative</u> actions becomes <u>stronger</u> in later funding stage.*

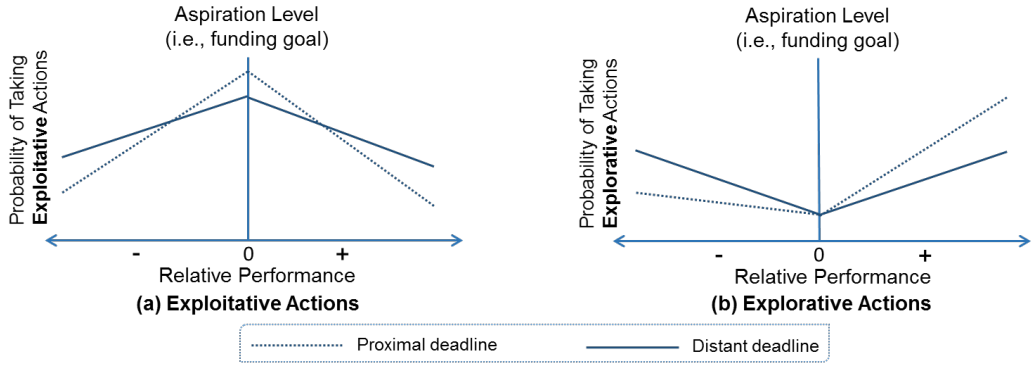
Likewise, we propose that the relationship between relative performance and explorative actions also varies with deadline proximity. Entrepreneurs in underperforming projects, especially those whose performance is far below the aspiration level, will tend to become less concerned with the funding goal attainment as deadline

approaches, since they are more likely to regard the aspiration level as unattainable. As a result, they may fall prey to learned helplessness (Abramson et al. 1980) and respond with greater rigidity because they are incapable of generating alternative courses of actions (Staw et al. 1981). In that event, the likelihood that they conduct explorative actions would decrease as remaining time wanes. For example, for entrepreneurs who only receive a small proportion of their pledging goal (e.g., 5%), it is reasonable to expect that they may choose to give up before the deadline arrives, as they are likely to perceive that there is little chance for them to compensate for the performance shortfall within a short period.

On the other hand, when the pledged level is beyond the goal by a large margin, as deadline approaches, entrepreneurs will tend to become increasingly drawn to experimenting with excess resources (e.g., financial resources) with deadline proximity as a result of slack-based search. The salience of slack resources in later funding stage stimulates entrepreneurs to engage in more explorative behaviors than at early funding stages. They believe that they have extra resources to explore new alternatives that might promote higher level of success (Baum et al. 2005; Lehman et al. 2011). Therefore, with deadline proximity as a moderator, the relationship between (relative) funding performance and explorative actions should be weakened when it is far underperforming and be strengthened when it is far outperforming (see Figure 6-2b). Taken together, we propose:

> ***Hypothesis 4a****: The effect of H2 is moderated by the proximity of crowdfunding deadline, such that when the project is underperforming, the relationship between relative performance and likelihood of taking explorative actions becomes weaker in later funding state.*
>
> ***Hypothesis 4b****: The effect of H2 is moderated by the proximity of crowdfunding deadline, such that when the project is outperforming, the relationship between relative performance and likelihood of taking explorative actions becomes stronger in later funding stage.*

Figure 6-2. Hypothesized Relationship Between Relative Performance and Strategic Actions



Notes. The hypothesized relationships (function lines) between relative performance and probability of taking the two types of actions are shown. The solid lines refer to the effects when campaign deadline is distant, and the dotted line represents the effects when deadline is approaching. We allow for a jump for these relationships when funding performance is at the aspiration level (i.e., funding goal), even though the curves on both sides of aspiration intersect at the same point in the figures.

6.2.3 Performance Determinants: The Effect of Strategic Behaviors

As previously discussed, concurrent project funding performance induces entrepreneurs to enact corresponding exploitative or explorative actions to their projects. During this dynamic fundraising process, entrepreneurs act as goal-directed problem solvers; they seek strategies to overcome potential problems arising from current and prospective backers and strengthen well-performed approaches to maintain growth (Jordan and Audia 2012). Stated differently, the actions they have taken during this process are intended towards better funding performance. It is thus reasonable to anticipate that, in the presence of such actions to refine their project, they would eventually achieve superior project performance.

Furthermore, early responses (i.e., actions taking) are seen to be more effective, as learning does not occur suddenly and the affluence of time allows more prospective problems to be fixed and more valuable opportunities to be met (Lehman et al. 2011). Time provides more opportunities for entrepreneurs to learn from their prior actions and in turn leads to more feasible strategies. Further, earlier responses may create slack resources, which enable entrepreneurs to adapt efficiently in the subsequent funding

process. Slack resources can also subsequently improve entrepreneurial performance (Jung et al. 2014; Sharfman et al. 1988). Thus, we propose:

> ***Hypothesis 5a****: Entrepreneurs who take actions to their project are more likely to receive crowdfunding success compared to those do not.*
>
> ***Hypothesis 5b****: The effect of H5a is moderated by the proximity of crowdfunding deadline, such that it is more salient if the actions are in earlier funding stage than in later stage.*

6.3 Data and Method

The data for this study is from *Kickstarter.com*, a leading online reward-based crowdfunding platform. We compiled a crawler to retrieve the data. We started tracking on-going campaigns from June 13, 2015 and the data collection lasted for six months, so our dataset contains daily observations of these crowdfunding projects. We collected *daily* snapshots of each campaign at 11:00 pm EST, each day. All the observable actions of entrepreneurs have been captured in our data collection process. Considering our focus on entrepreneurs' strategic behaviors, the projects in the three entrepreneurial categories (i.e., games, technology and design) (Yang and Hahn 2015) will be used for the empirical analysis. Finally, our dataset contains 322,779 daily records from 9,622 crowdfunding projects.

6.3.1 Identifying Explorative and Exploitative Actions

Table 6-1 summarizes the explorative and exploitative actions we identify. *Exploitative actions* are characterized by *refinement or incremental adjustment of existing competency* (Greve 2007), such as answering questions from current and prospective backers and posting product development progress. *Explorative actions* are characterized by *discovering new approaches and changing the status quo* (Greve 2007), such as adding new product features, changing existing product features, or pursue higher funding goals (i.e., stretch goals).

Table 6-1. Summarization of Two Types of Strategic Actions

Action Types	Indicators
Exploitative Actions *(*characterized by *refinement or incremental adjustments of existing competency)*	- Project update post about social promotion, progress reports, reminder, question answering, backer appreciation (Xu et al. 2014) - Entrepreneurs' comments about answering backers' questions - Post answers to frequently asked questions (FAQ) - Adjust "Risks and Challenges" description - Adjust existing reward tiers - Project description change about adjusting existing content (minor adjustments)
Explorative Actions *(*characterized by *discovering new approaches and changing status quo)*	- Change in campaign videos/images - Project update post about new content, new reward (Xu et al. 2014) - New reward launched (Yang et al. 2016) - Project description change about new content, such as stretch goal (Li and Jarvenpaa 2015), new product features

Based upon the classification of exploitative and explorative actions, we identify each actions from our data. Each actions were identified on daily basis by comparing the differences in project attributes (e.g., project updates, project comments, FAQ etc.) between two consecutive days. For example, by comparing project descriptions in two successive days, we were able to recognize the words or sentences added/deleted by entrepreneurs on a particular day. The actual content of changes (e.g., minor adjustments or new product features) were identified through content analysis on the added/deleted words and sentences. Other types of actions, such as reward tier changes, changes in campaign videos/images, were identified in a similar vein.

