Learning from Prior Experience: An Empirical Study of Serial Entrepreneurs in IT-enabled Crowdfunding

Completed Research Paper

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Abstract

Crowdfunding has gained momentum in recent years. Even though an increasing amount of research has been devoted to this domain, the dynamics of this phenomenon has yet to be fully studied. The current study strives to bridge this gap by examining the impacts of prior experiences from serial entrepreneurs' perspective. Drawing on organizational learning theory, we theorize about the differential effects from several experience dimensions: direct vs. indirect experiences, successful vs. failed experiences, experience richness and diversity of prior experiences. Employing a panel-level analysis approach, we document positive effects of both direct and indirect learning. However, the successful, rich and diverse experience do not always seem to facilitate learning and consequently lead to enhanced performance. Our study applies the organizational learning theory to the crowdfunding context to extend the existing crowdfunding literature in information systems by investigating the dynamics across campaigns. We also provide practical implications for entrepreneurs and platform operators.

Keywords: Organizational Learning, Crowdfunding, Entrepreneurship, Experience, Serial Entrepreneurs, Innovation

Introduction

In recent years, crowdfunding has emerged as a viable alternative for sourcing financial resources for innovations (Burtch et al. 2013; Burtch et al. 2014; Hahn and Lee 2013; Jung et al. 2014; Lin et al. 2014). It sprouts the development of small businesses – the economic and job engine of our economy. The crowdfunding platforms facilitate the democratization of entrepreneurship (Agrawal et al. 2010; Kim and Hann 2014) by directly tapping the general public for needed capital. The fundraising process is facilitated by the "wisdom of the crowd", which affords greater efficiency in resolving entrepreneurial problems compared to seeking capital from a few individuals or small teams of individuals (Howe 2008; Ingram et al. 2013; Malone et al. 2010; Schwienbacher and Larralde 2010; Surowiecki 2005). Pursuant to its rising popularity, an increasing number of entrepreneurs are making a transition to crowdfunding markets (Haas et al. 2014; Lin et al. 2014). Crowdfunding assists entrepreneurs in transforming inventions and innovative ideas into economically viable entities (Baumol 1993; Hu et al. 2015). Hence, these individual founders play a vital role in economic growth (Ward and Ramachandran 2010; Zhang and Liu 2012) and have become an important part of modern economic society (Bosma et al. 2000). It is thus imperative to explore the key mechanisms that facilitate entrepreneurial success in crowdfunding.

As to its salient economic impacts, a major research stream in crowdfunding has been devoted to examining the potential drivers of successful crowdfunding campaigns (i.e., projects) (e.g., Koch and Siering 2015; Marom 2013; Mollick 2014; Qiu 2013; Xu et al. 2014). By and large, existing studies have taken a factor-oriented approach. For instance, studies have sought to identify the influence of factors such as project quality (Mollick 2013), project updates (Xu et al. 2014), creator's backing history (Koch and Siering 2015; Zvilichovsky et al. 2013) and social media activities (Thies et al. 2014). Generally, such factor-oriented studies may shed light on the static aspects of entrepreneurial success. Furthermore, extant research implicitly assumes that projects, even though they are initiated by the same entrepreneur, are independent. Nevertheless, entrepreneurs, on crowdfunding platforms, develop necessary knowledge and skills over time when they create their own or back others' projects. Their entrepreneurial activities are prone to changes via the accumulation of experience. For example, entrepreneurs tend to strategically adjust their subsequent entrepreneurial activities based on their own interpretations of prior experiences (Gray and Gonsalves 2002). However, to date, such *dynamics* of entrepreneurial practices across campaigns have been previously under-explored. Entrepreneurship is a complex and risky behavior (Zahra 2007) where failure is typically a norm rather than an exception, it is therefore important to understand how entrepreneur develop necessary knowledge *over time* to become successful.

The present study therefore aims to bridge this gap in the literature by examining the role of entrepreneurs' experiences in crowdfunding projects. On crowdfunding platforms, entrepreneurs are able to play roles on both sides of the market (Zvilichovsky et al. 2013; Zvilichovsky et al. 2014) – not only can they initiate their own projects to raise funds (as sellers), they can also invest in others' projects (as buyers). The experiences gained from participating in such activities will shape how these entrepreneurs approach their own crowdfunding campaigns. Through each successful and failed experience, they *continuously* learn to recognize and react to opportunities, and develop the capability to act differently (Greenberg and Gerber 2014; Rae 2006). Learning has become an essential component in entrepreneurial activities (Kirzner 1978). 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, we aim to *examine entrepreneurial learning from several dimensions of experiences and investigate their impacts on entrepreneurial success in crowdfunding*.

In this study, we use the theoretical lens of organizational learning (Argote and Miron-Spektor 2011) to conceptualize the entrepreneurial learning process. We argue that learning on crowdfunding occurs in a feedback cycle, where entrepreneurs observe the performance of prior experiences and alter their subsequent behaviors accordingly (Fiol and Lyles 1985; Lehman and Hahn 2013). In particular, we focus on *serial entrepreneurs* – those entrepreneurs who have multiple founding experiences (Bayus 2013; Gompers et al. 2006). By investigating the influence of their past creating and backing experiences, we strive to uncover how they change entrepreneurial activities over time. Based on empirical data from *Kickstarter.com*, we employ a panel-level analysis approach and find empirical evidence of learning effects from several fine-grained dimensions of experience. Serial entrepreneurs learn *directly* via launching their own projects and *indirectly* by funding others' projects. The combined learning effects are greater than the sum of the independent effects. Further, we also find that successful experiences do not always lead to enhanced outcomes. Specifically, we find evidence of a "success trap" (Levitt and March 1988; Rhee and Kim 2015) from early founding success. We also found that only timely efforts in founding experience are shown to be beneficial, and too much diversity in backing experiences may actually impede learning.