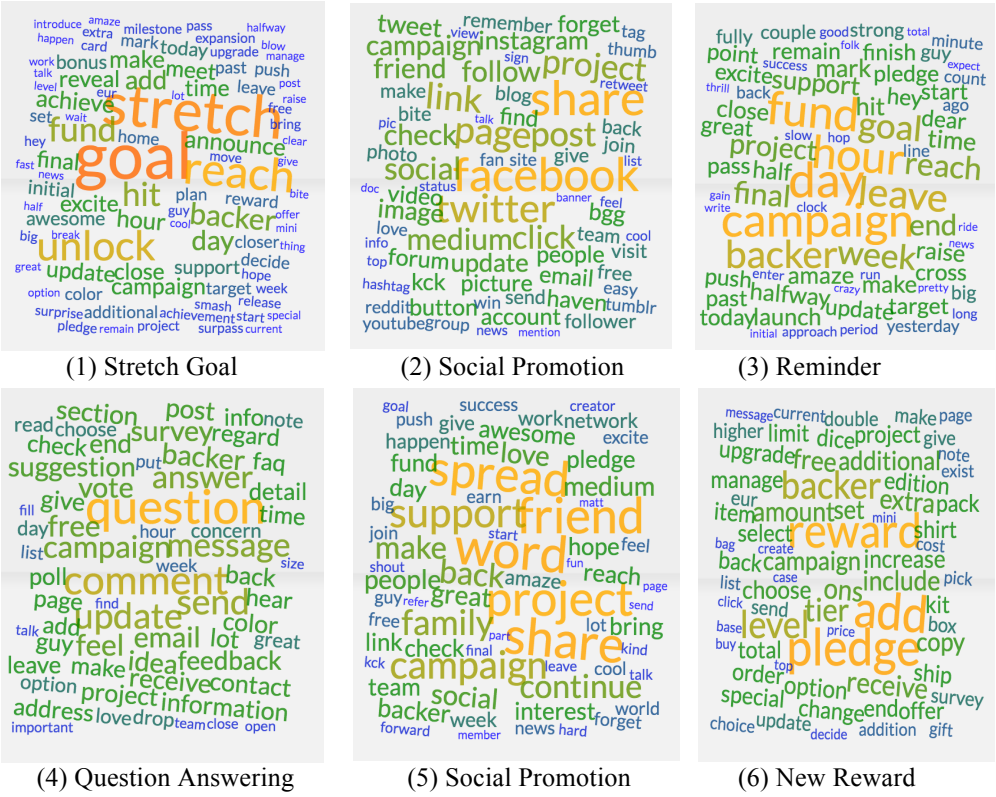
In particular, in order to identify the content of different project updates, we employ topic modeling from natural language processing (NLP) to extract potential topics from project updates (Xu et al. 2014).[34] Then explorative and exploitative actions

[34] We first attempted to perform topic modeling (LDA) on each update, but we found that the resulting topics had too much overlap, as some topics share the similar set of words, which makes the interpretation of the topics difficult.

To resolve this issue, we decomposed updates into sentences and conducted LDA at the sentence-level. In this approach, we observe less overlap among topics and the majority of sentences has a dominant topic. Thus, we identified the content of each sentence by using its dominant topic. Then we aggregate sentence-level action to the update-level. Therefore, it is possible for an update to

in project updates are further identified based on the contents of topics. Some examples of meaningful topics from project updates are shown in Figure 6-3.[35,36]

Figure 6-3. Examples of Topic Cloud from the Result of Topic Modeling on Project Updates



(1) Stretch Goal (2) Social Promotion (3) Reminder

(4) Question Answering (5) Social Promotion (6) New Reward

Notes. Topics are manually labelled through topic clouds and (reading) update sentences that have high loadings on the focal topic. In topic clouds, the size and color of words are proportional to the weight of each word on the focal topic. This figure presents some typical examples (topics) we labelled through conducting LDA on update sentences.

6.3.2 Measures and Estimation Approach

Antecedent of Taking Actions. H1 to H4 propose relative performance as behavioral antecedents of entrepreneurs' strategic behaviors during a crowdfunding campaign as

include multiple themes. For example, an entrepreneur may post a project update to appreciate existing backers and meanwhile announce the unlock of a new reward. Performing topic modeling at sentence-level enables us to capture granular content in project updates.

[35] We observed that not all the topics identified are meaningful. We disregarded those topics without any meaning when we manually label (interpret) each topic from their associated topic keywords.

[36] Here we present the results when setting the predetermined number of topic in LDA as 30. The resulting topics are similar when different predetermined numbers of topics are set as 30, 50 and 100.

well as the moderating role of deadline proximity. We construct our dataset at *campaign-day* level for hypotheses testing. Panel level logistic regression analyses are conducted by utilizing binary indicator variables for exploitative actions (*Exploitation*) and explorative actions (*Exploration*) as dependent variables, respectively. It designates whether an entrepreneurs take exploitative/explorative actions to her project on a particular day (if yes *Exploitation*/*Exploration* = 1; otherwise = 0).

The independent variables of interest are relative performance variables (with respect to aspiration level).[37] Following prior research conventions (Audia and Greve 2006; Greve 1998), we create a spline function by using different relative performance measures for below ($P \leq AL$) and above ($P > AL$) the aspiration level. Performance at or below the aspiration level (*PerformanceBelow*) equals 0 when performance is above the aspiration level and equals performance minus aspiration when performance is at or below it. Performance above the aspiration level (*PerformanceAbove*) equals 0 when performance is at or below the aspiration level and equals performance minus aspiration when performance is above it. The two relative performance measures are standardized by projects' funding goal, so essentially the two variables represent the relative percentage of funding level with respect to pledging goal. For example, when the value of *PerformanceBelow* equals -0.5, it means current pledged level is at the half of the project's funding goal. We take log transformations for the two performance variables to account for their skewed distributions. Furthermore, an indicator variable (*PerformanceIndicator* = 1 if $P > AL$ and 0 if $P \leq AL$) is also included in each estimation

[37] For each crowdfunding campaign, entrepreneurs need to set a fundraising goal to achieve by the project deadline. The funding goal is typically constructed by considering the entrepreneur's prior experience. It can be conceptualized as a natural aspiration level for entrepreneurs, as it is the borderline between project success and failure (Greve 2003b). It is worth noting that Kickstarter follows an All-or-Nothing model, where the entrepreneurs cannot collect any pledges if the funding goal has not been hit. In other words, even though the funding performances do not have much differences when they are around the funding goal, "just above" and "just below" the two situations would lead to totally disparate outcomes.

model to allow the curve to "jump" at the aspiration level rather than forcing the two functions to intersect at the same point (Greve 1998).

In order to test the moderating role of time in determining strategic behaviors, an additional variable that represents funding stage (*FundingStage*) is introduced. It is measured by the number of days passed since the launch date of project, and this number is standardized by project's duration (days). We interact the funding stage variable with relative performance variables to examine how the relationship between concurrent performance and actions varies as deadline draws near.

Following prior research, we also include a set of campaign level controls, including description word count (*DescriptoinWordCount*), number of videos and images (*VideoCount* and *ImageCount*) as well as the length of risks and challenges (*RiskLength*), to account for campaign characteristics (Yang et al. 2016). We incorporate entrepreneurs' prior experience – number of created and backed projects (*CreateNum* and *BackNum*), as their prior experience may affect their decision making and propensity to take actions to their ongoing project. Apart from relative funding performance, entrepreneurs also receive performance feedback from the market through backers' comments (*AccumulativeBackerComments*) and number of backers participated (*AccumulativeBackers*), which we incorporate as control variables as well. In addition, we include number of project updates (*AccumulativeUpdates*) and entrepreneurs' commenting behaviors (*AccumulativeCreatorComments*) to account for entrepreneurs' activeness in the focal project. Finally, entrepreneurs' actions on the previous day (i.e., lagged dependent variables: $Exploitation_{t-1}$ and $Exploration_{t-1}$) are also included in our estimations to control serial correlations and entrepreneurs' momentum in taking actions. For hypotheses testing, the key variables and predictions (in the form of IV → DV) are:

- *PerformanceBelow* → *Exploitation* $\beta > 0$ (H1)
- *PerformanceAbove* → *Exploitation* $\beta < 0$ (H1)
- *PerformanceBelow* → *Exploration* $\beta < 0$ (H2)

- *PerformanceAbove* → *Exploration* $\beta > 0$ (H2)
- *PerformanceBelow* × *FundingStage* → *Exploitation* $\beta > 0$ (H3)
- *PerformanceAbove* × *FundingStage* → *Exploitation* $\beta < 0$ (H3)
- *PerformanceBelow* × *FundingStage*→ *Exploration* $\beta > 0$ (H4a)
- *PerformanceAbove* × *FundingStage* → *Exploration* $\beta > 0$ (H4b)

The Hausman test (Allison 2005; Wooldridge 2012) suggests that fixed-effects models are preferred over random effects models for this data set, where time-invariant projects and entrepreneurs fixed-effects (e.g., project funding goal) were eliminated in our estimation. We performed logistic conditional fixed-effects in our estimations. It is worth emphasizing that in the campaign-day level analysis, the core independent variables capture the performance at day *t*, while the dependent variables capture the actions taken from day *t* to day *t+1*. The time difference between IVs and DV enables us to capture the performance feedback effect.