Theoretical Background and Framework

Organizational Learning and Entrepreneurship

Entrepreneurial learning enables entrepreneurs (or entrepreneur teams) to accumulate experience-based knowledge that serves as the basis for subsequent performance improvements (Holcomb et al. 2009; Hsu 2007; Lant and Mezias 1990; Politis 2005). This process naturally fits the basic theoretical mechanisms of organizational learning, where the basic 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 2012; 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 2013; Argote and Miron-Spektor 2011). *Experience* is the beginning of the learning process and it represents references transpired from prior tasks. *Context* refers to the "contingency that affects learning processes and moderates the relationship between experience and outcomes" (Argote and Miron-Spektor 2011, p. 1127). The third component, *knowledge*, is the outcome of 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 the principal source of advantage and increased performance (Argote and Ingram 2000). On crowdfunding platforms, entrepreneurs acquire *experience* by directly initiating their own or indirectly backing others' projects. During the process, they receive feedback from the crowdfunding market (*context*).[1] Gradually, these experiences and context feedback would be instilled into *knowledge*, which in turn will guide entrepreneurs' subsequent activities.

Hitherto, prior studies investigating learning effects have been primarily situated in manufacturing (e.g., Argote et al. 1990) and service industries (e.g., Reagans et al. 2005) where organization typically deal with *repeated* tasks, in which procedures are routinized (Cohen and Bacdayan 1994). There is however a paucity of understanding of the learning processes in *knowledge- and innovation-based work* (e.g., entrepreneurship) where less routinization (Boh et al. 2007) and more creative works are entailed. However, as aforementioned, entrepreneurship is, to large extent, considered as the process of learning from experience (Rae 2006). It is vital to view each entrepreneur's learning task as dynamic, contextualized, and cumulative (Cope 2005; Minniti and Bygrave 2001). We argue that the process of entrepreneurial learning is one where subjective knowledge is continuously updated (Cope 2005; Harrison and Leitch 2005). In essence, the sense-making process of learning enables entrepreneurs to develop capabilities to act differently, and to comprise knowledge, doing and understanding why something works and something does not (Mumford 1999; Rae 2005). We therefore expect that examining learning effects in an IT-enabled entrepreneurship context can inform and contribute further insight to organizational learning theory.

Direct and Indirect Experiences

The learning literature 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

[1] In crowdfunding, the context here may also refer to differing situations 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. 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*.

creation: *trial-and-error* and *search* (Levitt and March 1988). The two mechanisms follow the logics of *appropriateness* and *consequences* whereby experiences that produce favorable outcomes are repeated in hopes to sustain success whereas those that result in unfavorable outcomes are avoided in order to circumvent failures (Cyert and March 1963). Organizations' (and individuals') knowledge reservoirs are updated accordingly after they experience success or failure. 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 efficiency of this direct learning process depends on the history of successes and failures (Radner 1975). The rate of discovering appropriate courses of action is proportional to the abundance of the knowledge reservoir (Levitt and March 1988).

In the crowdfunding context, entrepreneurs may obtain direct experience by learning from their own founding behaviors and indirect experience by backing other entrepreneurs' initiatives. First, with respect to direct experiences, entrepreneurs observe the success and failure accompanying their prior founding experiences, and develop intuitions about the types of behaviors most likely to contribute to project success. More specifically, crowdfunding platforms enable entrepreneurs to obtain timely feedback through comments or personal messages from backers. When entrepreneurs receive positive performance feedback (i.e., achieve fundraising success), they would attribute success to the actions they had performed in the prior project and develop an inclination to repeat such behaviors with the expectation that subsequent success will follow. Otherwise, when entrepreneurs receive negative performance feedback (i.e., fail to achieve success), they may be more inclined to explore other possible courses of actions. Hence, serial entrepreneurs with prior founding experiences have a higher likelihood of developing and initiating projects that may be well-received, and this likelihood increases with the number of founding experience. In addition, entrepreneurs with a larger number of prior founding experiences will tend to have a more abundant knowledge reservoir, which provides a search pool of greater quantity – a larger number of alternatives both expectedly favorable and unfavorable. For example, an entrepreneur who has several successful or unsuccessful founding experiences, where he/she had posted timely updates to the project, is likely to have better sense of the types of updates and posts that are deemed to be favorable to (potential) investors. 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. Based on these arguments, we hypothesize:

> ***Hypothesis 1a:*** *The number of an entrepreneur's prior founding experiences is positively associated with the likelihood of success of a crowdfunding project.*

Second, organizations (and individuals) 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 and McClelland 1977). Organizations (and individuals) benefit from the experience of others through the transfer of experience in the form of procedures or similar routines (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".

One distinct feature of crowdfunding is that entrepreneurs may assume roles on both sides the online market – entrepreneurs may take the role of funders (i.e., invest in others' projects) in addition to their role of founders (i.e., initiate their own projects to raise funds) (Zvilichovsky et al. 2013). By participating in both sides of the market, entrepreneurs' knowledge reservoirs can be enriched through direct as well as indirect learning.[2] In indirect learning, entrepreneurs observe others' entrepreneurial activities and their associated consequences and link these observations to the possible occasions on which they are successful or unsuccessful (Bandura and McClelland 1977). When they observe 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. For instance, entrepreneurs as

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[2] In our paper we only consider as indirect learning when entrepreneurs are really engaged in others' projects through backing behavior. Those who only observe others projects without backing are not considered, since on crowdfunding platforms such as *Kickstarter.com*, only backers are allowed to post comments, and some timely project updates are targeting (posted to) them directly, through which they are able to have intensive interactions with other creators. It is hard for observers' to realize close engagement with certain projects.

backers would receive notifications about project's updates or personal messages from project owners. The updates may aim to build marketing momentum, share information on production progress, celebrate milestones, etc. From the backer's perspective, as observers, entrepreneurs will develop their own interpretations of the entrepreneurial experience from their individual inference and judgment. For example, when they observe other entrepreneurs respond to individual concerns frequently, and if the project turned out to be successful, they will interpret and store this behavior as positively associated with success in their knowledge reservoir; whereas, if other entrepreneurs do not provide frequent updates about project progress or about important project-related decisions, and if the project turned out to be unsuccessful, the entrepreneurs (as backers) are likely to interpret this behavior as being ineffective. Thus, with an increase in the number of indirect funding experiences, the number of potential actions-outcome associations they store in their knowledge reservoir will also increases. The knowledge obtained through such indirect experience may serve as guidance for future founding behaviors. We therefore hypothesize:

> ***Hypothesis 1b****: The number of entrepreneurs' prior funding experiences is positively associated with the likelihood of success of a crowdfunding project.*

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 than indirect experience in a product-development task. In our context of crowdfunding, we argue that entrepreneurial activities are manifold 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, an entrepreneur may perceive a particular reward scheme to be effective; but the reason underlying its effectiveness may be due to other factors in addition to the design of the reward scheme itself (e.g., personalized follow-ups by the entrepreneurs). Therefore, without knowing the underlying mechanisms that lead to success, it would be difficult for indirect learners to develop clear mappings of actions to outcomes. However, for founders (i.e., entrepreneurs with direct experience), 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 founding experiences on the likelihood of success of a crowdfunding project is stronger than that of funding experiences.*

In addition to these main effects, we also consider whether the effects of direct and indirect learning may in fact be supplementary. Through direct learning by initiating their own projects, entrepreneurs start to formulate their own interpretations between courses of actions and potential outcomes. This mapping process can be reinforced when indirect learning also occurs, where they observe or imitate others' behaviors. Bandura and McClelland (1977) propose that when direct and indirect learning occur together, their interactive effect on performance is of much greater significance than the sum of their independent effects. In the crowdfunding context, we expect entrepreneurs to be able to continuously adjust their knowledge repositories when they are reinforced or negated by others' behaviors. 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 founding experiences increase, the effect of funding experience will increase (and vice versa).*

Successful vs. Failed Experiences

A second dimension of experience relates to outcomes. Success is an indicator 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).

Successful experiences give entrepreneurs a better understanding of the characteristics of projects. Those favorable properties are likely to be used when they are associated with success and less likely when they are associated with failure (Cyert and March 1963). Therefore, a larger number of successful experiences facilitates the formation of a better appreciation of preferable properties, which in turn leads to higher likelihood of success. Similarly, the success history of entrepreneurs also increase the search efficiency and guide them search in the right direction (Radner 1975) for better solutions. These arguments apply for both direct and indirect experiences. Taken together, we propose:

> ***Hypothesis 2a:*** *Given the number of prior founding experiences, the number of an entrepreneur's successful founding experiences is positively associated with the likelihood of success of a crowdfunding project.*

> ***Hypothesis 2b:*** *Given the number of prior funding experiences, the number of an entrepreneur's successful funding experiences is positively associated with the likelihood of success of a crowdfunding project.*

Richness of Prior Experiences

In addition to the number and the outcomes, we argue that the richness of prior experience is also important to learning. The entrepreneurship literature finds that the extent and variety of management role entrepreneurs played in their previous jobs have an effect on the performance of their new business (Stuart and Abetti 1990). The variety of management roles played signifies the extent of job involvement, and can be conceptualized as *richness of experience*. Richness of experience indicates one's engagement in the relevant activities –the more they are engaged, the more knowledge is likely to be distilled from the experience, and consequently, the quality of the knowledge gained is higher.

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. Similarly, *project comments* can be used to answer questions from backers.[3] 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, and can be conceptualized as the *richness of experience*. We propose that, compared to those who do not update or comment often, entrepreneurs who frequently update or comment are inclined to have more interactions with backers (or other creators), so that they will tend to have more accurate and deeper understanding of crowdfunders' preferences towards project and those preferable project attributes. Therefore, more knowledge would be extracted through such interactions. We hypothesize:

> ***Hypothesis 3:*** *The richness of prior experiences is positively associated with the likelihood of success of a crowdfunding project.*

Diversity of Prior Experiences

Besides experience richness, we also consider the impact of the diversity (or variety) of prior experiences. Exposure to a variety of tasks enables individuals to tackle problems more effectively since they can obtain knowledge from a broader schema (Graydon and Griffin 1996; Paas and Van Merriënboer 1994). The knowledge in the schema aids the individual in distinguishing between knowledge that is relevant to the task at hand and that which is less relevant (Hwang et al. 2014; Narayanan et al. 2009). Stated differently, more appropriate actions that are conducive to the learning outcome will be discovered from the knowledge reservoir. Besides, the variety of experiences leads to implicit learning (Narayanan et al. 2009), through which tacit knowledge can be developed. Individuals unconsciously store knowledge as task requirements in different domains. They are also inclined to generate better understanding of interrelations of diverse domains (Reber 1989; Simon 1991; Wulf and Schmidt 1997). Implicit knowledge may also induce enhanced learning. Hence, through the two mechanisms, diversity of experiences leads to better performance.