Effect of Taking Actions. H5 proposes the effect of strategic actions on eventual crowdfunding performance and the moderating role of time. To test this hypothesis, the final dataset will be constructed at project level for regression analysis. The dependent variable is funding performance. we use the pledged amount (*Pledged*) as the performance measure and number of backers (*Backers*) as an alternative. To focal independent variable is a dummy variable (*ActionIndicator*) that represents whether the entrepreneurs took actions to the focal project during the fundraising process (1 = actions taken; 0 otherwise). A variable capturing the timing of first action taken (*FirstActionStage*) is introduced to test the role of time in action-taking. OLS regressions are applied during estimations. The key variables for hypotheses testing (in the form of IV → DV) are:

- *ActionIndicator* → *Pledged* $\beta > 0$ (H5a)
- *ActionIndicator* × *FirstActionStage* → *Pledged* $\beta < 0$ (H5b)

In addition, for campaign level analysis, the propensity score matching (PSM) method is employed to claim causality and to overcome concerns of endogeneity (Li

2013). In our case, potential endogeneity issue arises from self-selection; entrepreneurs may take action when their project's performance has a surge, thus, the sudden variations in performance may influence the decision to take actions as well as the project's final funding performance. They key benefit of the PSM is that it allows for the estimation of causal effects in spite of heterogeneity in treatment effects (Li 2013). Those projects in which entrepreneurs did take actions (i.e., treatment group) are matched with projects in which entrepreneurs did not take actions (i.e., control group). Projects in the two groups were matched based on project- and day- level variables that are likely to be the potential influencing factors of taking actions, so the only notable differences between projects in these two groups is that one entrepreneur took action on the project whereas the other did not. After the matching, then we are able to estimate the casual effects of taking actions and the timing of it on the final project fundraising outcome. Thus, the PSM approach enables us to examine whether project outcome would be different had an entrepreneur not taken action.

Specifically, the matched was conducted at campaign-day level, replying on a set of variables that influence the probability of taking *first* actions. The predictors for the selection model of PSM are as follows:

- Project level variables: funding goal, campaign duration, project category, entrepreneurs' platform maturity
- Project-day level variables: relative performance variables, funding stage, number of rewards, project description word count, whether a project has video(s), image count

In PSM, matched observations were selected based on the nearest available Mahalanobis distance. After finding the matched campaign-day observations, their corresponding projects were selected into the control group. As aforementioned, for H5, the empirical analysis was conducted at campaign level, where treatment group contains those projects involving action-takings whereas control group includes those who did not.

A summary of the measures of focal variables for hypotheses testing is presented in Table 6-2.

Table 6-2. Operationalization of Focal Variables

Variables	Measures
Campaign-day Level Analysis *(Panel Level Spline Logistic Regressions for H1 to H4)*	
Dependent Variables *(from day t to t+1)*	
Exploitation *Exploration*	Measured as whether an entrepreneur makes explorative/exploitative actions to the focal project on the focal day (1 = taking explorative/exploitative actions; 0 otherwise)
Independent Variables *(at day t)*	
PerformanceAbove	$Pledged\ level\ (above\ goal) = \begin{cases} 0 & (if\ pledged\ amount \leq goal) \\ \frac{pledged\ amount - goal}{goal} & (if\ pledged\ amount > goal) \end{cases}$
PerformanceBelow	$Pledged\ level\ (at\ or\ below\ goal) = \begin{cases} \frac{pledged\ amount - goal}{goal} & (if\ pledged\ amount \leq goal) \\ 0 & (if\ pledged\ amount > goal) \end{cases}$
PerformanceIndicator	An indicator variable to show whether the performance is below or above the aspiration level (1: $P > AL$; 0, otherwise)
FundingStage	Measured as the number of days passed since the launch date of project. To account for variations in funding duration for differing projects, we use the passed time (in percentage) in the measurement. Therefore, $FundingStage = \frac{number\ of\ days\ passed}{fundraising\ duration\ (days)}$
Controls	Backers' comments (*AccumulativeBackerComments*), entrepreneurs' comments (*AccumulativeCreatorComments*), number of backers (*AccumulativeBackers*), number of project updates (*AccumulativeUpdates*), entrepreneurs prior experience (*CreateNum* and *BackNum*), project description word count (*DescriptionWordCount*), number of videos and images (*VideoCount* and *ImageCount*), length of risks and challenges (*RiskLength*)
Campaign Level Analysis *(PSM and Panel Level Linear Regressions for H5)*	
Dependent Variable	
Pledged Backers	*Final pledged amount / Number of backers.*
Independent Variables	
ActionIndicator	Measured as whether entrepreneurs take actions to the focal project during fundraising process (1 = taking actions; 0 otherwise)
FirstActionStage	Measured in the same way as the *FundingStage* in campaign daily level analysis. It denotes the time of the first action taken by the entrepreneurs in the focal project.
Controls	Funding goal (*Goal*), campaign duration (*Duration*), number of rewards (*RewardNum*), number of images (*ImageCount*), description word count (*DescriptionWordCount*)

6.4 Results and Discussions

6.4.1 Antecedent of Taking Actions

Table 6-3 provides campaign-day level descriptive statistics of key dependent, independent and control variables, and Table 6-4 reports their correlations. The average

number of days when entrepreneurs take exploitative/explorative actions per project is 8.00/4.61 (the average campaign duration is 33.43 days). 80.15% projects had at least one exploitative actions and 84.38% projects had at lease one explorative actions. The frequency distribution designates the nonroutine nature of exploitative and explorative actions, and also points to the appropriateness of using logistic regression for analyzing the data. We also notice skewed distributions of both relative performance variables. Consistent with Mollick (2014), our data shows that projects tend to fail by a large margin (*PerformanceBelow*: mean=-0.72, std.dev=0.384) and succeed by a small extent (*PerformanceAbove*: mean=2.00, std.dev=69.052).

Table 6-3. Descriptive Statistics for Campaign-Day Level Analysis (*N*=313,157)

	Variables	Mean	Std. Dev	Min	Max
Actions	*Exploitation*	0.230	0.421	0	1
	Exploration	0.133	0.340	0	1
Relative Performance	*PerformanceBelow*	-0.720	0.384	-1	0
	PerformanceAbove	2.000	69.052	0	8239
	FundingStage	0.502	0.281	0.0167	1
Controls	*AccumulativeBackerComments*	23.864	486.499	0	60810
	AccumulativeCreatorComments	3.500	24.442	0	2225
	AccumulativeBackers	142.754	1043.970	0	68441
	AccumulativeUpdates	1.680	3.030	0	48
	CreateNum	0.795	2.553	0	71
	BackNum	4.662	21.442	0	881
	DescriptionWordCount	674.698	648.675	0	5798
	VideoCount	1.244	1.482	0	28
	RiskLength	757.908	604.882	64	10060
	ImageCount	11.414	13.938	0	137

Notes. Number of observations = 313,157; Number of projects = 9,622. Projects without variations in action-taking across all the live days are eliminated in the estimations.

Table 6-4. Correlation Matrix for Campaign-Day Level Analysis (*N*=313,157)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) Exploitation	1						
(2)Exploration	0.35***	1					
(3)PerformanceBelow	0.28***	0.25***	1				
(4)PerformanceAbove	0.02***	0.02***	0.05***	1			
(5)FundingStage	-0.08***	0.01***	0.12***	0.01***	1		
(6)AccumulativeBackerComments	0.07***	0.08***	0.09***	0.01***	0.02***	1	
(7)AccumulativeCreatorComments	0.16***	0.13***	0.23***	0.02***	0.06***	0.50***	1
(8)AccumulativeBackers	0.13***	0.11***	0.22***	0.03***	0.04***	0.53***	0.37***
(9)AccumulativeUpdates	0.26***	0.24***	0.52***	0.02***	0.24***	0.20***	0.31***
(10)CreateNum	0.08***	0.08***	0.28***	0.07***	0.00	0.06***	0.09***
(11)BackNum	0.12***	0.11***	0.25***	0.03***	0.01***	0.05***	0.13***
(12)DescriptionWordCount	0.19***	0.17***	0.30***	-0.00	0.02***	0.07***	0.14***
(13)VideoCount	0.15***	0.15***	0.27***	0.00*	0.03***	0.06***	0.14***
(14)RiskLength	0.11***	0.10***	0.15***	-0.00	0.00	0.06***	0.09***
(15)ImageCount	0.23***	0.23***	0.46***	0.00*	0.02***	0.12***	0.23***