In crowdfunding, entrepreneurs may initiate their own and back others' innovative ideas in a variety of product categories. Participating in projects in a variety of categories exposes entrepreneurs to various project framing styles, different reward scheme designs as well as interaction with backers from diverse backgrounds. They also have a chance to learn how different components across categories can be

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

composed and related to one another. Greater diversity of experience (in both founding and funding) should provide entrepreneurs with a better appreciation of their own projects. We therefore hypothesize:

> ***Hypothesis 4:*** *The diversity of prior experiences is positively associated with the likelihood of success of a crowdfunding project.*

Data and Empirical Context

Our data was retrieved from *Kickstarter.com*, one of the largest reward-based crowdfunding platforms. Using a dedicated software crawler, we collected relevant information on all crowdfunding projects that ended before December 8, 2014. Our data covers all projects since the inception of *Kickstarter.com* – 186,174 projects created by 158,857 unique creators. These projects collectively received a total amount of USD $1,396M from over 7M unique backers. The time span of our data is from April 22, 2009 to December 8, 2014. The number of projects and success rates across years are shown in Figure 1. It suggests the projects are persistently increasing since 2009, however the overall success rate is decreasing.

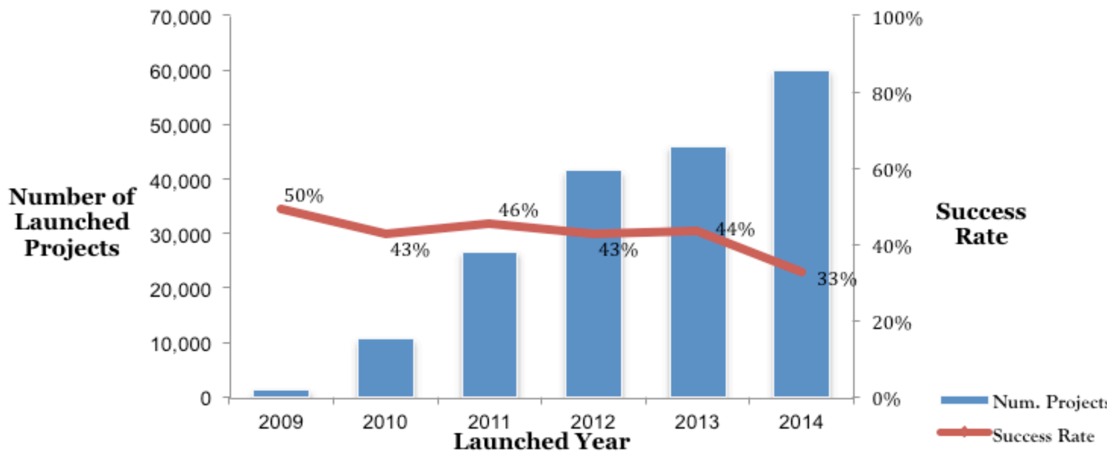

Figure 1. Number of projects and success rates from 2009 to 2014

Kickstarter.com categorizes projects into 15 broad category domains: art, comics, journalism, photography, publishing, crafts, dance, film, music, theater, fashion, food, games, technology and design. The most active category is *film*, with a total of 40,692 projects and the least active one is *dance*, with only 2,267 projects. However, in terms of project success rates, the dance category has the highest success rate at 68%, whereas the technology category had the lowest success rate at 25%. Since our research focus is on *entrepreneurial* learning, we focus our analysis on three entrepreneurship-related categories: *games* (13,252 projects; 35% success rate), *technology* (8,600 projects; 25% success rate), and *design* (10,806 projects; 36% success rate).[4] 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 entrepreneur teams). We define *serial entrepreneurs* here as those who launched at least two projects *within these three entrepreneurship-related categories*. Ultimately, our analysis data consists of 3,545 serial entrepreneurs, with a total of 9,242 launched projects (average = 2.6 projects).

The Empirical Study

In this section, the hypotheses developed earlier are formally tested. An unbalanced panel data set was constructed with the entrepreneur-project as the unit of analysis.

[4] These three categories are chosen because nearly all the projects in the categories are related to entrepreneurial activities. Individual entrepreneurs, entrepreneur teams, or small businesses post their innovative projects mostly in these categories. Typical examples include: an E-paper smart-watch, a creative portable cooler, an instant iPhone camera, etc. However, in other categories, many (if not most) projects are not entrepreneurially-oriented.

Measures

Dependent Variable. The successful attainment of the crowdfunding project fundraising goal is used as a proxy for entrepreneurial success. To better capture the extent of success, rather than using a simple binary variable (i.e., success vs. failure), we use the pledged percentage ($PledgedPercentage_{ij}$) as the dependent variable, where $PledgedPercentage_{ij} = PledgedAmount_{ij}/FundingGoal_{ij}$, where j is the j^{th} project entrepreneur i launched *in the entrepreneurship-related categories*. 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 the skewed distribution.

Direct/Indirect Experiences. 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-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 ($Created_{ij} \times Backed_{ij}$). To test whether the learning effects are applicable to only entrepreneurship-related categories, we also tested the models using two variables $NumCreatedEntProjects_{ij}$ and $NumBackedEntProjects_{ij}$ to capture direct/indirect experiences only in the entrepreneurship-related categories.

Successful/Failed Experiences. 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. Further, we also generated four variables, $NumCreatedEntSuccess_{ij}$, $NumCreatedEntFailure_{ij}$, $NumBackedEntSuccess_{ij}$ and $NumBackedEntFailure_{ij}$, to test the robustness of the effects in entrepreneurship-related categories. For Hypotheses 2a and 2b, we expect significantly positive coefficients for $CreatedSuccessRatio_{ij}$ and $BackedSuccessRatio_{ij}$.

Experience Richness. Entrepreneurs' can 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 (i.e., *NumUpdates* + *NumComments*). We take the average across all of entrepreneur i's prior launched projects in all domain categories as the measure of richness for focal project j ($AvgCreatedRichness_{ij}$). Similarly, the indirect experience richness is operationalized by the number of comments the entrepreneur posts on projects he/she is backing. 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 3, we expect significantly positive coefficients for both direct and indirect richness variables.

Experience Diversity. The operationalization of experience diversity also consists of two parts: diversity for direct and indirect experience. We construct both diversity measures using entropy over all project categories: $-\sum p_{cij} \times \ln(p_{cij})$ (Harrison and Klein 2007), where p_{cij} (c=1,…,15 categories) is the proportion of launched (backed) projects in category c by the focal entrepreneur i prior to the focal project j.[5] Two variables are generated: $CreatedDiversity_{ij}$ and $BackedDiversity_{ij}$. For Hypothesis 4, we expect significantly positive coefficients for both diversity variables.

Control Variables. Several variables are included in the analysis to control for possible effects due to project specific factors – 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

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[5] The entropy measure captures whether the experiences are evenly distributed across categories. Diversity is highest when experiences are uniformly distributed across categories. Otherwise, if experiences are concentrated in a certain or in a few categories, the diversity is reduced.

the entrepreneur (*CampaignDuration*), the length of general project description (*DescriptionLength*), the length of description of risks and challenges for the project (*RiskLength*), the funding goal of the project (*Goal*),[6] the number of reward levels (*NumProjectRewards*), and project domain (*Category* dummies). Moreover, we control for project quality using an indicator variable *QuickUpdate* which is coded as 1 when the entrepreneur posted updates within three days of launch (Mollick 2013). The year and month controls are included to account for platform-level shocks over time. Descriptive statistics of all variables are presented in Table 1.

Table 1. Summary Statistics for Estimation Sample

	Variables	Mean	Std. Dev.	Min	Max
Outcome	*PledgedPercentage*	2.698	13.67	0	631.7
Experience	*NumCreatedProjects*	1.131	1.451	0	17
	NumBackedProjects	8.113	22.08	0	735
	NumCreatedSuccess	0.550	1.143	0	17
	NumCreatedFailure	0.581	0.880	0	10
	NumBackedSuccess	6.501	17.22	0	552
	NumBackedFailure	1.612	6.442	0	198
	CreatedSuccessRatio	0.254	0.407	0	1
	BackedSuccessRatio	0.536	0.435	0	1
Richness	*AvgCreatedRichness*	28.59	111.7	0	3,392
	AvgBackedRichness	7.357	138.7	0	8,873
Diversity	*CreatingDiversity*	0.0116	0.0553	0	0.301
	BackingDiversity	0.183	0.241	0	1.098
Entrepreneurship-related experience	*NumCreatedEntProjects*	1.004	1.252	0	9
	NumBackedEntProjects	5.907	14.97	0	363
	NumCreatedEntSuccess	0.492	1.009	0	9
	NumCreatedEntFailure	0.512	0.767	0	9
	NumBackedEntSuccess	4.812	12.07	0	269
	NumBackedEntFailure	1.095	3.913	0	123
Controls	*NumProjectRewards*	9.627	6.458	0	137
	ImageCount	12.77	13.73	0	167
	HasVideo	0.631	0.483	0	1
	Goal	30,729	336,938	0.931	2.856e+07
	DescriptionLength	5,307	4,420	0	30,573
	RiskLength	678.2	658.1	0	8,801
	QuickUpdate	0.553	0.497	0	1
	CampaignDuration	33.99	11.63	1	91

Notes: Number of observations: 8,868; Number of serial entrepreneurs: 3,525. We exclude those serial entrepreneurs (20) with more than ten launched entrepreneurial projects as these observations are likely to be existing corporations rather than entrepreneurial start-ups. The sample also excludes 9 outliers whose *PledgedPercentage* values exceeded three standard deviations above the mean. The regression results (presented later) are consistent with or without these outliers.

Estimation Approach

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

$$PledgedPercentage_{ij} = \beta \ ExperienceRelatedVars_{ij} + CONTROL + \alpha_i + u_{ij}$$

where the $ExperienceRelatedVars_{ij}$ represents our focal variables that vary over each entrepreneurs and projects, and α_i captures the individual entrepreneur's unobserved heterogeneity (e.g., entrepreneur's individual ability) that are stable over time. Since most of the explanatory variables (except for success ratios, richness, diversity 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

[6] 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.

are preferred over random effects models for this data set, where time-invariant entrepreneurs fixed-effects α_i was eliminated in our estimation.[7] 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).

Results and Discussions

Table 2 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 through 5. As shown in Model 1, *ImageCount* is positive and significant (β=0.0284, p<0.01), which suggests that including more images to highlight the project increase the likelihood of project success. It is not surprising that longer campaign duration lends to higher pledged percentage (*CampaignDuration*: β=0.00990, p<0.01). Consistent with our expectation, the coefficient of *DescriptionLength*, *NumRewards* and *QuickUpdate* are positive and significant (ln(*DescriptionLength*): β=0.124, p<0.01; *NumProjectRewards*: β=0.0341, p<0.01; *QuickUpdate*: β=0.680, p<0.01). Longer descriptions and a greater number of reward levels signal better preparation of entrepreneurs, in turn resulting in higher likelihood of success. *RiskLength* and *HasVideo* are not significant (ln(*RiskLength*): β=-0.0148, ns; *HasVideo*: β=0.105, ns). But *HasVideo* becomes positively significant after we add in variables of interest (Model2-5, *HasVideo*: β>0.114, p<0.1). Finally, the more ambitious the fundraising goal, the less likely the project was to succeed (ln(*Goal*): β=-0.740, p<0.01).