	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
(8)AccumulativeBackers	1							
(9)AccumulativeUpdates	0.23***	1						
(10)CreateNum	0.06***	0.12***	1					
(11)BackNum	0.10***	0.18***	0.31***	1				
(12)DescriptionWordCount	0.13***	0.36***	0.06***	0.16***	1			
(13)VideoCount	0.10***	0.29***	0.04***	0.08***	0.38***	1		
(14)RiskLength	0.07***	0.21***	0.05***	0.09***	0.40***	0.25***	1	
(15)ImageCount	0.21***	0.40***	0.10***	0.16***	0.52***	0.40***	0.29***	1

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

Table 6-5 provides the results of the logistic regressions on exploitative actions using project- and day-level fixed effects. We estimate our parameters progressively by first estimating the null model with only control variables (Model 1) and then adding the independent variables of interest in Models 2 and 3. Most control variables are shown to be significant predictors of the dependent variable. As shown in Model 1, the likelihood of taking exploitative actions is higher when more backers left comments (*AccumulativeBackerComments:* β=0.00169, p<0.01) or supported a project (*AccumulativeBackers:* β=9.71e-05, p<0.05); when more backers join a project, their feedback reminds entrepreneurs to further refine their project. Entrepreneurs whose

project has longer project descriptions (*DescriptionWordCount:* β=0.000335, p<0.01) or have more backing experience (*BackNum*: β=0.0173, p<0.01) are more inclined to take exploitative actions. Having posted more updates (*AccumulativeUpdates*: β=-0.0499, p<0.01), longer risks and challenges (*RiskLength*: β=-0.205, p<0.01) and more images (*ImageCount*: β=-0.284, p<0.01) reduce entrepreneurs' likelihood to take exploitative actions. Finally, *AccumulativeCreatorComments*, *CreateNum* and ln(*VideoCount*) are not significant (*AccumulativeCreatorComments:* β=-0.00167, ns; *CreateNum:* β=-0.138, ns; ln(*VideoCount*): β=-0.0918, ns), suggesting that creator's commenting behaviors, creating experience as well as project's video information do not significantly influence exploitative actions. The effects of control variables are largely consistent across models.

Models 2 and 3 show the results of the logistic regression of the hypothesized effects for exploitative actions (H1 in Model 2, and H3 in Model 3). After adding the relative performance variables, the overall fit of Model 2 is satisfactory (i.e., $LR\ \chi^2$ = 7521.25, p < 0.01), and the likelihood ratio (LR) test for improvement over the null model (Model 1) is significant ($\Delta LR\ \chi^2$ = 133.23, p < 0.01). H1 proposed that entrepreneurs are more likely to take exploitative actions when the concurrent funding performance is closer to the funding goal. The positive and significant coefficients for ln(*PerformanceBelow*) (β = 0.0519, p < 0.01) and ln(*PerformanceAbove*) (β = 0.368, p < 0.01) indicate that there is a positive relationship between performance and probability of taking exploitative actions on both sides of aspiration. H1 is partially supported. When the funding performance is less than the pledge goal, entrepreneurs tend to make refinement to their existing competency when the performance is near the goal, as the existing strategies have shown to be effective. But in contrast to our expectation, their likelihood of taking exploitative actions does not decrease when the funding performance is above the goal. A possible reason is that the increasing number of backers exposes entrepreneurs to richer feedback about their current project, which incentivize them to

further polish existing strategies to fulfill backers' expectations.

Model 3 adds the interaction terms of funding stage and relative performance. The overall fit of Model 3 is satisfactory ($LR\ \chi^2 = 8130.71$, $p < 0.01$), and the likelihood ratio test for improvement over Model 2 is also significant ($\Delta LR\ \chi^2 = 609.46$, $p < 0.01$). H3 proposes that the relationship between relative performance and probability of taking exploitative actions would be stronger in later funding stage. In Model 3, each of the interaction terms are positive and significant (*Below* × *FundingStage*: $\beta = 0.0795$, $p < 0.01$; *Above* × *FundingStage*: $\beta = 0.248$, $p < 0.01$), which only lends partial support for H3. In the case of under-performing, the relationship becomes stronger when deadline draws near. While when it is over-performing, the overall positive effect of performance increase on exploitation only comes from later funding stage (i.e., insignificance of the main effect of ln(*PerformanceAbove*) in Model 3). It suggests that if a project reaches funding goal at early stage, its entrepreneurs tend to be less concerned about losing backers, given that sufficient time remains. Entrepreneurs are more sensitive to performance change in later stage, such that they are more likely to keep refining their initiative no matter when it is over-performing to a small or great extent.

Table 6-5. Fixed-effects Logistic Regressions for Exploitative Actions

	DV: *Exploitation*		
VARIABLES	Model1	Model2	Model3
Explanatory Variables			
ln(PerformanceBelow)		**0.0519*****	**0.0591*****
		(0.0112)	(0.0111)
ln(PerformanceAbove)		**0.368*****	**0.0322**
		(0.0417)	(0.0501)
PerformanceIndicator		0.139***	0.103***
		(0.0289)	(0.0306)
FundingStage			1.689***
			(0.0936)
PerformanceBelow × FundingStage			**0.0795*****
			(0.00724)
PerformanceAbove × FundingStage			**0.248*****
			(0.0420)
Controls			
AccumulativeBackerComments	0.000169***	0.000229***	0.000231***
	(5.46e-05)	(5.62e-05)	(5.67e-05)
AccumulativeCreatorComments	0.00167	-0.00120	-0.00243*
	(0.00138)	(0.00142)	(0.00146)
AccumulativeBackers	9.71e-05***	4.79e-05**	5.86e-05***
	(1.94e-05)	(1.87e-05)	(1.97e-05)
AccumulativeUpdates	-0.0499***	-0.0640***	-0.0926***
	(0.00419)	(0.00441)	(0.00476)
CreateNum	-0.138	-0.149	-0.174
	(0.108)	(0.108)	(0.108)
BackNum	0.0173***	0.0153***	0.0148***
	(0.00425)	(0.00422)	(0.00426)
DescriptionWordCount	0.000335***	0.000312***	0.000296***
	(7.43e-05)	(7.45e-05)	(7.45e-05)
ln(*VideoCount*)	-0.0918	-0.0880	-0.123**
	(0.0606)	(0.0606)	(0.0608)
ln(*RiskLength*)	-0.205**	-0.189**	-0.128
	(0.0920)	(0.0921)	(0.0924)
ln(*ImageCount*)	-0.284***	-0.306***	-0.307***
	(0.0454)	(0.0456)	(0.0458)
$Exploitation_{t-1}$	0.535***	0.535***	0.539***
	(0.0117)	(0.0117)	(0.0117)
$Exploration_{t-1}$	-0.0698***	-0.0680***	-0.0598***
	(0.0167)	(0.0167)	(0.0167)
No. of obs. (N)	243,499	243,499	243,499
Log likelihood (LL)	-101233.61	-101166.99	-100862.26
$LR\ \chi^2$	7388.02***	7521.25***	8130.71***
df	71	74	77
$\Delta LR\ \chi^2$		133.23***	609.46***

Notes. Number of projects = 7,447; project-level and day-level fixed effects were included in the analysis; standard errors are shown in parentheses.
Significance Levels: $^{***}p<0.01$, $^{**}p<0.05$, $^{*}p<0.1$.

Table 6-6 offers the results of the logistic regressions on explorative actions using project- and day-level fixed effects. Following the same convention, we provide the results of baseline model with only control variable in Model 4 and add explanatory variables related to hypotheses in Model 5 and 6. The estimation results of control variables remain consistent across models and the majority of them are significant predictors of explorative actions. Backers', creators' comments and project image positively influence the likelihood of exploration (*AccumulativeBackerComments*: β = 0.000141, $p < 0.01$; *AccumulativeCreatorComments:* β = 0.00150, $p < 0.01$; ln(*ImageCount*): β = 1.336, $p < 0.01$), whereas the number of project updates, description length, risk length and image count have a negative effect (*AccumulativeUpdates*: β = -0.0577, $p < 0.01$; *DescriptionWordCount*: β = -0.000744, $p < 0.01$; ln(*VideoCount*): β = -0.557, $p < 0.01$; ln(*RiskLength*): β = -0.390, $p < 0.01$). In general, it seems that project comments are important drivers for entrepreneurs to take actions, and having richer project presentation, such as descriptions, only induces slight changes (i.e., exploitative actions) rather than major changes to the status quo.

H2 proposes that entrepreneurs are less inclined to take explorative actions when the funding performance is closer to the funding goal. Model 5 therefore introduces variables about the main effects of relative performance. The overall fit of the model is satisfactory ($LR\ \chi^2$ = 12041.23, $p < 0.01$), and the likelihood ratio test for improvement over Model 4 is also significant ($\Delta LR\ \chi^2$ = 67.48, $p < 0.01$). The effect of performance above the aspiration level is positive and significant (ln(*PerformanceAbove*): β = 0.0841, $p < 0.01$), whereas the effect of performance below the aspiration level is not significant (ln(*PerformanceBelow*): β = -0.0138, *ns*). H2 receives partial support. It appears that large performance shortfall does not motivate entrepreneurs to explore new strategies that may be more suitable for their project.

Model 6 adds the interaction terms between relative performance and funding

stage. H4a proposes that if the performance is below the aspiration level, the relationship between performance and exploration becomes stronger in later stage, which is not supported due to the positive significance of the interaction term (*Below* × *FundingStage*: $\beta = 0.0311$, $p < 0.01$). If it is underperforming, entrepreneurs are more likely to take explorative actions to when the performance is closer to funding goal. Rather than avoiding potential risks from exploration, they are trying to pursue new strategies that may be more well-received among backers. It is possibly because of the All-or-Nothing fundraising model so that entrepreneurs would not face the survival point in traditional organizations. Their immediate target is reaching funding goal, and otherwise, no funding can be obtained. Under such circumstances, they would rather take explorative actions, which produces major changes to existing content, to appeal attention of prospective backers. Furthermore, H4b proposes stronger positive relationship between performance and the likelihood of taking explorative actions in later funding stage. The positive interaction term *Above* × *FundingStage* ($\beta = 0.150$, $p < 0.01$) lends support for H4b. We also notice that the main effect of ln(*PerformanceAbove*) ($\beta = 0.-1.146$, $p < 0.01$) turned negative after we add the interaction terms. It suggests that if a project slightly passes its goal in early funding stage, entrepreneurs tend to have more confidence in choosing explorative actions with potential risks involved, such as stretch goal or adding new product features. It is possibly because the remaining time gives them confidence to attract more ensuing backers and the accumulated financial resources facilitate them to better fulfil the project. If this occurs in later funding stage, explorative actions are less likely to happen. Conversely, as remaining time wanes, it is usually only those who have sufficient excess resources (i.e., over-performing by a large margin) that choose explorative actions.

Table 6-6. Fixed-effects Logistic Regressions for Explorative Actions

	DV: *Exploration*		
VARIABLES	Model4	Model5	Model6
Explanatory Variables			
ln(PerformanceBelow)		**0.0138**	**0.0170**
		(0.0134)	(0.0133)
ln(PerformanceAbove)		**0.0841****	**-0.146*****
		(0.0409)	(0.0489)
PerformanceIndicator		0.223***	0.156***
		(0.0303)	(0.0323)
FundingStage			4.888***
			(0.109)
PerformanceBelow × FundingStage			**0.0311*****
			(0.00863)
PerformanceAbove × FundingStage			**0.150*****
			(0.0426)
Controls			
AccumulativeBackerComments	0.000141***	0.000166***	0.000151***
	(4.08e-05)	(4.31e-05)	(4.16e-05)
AccumulativeCreatorComments	0.00150**	0.00132**	0.00108*
	(0.000604)	(0.000613)	(0.000626)
AccumulativeBackers	1.00e-05	1.34e-06	2.12e-05
	(1.24e-05)	(1.31e-05)	(1.35e-05)
AccumulativeUpdates	-0.0577***	-0.0671***	-0.0913***
	(0.00399)	(0.00420)	(0.00446)
CreateNum	-0.123	-0.134	-0.0988
	(0.143)	(0.143)	(0.140)
BackNum	-0.00170	-0.00237	0.00172
	(0.00407)	(0.00407)	(0.00412)
DescriptionWordCount	-0.000744***	-0.000762***	-0.000797***
	(7.23e-05)	(7.25e-05)	(7.31e-05)
ln(*VideoCount*)	-0.557***	-0.557***	-0.545***
	(0.0616)	(0.0616)	(0.0615)
ln(*RiskLength*)	-0.390***	-0.376***	-0.245**
	(0.102)	(0.102)	(0.102)
ln(*ImageCount*)	1.336***	1.331***	1.345***
	(0.0357)	(0.0357)	(0.0358)
$Exploitation_{t-1}$	-0.127***	-0.128***	-0.139***
	(0.0166)	(0.0166)	(0.0167)
$Exploration_{t-1}$	0.649***	0.649***	0.661***
	(0.0156)	(0.0157)	(0.0158)
No. of obs. (N)	261,747	261,747	261,747
Log likelihood (LL)	-77638.224	-77604.483	-76457.942
LR χ^2	11973.75***	12041.23***	14334.31***
df	71	74	77
ΔLR χ^2		67.48***	2293.08***

Notes. Number of projects = 7,979; project-level and day-level fixed effects were included in the analysis; standard errors are shown in parentheses.
Significance Levels: $^{***}p<0.01$, $^{**}p<0.05$, $^{*}p<0.1$.

Supplementary Analysis. In previous discussions, we consider the exploitative and explorative actions separately, where entrepreneurs' probabilities of choosing each type of actions are examined in an independent way. Aiming to obtain further insights on the relationship between the two types of actions, so in Model 7 to 9 (see Table 6-7), we conduct additional analysis by using different set of dependent variables: *ExploitationOnly* (=1 if taking exploitative but no explorative actions; 0 otherwise), *ExplorationOnly* (=1 if taking explorative but no exploitative actions; 0 otherwise) and *BothActions* (=1 if taking both exploitative and explorative actions; 0 otherwise). The results suggest that the probability of simultaneously taking both types of action increase along with performance (Model 9: ln(*PerformanceBelow*): $\beta = 0.137$, $p < 0.01$; ln(*PerformanceAbove*): $\beta = 0.286$, $p < 0.01$). When the performance is below the funding goal, there is a negative relationship between performance and likelihood of only taking explorative actions (Model 8: ln(*PerformanceBelow*): $\beta = -0.0499$, $p < 0.01$), which indicates that entrepreneurs may only come up with new content (without refining existing ones) if there is a huge performance shortfall, but this probability declines with the increase of performance. If they choose exploration when performance rises, it is usually accompanied by exploitation. In addition, when the performance is above the funding goal, their probability of merely choosing exploitative actions would increase (Model 7: ln(*PerformanceAbove*): $\beta = 0.306$, $p < 0.01$).

Table 6-7. Additional Analysis for Exploitation and Exploration

VARIABLES	DV *ExploitationOnly* Model7	*ExplorationOnly* Model8	*BothActions* Model9
Explanatory Variables			
ln(PerformanceBelow)	**-0.000558**	**-0.0499*****	**0.137*****
	(0.0120)	(0.0172)	(0.0211)
ln(PerformanceAbove)	**0.306*****	**-0.0656**	**0.286*****
	(0.0417)	(0.0756)	(0.0453)
PerformanceIndicator	-0.0489	0.198***	0.204***
	(0.0323)	(0.0510)	(0.0336)
Controls			
AccumulativeBackerComments	-5.62e-05	7.09e-06	0.000154***
	(3.87e-05)	(9.61e-05)	(4.05e-05)
AccumulativeCreatorComments	0.000295	-0.00226	0.00192***
	(0.000561)	(0.00332)	(0.000624)
AccumulativeBackers	1.20e-05	-7.88e-05*	-3.73e-06
	(1.34e-05)	(4.28e-05)	(1.30e-05)
AccumulativeUpdates	0.00102	-0.00156	-0.0415***
	(0.00416)	(0.00841)	(0.00468)
CreateNum	-0.0730	0.0149	-0.172
	(0.113)	(0.202)	(0.192)
BackNum	0.00795*	-0.0218***	0.0196***
	(0.00452)	(0.00616)	(0.00579)
DescriptionWordCount	0.000239***	-0.00169***	0.000201**
	(8.06e-05)	(0.000132)	(7.82e-05)
ln(*VideoCount*)	0.449***	-0.172*	-0.479***
	(0.0691)	(0.101)	(0.0687)
ln(*RiskLength*)	-0.117	-0.145	-0.184
	(0.111)	(0.162)	(0.114)
ln(*ImageCount*)	0.0769	1.981***	-0.493***
	(0.0540)	(0.0434)	(0.0550)
$Exploitation_{t-1}$	0.592***	-0.254***	0.0172
	(0.0125)	(0.0272)	(0.0190)
$Exploration_{t-1}$	-0.192***	1.006***	0.161***
	(0.0185)	(0.0221)	(0.0198)
No. of obs. (N)	225,984	210,541	174,622
No. of prj.	6,893	6,266	5,446
Log likelihood (LL)	-86651.959	-39762.744	-48672.649
$LR\ \chi^2$	4806.79	10206.96***	4053.70***
df	74	74	74

Notes. Project-level and day-level fixed effects were included in the analysis; standard errors are shown in parentheses.
Significance Levels: $^{***}p<0.01$, $^{**}p<0.05$, $^{*}p<0.1$.