Table 2. Panel OLS Fixed-effects Regression Results for Learning from Direct/Indirect Experiences

	DV: ln(*PledgedPercentage*)				
Variables	Model 1	Model 2	Model 3	Model 4	Model 5
ln(*NumCreatedProjects*)		**0.284*****	**0.285*****	**0.301*****	**0.298*****
		(0.0444)	(0.0444)	(0.0442)	(0.0443)
ln(*NumBackedProjects*)		**0.0826****	**0.0408**	**0.110*****	**0.0474**
		(0.0367)	(0.0414)	(0.0383)	(0.0446)
Created×Backed			**0.0464****		**0.0642*****
			(0.0220)		(0.0232)
ImageCount	0.0206***	0.0193***	0.0194***	0.0191***	0.0191***
	(0.0020)	(0.0019)	(0.0019)	(0.0019)	(0.0019)
HasVideo	0.105	0.115*	0.121*	0.114*	0.120*
	(0.0651)	(0.0647)	(0.0646)	(0.0647)	(0.0646)
CampaignDuration	0.00990***	0.00917***	0.00929***	0.00915***	0.00938***
	(0.0016)	(0.0016)	(0.0016)	(0.0016)	(0.0016)
ln(*DescriptionLength*)	0.124***	0.123***	0.123***	0.123***	0.123***
	(0.0251)	(0.0246)	(0.0246)	(0.0245)	(0.0244)
ln(*RiskLength*)	-0.0148	-0.0154	-0.0153	-0.0152	-0.0151
	(0.0130)	(0.0130)	(0.0130)	(0.0130)	(0.0129)
ln(*Goal*)	-0.740***	-0.713***	-0.715***	-0.713***	-0.715***
	(0.0203)	(0.0207)	(0.0208)	(0.0207)	(0.0207)
QuickUpdate	0.680***	0.686***	0.686***	0.686***	0.686***
	(0.0386)	(0.0384)	(0.0384)	(0.0383)	(0.0383)
NumRewards	0.0341***	0.0349***	0.0352***	0.0353***	0.0358***
	(0.0045)	(0.0044)	(0.0044)	(0.0044)	(0.0045)
Constant	3.471***	2.734***	2.761***	2.689***	2.727***
	(0.252)	(0.266)	(0.266)	(0.262)	(0.263)
R^2	0.441	0.447	0.448	0.448	0.449
Observations	8,868	8,868	8,868	8,868	8,868
Number of entrepreneurs	3,525	3,525	3,525	3,525	3,525

Note: Category, month and year dummies are included; Robust standard errors are reported in parentheses.
Significance Levels: $^{***}p$<0.01, $^{**}p$<0.05, $^{*}p$<0.1.

[7] Importantly, the fixed-effects model removes any unobserved, time-invariant heterogeneity across entrepreneurs. This approach allows the individual specific effects to be correlated with the focal variables. Thus, the estimation is less likely to be undermined by bias arising from endogeneity issues.

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 (Model 1 vs. 2: ΔR^2=0.006, p<0.01). The coefficients and significance of the control variables remain consistent after we add in focal variables (except for the slight difference for *HasVideo*). The positive and significant coefficient for ln(*NumCreatedProjects*) (β=0.284, p<0.01) and ln(*NumBackedProjects*) (β=0.0826, p<0.05) supports H1a and H1b. Serial entrepreneurs are more likely to succeed in their crowdfunding campaigns not only when own direct (founding) experience is greater but also when indirect (funding) experience is greater. To find out the relative strength of direct and indirect learning, we compare the magnitude of coefficients in Model2. The result suggests the coefficient of direct experience is significantly higher than that of indirect experience (F=9.90, 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 increasing of both direct and indirect experience, those serial entrepreneurs who have more abundant founding experience are more likely to harvest more, which give rise to higher likelihood of entrepreneurial success.

In Model 3, we include the interaction terms of created and backed experiences (ΔR^2=0.001, p<0.05). We find a positive interaction effect (*Created*×*Backed*: β=0.0464, p<0.05), supporting H1d. But the estimated coefficient for backed experience becomes insignificant (ln(*NumBackedProjects*): β=0.0408, 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 after they initiate their own projects, their backing experiences reinforce their direct learning effects. Thus, H1d is partially supported.

Further, we conduct additional analysis to see whether the above results hold if we only consider entrepreneurship-related experiences (i.e., experiences in the *games*, *technology* and *design* categories). In Model 4 and Model 5, the variables ln(*NumCreatedEntProjects*), ln(*NumBackedEntProjects*) and their interaction term are included in lieu of the experience variables in Model 2 and Model 3. As can be seen, the results are consistent with the previous models that considered all prior experiences in all category domains. This highlights the robustness of the results to entrepreneurship-related experience.

Table 3 Learning Dynamics Results for Direct/Indirect Experiences

	DV: ln(*PledgedPercentage*)		
Variables	Model6	Model7	Model8
ln(*NumCreatedLast1*)	**0.242*****	**0.280*****	**0.298*****
	(0.0393)	(0.0422)	(0.0438)
ln(*NumCreatedLast2*)		**0.207*****	**0.240*****
		(0.0767)	(0.0837)
ln(*NumCreatedLast3*)			**0.0571**
			(0.127)
ln(*NumBackedLast1*)	**0.0717****	**0.0710****	**0.0758****
	(0.0336)	(0.0336)	(0.0336)
ln(*NumBackedLast2*)		**-0.00159**	**-0.00249**
		(0.0300)	(0.0299)
ln(*NumBackedLast3*)			**0.0725**
			(0.0454)
Constant	3.054***	2.914***	2.838***
	(0.268)	(0.272)	(0.273)
R^2	0.456	0.458	0.458
Observations	7,987	7,987	7,987
Number of entrepreneurs	3,353	3,353	3,353

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

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 the platform experiences 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.[8] Table 3 reports the results for learning dynamics, which are presented in a hierarchical manner to understand whether the impact is sensitive to the experience in previous year(s). The results for control variables are consistent with prior results presented in Table 2.[9] In Model 8, the positive coefficients of ln(*NumCreatedLast1*) (β=0.298, p<0.01) and ln(*NumCreatedLast2*) (β=0.240, p<0.1) shows that direct learning effect persist over certain period of time (2 years), but then fade away (ln(*NumCreatedLast3*): β=0.0571, *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=0.0758, p<0.05), but depreciate for longer lags (ln(*NumBackedLast2*): β=-0.00249, *ns;* ln(*NumBackedLast3*): β=0.0725, *ns*). The results suggest that the learning depreciation (Argote et al. 1990; Darr et al. 1995; Kang and Hahn 2009) 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 founding experiences can be said to be stronger than that of funding experiences.