6.4.2 Effect of Taking Actions

We now turn to the effect of strategic actions on eventual crowdfunding performance. H5 proposes that entrepreneurs who take actions (i.e., exploitative or explorative actions) during funding process tend to have higher likelihood of crowdfunding success, and such

effect is moderated by deadline proximity. Campaign level analyses are conducted to test this hypothesis. Table 6-8 provides descriptive statistics of variables in PSM and regressions, and Table 6-9 reports their correlations.

Table 6-10 presents the results using the matching approaches on the ATT values for the unmatched sample, and the Mahalanobis distance matched sample. Different levels of calipers are chosen in the PSM. Compared with the unmatched sample, the estimated ATTs (difference between treatment and control group) on the Mahalanobis distance matched sample are still positive and significant, albeit smaller in magnitude. In addition, we compared the covariates in treatment and control group in the two samples (i.e., unmatched and matched) (see Table 6-11). The standardized bias (in percentage) (Caliendo and Kopeinig 2008; Rosenbaum and Rubin 1985) is reduced significantly into acceptable magnitudes in the matched sample and t-values suggest that the covariates are quite similar across treatment and control groups after matching (i.e., most t-values are not significant except for *ImageCount*, but the mean values in the two groups are quite similar). The results suggest the positive effect of strategic actions on crowdfunding performance after accounting for systematic difference between projects with and without actions. Thus, H5a receives support.

Table 6-12 provides the campaign level regression analysis by using performance measures – *pledged amount* and *number of backers* – as dependent variables and the matched sample.[38] Model 10 (*Treatment*: $\beta = 0.727$, $p < 0.01$) and Model 12 (Treatment: $\beta = 0.394$, $p < 0.01$) confirm the positive effects of strategic actions. To test the moderating role of deadline proximity, we introduce the interaction term between treatment and funding stage of the first strategic actions in Model 11 and 14. Consistent

[38] Here we present the regressions on the matched sample by using caliper of 0.7. This is chosen by considering the tradeoff between sample size and differences between the treatment and control group. It is worth mentioning that regression results with samples based on different calipers are consistent.

with our expectation, the negative and significant coefficient of *Treatment* × *FirstActionStage* (Model 11: β = -1.021, $p < 0.01$; Model 14: β = -0.506, $p < 0.01$) implies that projects whose entrepreneurs start strategic actions at early stages can benefit more, lending support to H5b.

Table 6-8. Descriptive Statistics for Campaign Level Analysis (*N*=3,686)

Variables	Mean	Std. Dev	Min	Max
Pledged	599.334	2912.794	0	83722
Backers	8.358	41.770	0	1419
FirstActionStage	0.190	0.280	0	1
Goal	43223.500	166586.600	25	5000000
Duration	31.503	8.402	3	60
RewardNum	4.059	2.621	1	17
ImageCount	2.674	3.782	0	47
DescriptionWordCount	338.139	282.260	0	4616
HasVideo	0.448	0.497	0	1

Note. Descriptive statistics for the sample after PSM. Number of observations: 3,686 (1,843 in each treatment and control group)

Table 6-9. Correlation Matrix for Campaign Level Analysis (*N*=3,686)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) Pledged	1								
(2) Backers	0.63***	1							
(3) FirstActionStage	-0.06***	-0.05**	1						
(4) Goal	-0.02	-0.03	-0.03	1					
(5) Duration	-0.02	-0.01	0.03	0.13***	1				
(6) RewardNum	0.18***	0.14***	-0.05**	-0.04*	-0.09***	1			
(7) ImageCount	0.30***	0.23***	-0.07***	-0.05**	-0.05**	0.46***	1		
(8) DescriptionWordCount	0.18***	0.10***	-0.04*	0.00	-0.06***	0.35***	0.47***	1	
(9) HasVideo	0.17***	0.13***	0.13***	-0.08***	-0.16***	0.36***	0.23***	0.25***	1

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

Table 6-10. The Treatment Effect of Taking Actions using PSM

Outcomes	Metrics	Unmatched	No Caliper	Caliper = 0.7	Caliper = 0.5	Caliper = 0.3
Pledged	**ATT**	5691.97***	**4074.17*****	**543.97*****	**367.17*****	**150.74*****
	t-value	24.96	10.65	7.13	4.97	3.41
Backers	**ATT**	63.57***	**43.84*****	**7.86*****	**5.97*****	**1.36*****
	t-value	31.85	9.13	7.01	4.96	4.20
Matched prj.	**-**	5,598	5,598	**1,843**	1,378	867

Notes. Mahalanobis distance matching with replacement were used in PSM. The results are qualitatively consistent when different calipers are used.
Significance Levels: *** p<0.01, ** p<0.05, * p<0.1

Table 6-11. Mean Comparison Between Treatment and Matched Control Group

Variable	Sample	Treated	Control	%bias	t-value
ln(PerformanceBelow)	Unmatched	-5.009	-7.348	82.1	59.79
	PSM	-7.009	-7.081	**2.5**	**0.84**
ln(PerformanceAbove)	Unmatched	0.050	0.001	100.0	20.40
	PSM	0	0	**0.0**	**.**
FirstActionStage	Unmatched	0.186	0.501	-107.0	-70.59
	PSM	0.188	0.192	**-1.2**	**-0.40**
ln(Goal)	Unmatched	9.169	9.435	-13.8	-9.09
	PSM	9.362	9.356	**0.3**	**0.11**
Duration	Unmatched	32.540	32.872	-3.1	-2.05
	PSM	31.531	31.474	**0.5**	**0.21**
RewardNum	Unmatched	6.436	3.983	62.4	46.44
	PSM	4.096	4.022	**1.9**	**0.84**
ImageCount	Unmatched	8.560	2.893	66.9	46.44
	PSM	2.804	2.544	**3.1**	**2.09**
DescriptionWordCount	Unmatched	5.894	5.352	52.0	35.54
	PSM	5.572	5.546	**2.5**	**1.05**
HasVideo	Unmatched	0.704	0.157	132.5	94.50
	PSM	0.447	0.447	**0.0**	**-0.00**

Note. Unmatched: sample without matching. PSM: sample with Mahalanobis matching. The matched and treatment group comparison from the result by using caliper as 0.7 – the sample we used for campaign level analysis.

Table 6-12. OLS Regression Results for the Effect of Taking Actions on Crowdfunding Performance

	DV: ln(*Pledged*)		DV: ln(*Backers*)	
VARIABLES	Model10	Model11	Model12	Model14
Explanatory Variables				
Treatment (ActionIndicator)	**0.727*****	**0.939*****	**0.394*****	**0.497*****
	(0.101)	(0.112)	(0.0420)	(0.0469)
FirstActionStage		-0.661***		-0.240***
		(0.188)		(0.0781)
Treatment × FirstActionStage		**-1.021*****		**-0.506*****
		(0.273)		(0.114)
Controls				
ln(Goal)	-0.216***	-0.217***	-0.123***	-0.124***
	(0.0248)	(0.0245)	(0.0103)	(0.0102)
Duration	0.00491	0.00639	0.00350*	0.00410**
	(0.00465)	(0.00461)	(0.00194)	(0.00192)
RewardNum	0.191***	0.181***	0.0680***	0.0640***
	(0.0171)	(0.0170)	(0.00713)	(0.00706)
ImageCount	0.185***	0.178***	0.0943***	0.0914***
	(0.0118)	(0.0117)	(0.00494)	(0.00489)
ln(DescriptionWordCount)	0.366***	0.359***	0.124***	0.120***
	(0.0599)	(0.0593)	(0.0250)	(0.0247)
HasVideo	1.280***	1.418***	0.471***	0.530***
	(0.0923)	(0.0925)	(0.0385)	(0.0386)
Constant	0.741*	0.714*	0.417**	0.397**
	(0.430)	(0.427)	(0.179)	(0.178)
R^2	0.367	0.381	0.376	0.391
No. of obs. (N)	3,686	3,686	3,686	3,686

Notes. Regression Analysis was conducted at project level by using matched and treatment sample from PSM (caliper = 0.7). Project categories and entrepreneurs' platform maturity fixed effects were included in the estimations. Standard errors are reported in parentheses.
Significance Levels: *** p<0.01, ** p<0.05, * p<0.1.

Supplementary Analysis. In order to obtain nuanced insights on the effect of exploitative and explorative actions on daily funding performance, we also conduct campaign-day level analysis by using daily pledged amount and daily number of backers (on the next day of actions) as dependent variables (see Table 6-13). As shown in Model 15, both types of actions result in higher funding speed (*Exploitation*: $\beta = 0.0753$, $p < 0.01$; *Exploration*: $\beta = 0.0807$, $p < 0.01$). Model 17 using backers as dependent variable shows consistent results. The effect of exploitative actions does not vary in different funding stage (*Exploitation × FundingStage* in Model 16: $\beta = 0.0360$, *ns*), while the positive effect of the explorative actions will be diminished when deadline arrives (*Exploration × FundingStage* in Model 16: $\beta = -0.100$, $p < 0.1$). We also notice that, in

later stage, exploitative action is helpful in attracting more backers (*Exploitation* × *FundingStage* in Model 18: $\beta = 0.0232$, $p < 0.1$), even though their backing amount may not rise (c.f., Model 16). Moreover, the positive effect of explorative actions on backers would be offset in later stage (*Exploration* × *FundingStage* in Model 18: $\beta = -0.0524$, $p < 0.01$). Specifically, when *FundingStage* is greater than 3/4, explorative actions may demotivate new backers to support the project.

Table 6-13. Panel OLS Fixed-effects Regression Results for the Effect of Taking Actions on Daily Funding Performance

	DV: ln(*DailyPledged*)		DV: ln(*DailyBackers*)	
VARIABLES	Model15	Model16	Model17	Model18
Explanatory Variables				
Exploitation	**0.0753*****	**0.0619****	**0.0319*****	**0.0234*****
	(0.0153)	(0.0240)	(0.00387)	(0.00608)
Exploration	**0.0807*****	**0.120*****	**0.0179*****	**0.0383*****
	(0.0186)	(0.0298)	(0.00471)	(0.00755)
Exploitation × FundingStage		**0.0360**		**0.0232***
		(0.0539)		(0.0136)
Exploration × FundingStage		**-0.100***		**-0.0524*****
		(0.0607)		(0.0154)
Controls				
AccumulateBackerComments	-0.0292**	-0.0292**	0.00186	0.00184
	(0.0118)	(0.0118)	(0.00299)	(0.00299)
AccumulateCreatorComments	0.0729***	0.0724***	0.00366	0.00335
	(0.0229)	(0.0229)	(0.00580)	(0.00580)
AccumulateBackers	-0.00348***	-0.00347***	-0.00189***	-0.00189***
	(0.000409)	(0.000409)	(0.000104)	(0.000104)
AccumulateUpdates	-0.106***	-0.106***	-0.0235***	-0.0235***
	(0.0102)	(0.0103)	(0.00259)	(0.00260)
CreateNum	0.0417	0.0410	0.0149	0.0145
	(0.0874)	(0.0874)	(0.0221)	(0.0221)
BackNum	-0.102***	-0.103***	-0.0339***	-0.0342***
	(0.0204)	(0.0204)	(0.00517)	(0.00517)
DescriptionWordCount	1.13e-05	1.52e-05	-1.56e-06	5.15e-07
	(0.000137)	(0.000137)	(3.46e-05)	(3.46e-05)
ln(*VideoCount*)	0.238***	0.242***	0.0831***	0.0852***
	(0.0788)	(0.0789)	(0.0200)	(0.0200)
ln(*RiskLength*)	0.0736	0.0726	0.00933	0.00875
	(0.0993)	(0.0993)	(0.0251)	(0.0251)
ln(*ImageCount*)	-0.104***	-0.102***	-0.0260***	-0.0247***
	(0.0249)	(0.0250)	(0.00630)	(0.00632)
Constant	0.489	0.489	0.195	0.195
	(0.605)	(0.605)	(0.153)	(0.153)
R^2	0.027	0.027	0.041	0.042
No. of obs. (N)	70,881	70,881	70,881	70,881
No. of prj.	2,336	2,336	2,336	2,336

Notes. Regression Analysis was conducted at project-day level by using matched and treatment sample from PSM (caliper = 0.7). Project-level and day-level fixed effects were included in the analysis. Standard errors are reported in parentheses.
Significance Levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

6.5 Conclusion and Contribution

Decision makers' behaviors are prevalently taken within the confines of performance periods with predefined durations and targets for desired level of performance. In this study, we set out to investigate the dynamic interplay between concurrent funding performance and entrepreneurs' strategies in managing the project during the fundraising process. In particular, we explore how the concurrent fundraising performance influence entrepreneurial strategies in managing the project during fundraising process and how these strategies in turn affect final crowdfunding performance. Drawing upon the performance feedback model from organizational learning theory, we propose hypotheses related to the effects of relative performance with respect to the aspiration level on entrepreneurs' exploitative and explorative actions, the effects of entrepreneurial actions on crowdfunding success as well as the role of deadline proximity in these relationships. The proposed hypotheses are empirically tested using a unique dataset that includes over six months' daily snapshots of live projects from a leading reward-based crowdfunding platform.

We find that there is a positive relationship between concurrent funding performance and entrepreneurs' probability of taking exploitative actions (i.e., actions characterized by refinement and incremental adjustments of existing competency), and such relationship becomes stronger when deadline approaches. In addition, when the performance is above the funding goal, there is a positive relationship between performance and entrepreneurs' likelihood of taking explorative actions (i.e., actions characterized by discovering new approaches and changing status quo). The relationship is strengthened when deadline draws near due to the salience of slack resources. Additional analysis suggests that entrepreneurs are less likely to merely choose explorative actions when performance increases, and when it occurs, it is usually accompanied by exploitative actions. Moreover, entrepreneurial strategies during the

fundraising process are found to be helpful in improving crowdfunding performance, and those who take actions at early funding stage can benefit more.

This research offers a number of important theoretical implications. We contribute to the IS literature on crowdfunding by examining the dynamics of entrepreneurial strategies within fundraising duration, which has yet to be investigated. The IT-enabled nature of crowdfunding platforms facilitates entrepreneurs to bypass intermediaries, such as professional wealthy investors, and to bring capital-raising to the crowd directly (Beaulieu and Sarker 2013), whereby they can obtain ongoing and timely interactions with the market. The immediate feedback from the market informs their subsequent entrepreneurial practices and product development processes. This study is one of the first to delve into this fundraising process. Investigating the *within-campaign dynamics* facilitates the exploration of what entrepreneurs do that finally lead to crowdfunding success and what actually works or doesn't work in the process. In addition, our study uncovers the qualitative aspects of crowdfunding projects by analyzing contents of project descriptions and updates. These aspects are particularly important as they are the major channels through which entrepreneurs convey their ideas to prospective backers (Wang et al. 2016). Our investigation on these components promotes better understanding of entrepreneurs' intentions and conditions under which they may enact exploitative and explorative actions.

Furthermore, our study extends performance feedback theory by offering more nuanced dimensions about strategic actions induced by prior performance. Decision markers' actions are the outcomes of initiating organizational search (Baum and Dahlin 2007). Existing literature show that the process of search result in behaviors that more or less involve potential risks, such as organizational change/innovation (Greve 1998), risk taking (Deephouse and Wiseman 2000) and capital investment (Greve 2003b). We suggest that organizational search may lead to diverse actions depending on decision

makers' intentions of conducting them; stated differently, actions are heterogeneous in nature, and not all of them are related to risks. This is more salient in the context where *knowledge-* and *innovation-based creative* tasks are dominant. The course of executing a task (e.g., fundraising process) is a sense-making process where entrepreneurs continuously realize what seems to be favorable and what seems not. Diverse actions are conducted with different intentions. In our context, explorative actions, which entail more risks, are conducted with an expectation of discovering new alternatives for the project, while exploitative actions, which involve less risks or no risks, are enacted with an objective to refining existing competency. Examining the influence of performance on exploitative and explorative actions gives us a fine-grained understanding of organizational search behaviors and their possible outcomes.