Table 4. Panel OLS Fixed-effects Regression Results for Learning from Successful/Failed Experiences

	DV: ln(*PledgedPercentage*)					
Variables	Model 9	Model 10	Model 11	Model 12	Model 13	Model 14
ln(*NumCreatedProjects*)	**0.546*****		**0.585*****			
	(0.0443)		(0.0439)			
ln(*NumBackedProjects*)	**0.153*****		**0.178*****			
	(0.0356)		(0.0373)			
CreatedSuccessRatio	**-1.052*****		**-1.074*****			
	(0.0498)		(0.0490)			
BackedSuccessRatio	**0.126***		**0.113***			
	(0.0713)		(0.0689)			
ln(*NumCreatedSuccess*)		**-0.655*****		**-0.664*****	**-0.638*****	**-0.428*****
		(0.0608)		(0.0609)	(0.0803)	(0.104)
ln(*NumCreatedFailure*)		**0.728*****		**0.758*****	0.561***	0.699***
		(0.0429)		(0.0428)	(0.125)	(0.0539)
ln(*NumBackedSuccess*)		**0.272*****		**0.302*****	0.178***	0.379***
		(0.0439)		(0.0442)	(0.0597)	(0.0615)
ln(*NumBackedFailure*)		**-0.00827**		**0.000969**	-0.0105	0.0229
		(0.0445)		(0.0459)	(0.0589)	(0.0660)
Constant	2.498***	2.266***	2.478***	2.259***	4.023***	1.281***
	(0.250)	(0.247)	(0.247)	(0.245)	(0.409)	(0.317)
R^2	0.491	0.497	0.495	0.501	0.460	0.525
Observations	8,868	8,868	8,868	8,868	3,247	5,621
Number of Entrepreneurs	3,525	3,525	3,525	3,525	1,174	2,351

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

[8] 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.

[9] From Table 3 onwards, the estimation results for control variables are all consistent with those of Table 2. To conserve space, we no longer display them.

Table 4 shows the estimation results for learning from successful and failed experiences. The explanatory power of the estimation models increases significantly when we include the focal variables for successful (and failed) experiences (Model 2 vs. 9: ΔR^2=0.044, p<0.01; Model 1 vs. 10: ΔR^2=0.056, p<0.01). H2a and H2b proposed higher proportions of successful experiences would lead to higher likelihood of success. In Table 4, Model 8 therefore introduces the two success ratio variables. In contrast to our hypotheses, we find a negative and significant coefficient estimate for *CreatedSuccessRatio* (β=-1.052, p<0.01). This suggests that having successful founding experience is negatively associated with the success rate of subsequent projects. One possible reason may be that entrepreneurial activities are much more complex than simple procedural behaviors (Cope 2005) and/or that the context is volatile. Even though each entrepreneurial campaign may be inherently different, upon success, entrepreneurs may be replicating their prior strategies rather than exploring new actions specific to their immediate situations, ultimately leading to negative outcomes. Therefore H2a is *not* supported. However, we obtained support for H2b (*BackedSuccessRatio*: β=0.126, p<0.1). The higher proportion of successful indirect (funding) experience, the more likely entrepreneurs are to be successful in a subsequent project. Further, to gain additional insights, we estimate a model using the *number* of successful and failed experiences as explanatory variables (rather than ratios) (see Model 10). The results show that entrepreneurs' prior successful founding experiences negatively influence subsequent success (ln(*NumCreatedSuccess*): β=-0.655, p<0.01) but they can benefit from their own (i.e., direct) failures (ln(*NumCreatedFailure*): β=0.728 , p<0.01) and others' (i.e., indirect) successes (ln(*NumBackedSuccess*): β=0.272, p<0.01). Interestingly, the positive support from previous founding experiences (ln(*NumCreatedProjects*) in Table 2) comes primarily from one's failed founding experiences; and the positive funding experience (ln(*NumBackedProjects*) in Table 2) is only from successful funding experiences. Models 11 and 12 replicate the analysis using explanatory variables that only consider prior experiences with the three entrepreneurship-related categories. The results are consistent with Models 9 and 10, which highlights the robustness of results to entrepreneurship-related experience.

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 13, where we focus our analysis to a subsample of entrepreneurs who were successful in their first project. Model 14 shows the results for rest of the sample (i.e., those that were unsuccessful in their first project). We compare the magnitude of coefficients of *NumCreatedSuccess* across these two models. The result suggests the coefficient in Model 13 is significantly smaller than that in Model 14 (χ^2=3.94, p<0.05), suggesting the occurrence of an "early success trap" whereby the impact of earlier successful experience is more destructive than later ones.