Finally, this study echoes the call from existing organization theory literature (Ancona et al. 2001; Gavetti and Levinthal 2000; Mitchell and James 2001; Zaheer et al. 1999) by emphasizing the role of time in organization processes, especially in the process of learning from performance feedback. Following the nascent research in this regard (i.e., Lehman and Hahn 2013; Lehman et al. 2011), we investigate the moderating role of time availability within a well-defined performance period in determining the actions chosen by decision markers. Given the prevalence of temporal performance requirements in organization context (Lehman et al. 2011), time serves as a critical resource and also as an important constraint for within-period target attainment. Furthermore, we explicitly emphasize the importance of timing of action taking (Greve 2002) for end-of-period performance. Our arguments suggest that time "shapes the learning curve" (Wiersma 2007) by providing opportunities to learn from performance feedbacks and constraining the limited temporal resource for exploiting lessons learnt.

From practitioners' perspective, we provide guidance to entrepreneurs in IT-enabled crowdfunding platforms on how to respond to high/low funding performance

relative to their funding goals. Besides, entrepreneurs are encouraged to dynamically adjust their strategies responding to performance feedback, as timely actions are likely to further entrepreneurial success.

CHAPTER 7 CONCLUSION

7.1 Summary

This dissertation seeks to extend our understanding of the dynamics of IT-enabled crowdfunding. In the first essay, I explore the *across-campaign dynamics* by examining entrepreneurial learning effects from the influence of several fine-grained experience dimensions. Using six years of panel data involving 3,521 serial entrepreneurs, I find that entrepreneurs not only learn directly by creating their own projects but also indirectly by backing others' projects. Generally, the effect of direct learning is relatively higher than that of indirect learning. Indirect learning is also more prone to suffer from learning depreciation. When these two types of learning occur together, their interactive effect on subsequent performance is much higher than the sum of their independent effects. Surprisingly and importantly, I found that successful founding experiences may have a detrimental effect on subsequent success, while successful funding experiences have positive impacts. Further analysis shows a prevalence of the "early success trap" (Rhee and Kim 2015) in our context; that is, earlier successful founding experience can be more destructive than later ones. This is probably because entrepreneurs tend to be overconfident (Camerer and Lovallo 1999; Moore and Cain 2007), and they are likely to fixate their strategies to prior successful ones without exploring more situational ones. This finally leads to less than ideal outcomes. In addition, I find only relatedness of prior founding experience facilitates learning process, and only timely efforts in direct experiences are helpful.

In the second essay, I investigate the *within-campaign dynamics* by investigating the interplay between contemporaneous funding performance and entrepreneurial strategic behaviors. Specifically, I explore how the concurrent funding performance influences entrepreneurs' actions during fundraising process and how these actions in

turn affect final funding performance. Hypotheses are proposed based on the performance feedback model from organizational learning theory. The proposed hypotheses not only take into account goal-setting in the relationships between performance and strategic actions, but also considers the role of time in aspiration attainment. They are specifically related to the effects of contemporaneous performance relative to aspiration levels on entrepreneurs' explorative and exploitative actions during the fundraising process, the effects of taking actions on final project performance as well as the moderation effect of time on these relationships. Based on half-year's daily observations of all live projects from a leading reward-based crowdfunding platform, I find that there is a positive relationship between concurrent funding performance and entrepreneurs' probability of taking exploitative actions, and such relationship is strengthened when deadline approaches. Entrepreneurs are less likely to only taking explorative actions when performance increases, as it is usually accompanied by exploitative actions. Generally, entrepreneurs are more sensitive to performance changes in later funding stage. Furthermore, entrepreneurial strategies in managing the project are shown to be effective, and those who start to take actions at early funding stages can harvest more.

In summary, this dissertation aims to uncover the *across*- and *within-campaign* dynamics in crowdfunding – an important IS phenomenon. Overall, our findings suggest that entrepreneurship is a process of learning; entrepreneurs strategically adjust their behaviors along with their accumulation of prior experiences and concurrent feedback. The learning process occurs at macro- and micro- levels. At the macro level, entrepreneurs in crowdfunding platforms acquire knowledge when they create their own or back others' projects. At the micro level, they obtain feedback during fundraising process and in turn adapt their strategic actions based on the market response. Essentially, this dissertation shows that dynamic learning is an imperative component in

entrepreneurship. It reveals the importance of this perspective in understanding entrepreneurial activities.

7.2 Contributions and Implications

7.2.1 Theoretical Contributions

This dissertation yields several theoretical implications. This dissertation contributes to the IS literature on crowdfunding by initiating the first step to unveil the dynamics of entrepreneurial actions across- and within-campaigns. Even though the dynamic aspect has been deemed as an important component in entrepreneurship (Lant and Mezias 1990), related literature in crowdfunding have largely focused on potential drivers of crowdfunding success. Some project features, such as media richness (Beier and Wagner 2015) and project description (Mollick 2014), have shown to be impactful. But till now existing studies are not sufficient to reflect the developmental growth of entrepreneurial process and to explain how to make entrepreneurship work. Facilitated by the special feature of crowdfunding platforms – i.e., information transparency (Burtch et al. 2013a), we are able to observe the entrepreneurs' behaviors on the platforms. By analyzing the entrepreneurial activities on the crowdfunding platform, we find that entrepreneurs acquire necessary knowledge and skills over time when they create their own and back others' projects, and such experiences result in higher performance in their following projects. Besides, we propose that concurrent performance as a feedback in their fundraising process based upon which entrepreneurs can strategically adjust their subsequent practices. The final objective of such behaviors is to increase crowdfunding performance.

Second, and broadly, we extend organizational learning theory, including the performance feedback model, from typically *repeated tasks* to *innovation-based creative tasks* (e.g., entrepreneurship) where less routinization is the norm (Boh et al. 2007). The

emergent phenomenon of IT-enabled entrepreneurship (e.g., crowdfunding) provides us with this golden opportunity to examine the learning effects in this new form of work, and to uncover what might be different from traditional work processes. The findings to date have highlighted the salience of learning process in entrepreneurial practices. Prior experience are shown to be helpful, but it is vital to view each entrepreneur's learning task as dynamic, contextualized and cumulative (Cope 2005), because the naturally-occurring experiential learning-based strategy (i.e., repeating what seems to produce success and avoiding what seems to produce failures) does not ensure continued success in entrepreneurship.

Third, and specifically, we echo calls from prior organizational learning literature by characterizing experience at a fine-grained level (Argote and Miron-Spektor 2011) and explicitly considering the role of time in the feedback-learning cycle (Ancona et al. 2001; Lehman and Hahn 2013). Our fine-grained analyses have developed nuanced theoretical insights into the learning effects; different dimensions of experience are revealed to vary in their effects. Some of the findings are consistent with existing organizational learning literature, such as the experiential and vicarious learning (Schilling et al. 2003), whereas some are in contrast to prior research, such as learning from successful experiences. In addition, by considering the moderating role of time availability, we suggest that time "shapes the learning curve" (Wiersma 2007) by providing opportunities to learning from performance feedbacks and constraining the limited temporal resource for exploiting lessons learnt.

Besides, our empirical evidence enriches the growing corpus of work that investigates entrepreneurial learning (Cope 2005; Harrison and Leitch 2005; Rae 2006), especially the learning behaviors in entrepreneurial practices, most of which are still conceptual or anecdotal. Learning has gained broad acceptance as an inseparable part of entrepreneurial practice and study (Cope 2005). The emerging term "entrepreneurial

learning" refers to learning to identify and act on opportunities, through initiating, organizing and managing ventures in social and behavioral ways (Rae 2006). Given the importance but dearth of research in this area, we take the first step to explore how entrepreneurial behaviors are informed by their prior experience and specifically how entrepreneurs construct knowledge through experience.

7.2.2 Practical Implications

Practically, this dissertation offers guidance to entrepreneurs in crowdfunding on how to design experience to promote learning and how to adjust their strategies along fundraising process to increase project performance. During the learning process, entrepreneurs are encouraged to explore new strategies that suit well with their emergent innovative ideas. We also provide implications to entrepreneurs on how to respond to high/low funding performance relative to their funding goals. Besides, entrepreneurs are encouraged to dynamically adjust their strategies responding to performance feedback, as timely actions are likely to further entrepreneurial success. In addition, we offer design implications to crowdfunding platforms. They are encouraged to create a recommendation system to entrepreneurs and backers, where some relevant projects can be recommended to entrepreneurs according to their backing history. Also, interactive communication forums can be constructed to facilitate experience sharing among entrepreneurs.

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