Table 5. Mean Comparisons of Project Attributes Changes

	1st Campaign	2nd Campaign	*t*-value	1st Campaign	2nd Campaign	*t*-value
	Panel 1: Success → Failure (*N*=645)			Panel 3: Failure → Success (*N*=1205)		
Goal	11706	25792	**6.82*****	38055	9977	**-3.04*****
ImageCount	13.89	13.26	**-1.12**	12.41	16.25	**11.81*****
DescLength	5372	4981	**-2.50*****	5455	6032	**5.07*****
NumRewards	10.29	8.90	**-5.34*****	10.28	10.52	**1.21**
QuickUpdate	0.68	0.43	**-10.69*****	0.56	0.73	**9.89*****
	Panel 2: Success → Success (*N*=1623)			Panel 4: Failure → Failure (*N*=1872)		
Goal	11798	14271	**3.12*****	63851	34882	**-1.81***
ImageCount	14.71	17.51	**7.37*****	8.71	9.97	**5.87*****
DescLength	6135	6335	**1.84***	4202	4320	**1.54***
NumRewards	11.21	10.96	**-1.28**	8.14	7.82	**-2.97*****
QuickUpdate	0.78	0.75	**-0.72**	0.37	0.36	**0.48**
Significance Levels: $^{***}p$<0.01, $^{**}p$<0.05, $^{*}p$<0.1.						

Aiming to obtain further insights of changes of project attributes after entrepreneurs experience success and failure, we conduct further analysis to show how changes in various project attributes impact project success (see Table 5). The results suggest that for those entrepreneurs who fail after success (see Panel 1;

Success→Failure), they tend to dramatically increase their funding goals, however, other project properties (i.e., the number of images used in project descriptions, 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 rationally increase their goal. The significantly increased means of *ImageCount* and *DescLength* further suggest that they are still well-prepared for subsequent projects. Even though the mean of *QuickUpdate* does not significantly change, but it still remains relatively high (from 0.78 to 0.75) especially compare to that in Panel 1 (from 0.68 to 0.43). These results are consistent with our previous arguments about "early success traps" in that they tend to follow/replicate previous successful strategies without additional exploration but with an expectation of further success. Unfortunately, the lack of preparedness and responsiveness resulted in failed outcomes. This is also consistent with the commonly observed characteristic of entrepreneurs – overconfidence (Moore and Cain 2007). Entrepreneurs are inclined to overestimate their likelihood of success and erroneously expect success for themselves. Early success motivates entrepreneurs to seek new and greater challenges to launch more risky projects (higher funding goals), which leads to higher probability of failure.

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 make certain efforts to be better-prepared for their subsequent projects (c.f., significant increase of *ImageCount* and *DescLength* 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., significantly decrease of *NumRewards* and relatively low means of *QuickUpdate* in Panel 4).

Table 6. Regression Results for Experience Richness

	DV: ln(*PledgedPercentage*)	
Variables	Model 15	Model 16
ln(*NumCreatedProjects*)	0.297***	0.287***
	(0.0447)	(0.0446)
ln(*NumofBackedProjects*)	0.0966***	0.103***
	(0.0367)	(0.0369)
AvgCreatedRichness	**-0.00065****	
	(0.000280)	
AvgBackedRichness	**0.00005**	
	(8.18e-05)	
CreatedRichnessBefore		**0.00100****
		(0.000435)
CreatedRichnessAfter		**-0.00368*****
		(0.00129)
BackedRichnessBefore		0.00755
		(0.00662)
BackedRichnessAfter		**-0.000162*****
		(5.80e-05)
Constant	2.732***	2.749***
	(0.265)	(0.265)
R^2	0.449	0.451
Observations	8,868	8,868
Number of Entrepreneurs	3,525	3,525

Table 7. Regression Results for Experience Diversity

	DV: ln(*PledgedPercentage*)	
Variables	Model 17	Model 18
ln(*NumCreatedProjects*)	0.287***	0.296***
	(0.0447)	(0.0446)
ln(*NumBackedProjects*)	0.139***	0.145***
	(0.0439)	(0.0440)
CreatingDiversity	0.179	
	(0.362)	
BackingDiversity	**-0.406****	
	(0.161)	
CreatingDiversity		-1.22e-05
		(0.580)
CreatingDiversity×>2Exp		0.371
		(0.458)
BackingDiversity		-0.0327
		(0.195)
BackingDiversity×>2Exp		**-0.764*****
		(0.199)
Constant	2.738***	2.705***
	(0.265)	(0.266)
R^2	0.448	0.449
Observations	8,868	8,868
Number of Entrepreneurs	3,525	3,525

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

Table 6 shows the results for experience richness. The explanatory power of the estimation models has significantly increased after we include the focal variables for experience richness (Model 2 vs. 15: ΔR^2=0.002, p<0.05). As reported in Table 6 (Model 15), there is seemingly no support for H3 as per the insignificant coefficient for *AvgBackedRichness* (β=0.00005, ns) and negatively significant coefficient for *AvgCreatedRichness* (β=0.00065, p<0.05). Since on *Kickstarter.com*, updates and comments may be posted before or after the project fundraising campaign deadline, additional analysis (in Model 16) is conducted by including the richness measures before and after the campaign deadline separately. Interestingly, the results show that detrimental effects of richness of direct experiences comes from those updates and comments posted *after* the campaign deadline (*CreatedRichnessAfter:* β=-0.00368, p<0.01), whereas those before the deadline show a positive effect (*CreatedRichnessBefore:* β=0.001, p<0.05). Indirect experience richness for post-campaign activities also exhibits negative effects (*BackedRichnessAfter:* β=-0.000162, p<0.01). 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 direct/indirect experience after project deadline is negatively associated with success.[10] A possible reason for the result is that richer experiences in the later stage impedes the learning process by distracting entrepreneurs to negative and unnecessary post funding issues. But they do learn by increasing their engagement with backers' community during the fund raising stage. Therefore, H3 receives partial support.

Table 7 reports the results for experience diversity. The explanatory power of the estimation models has significantly increased after we include the focal variables for experience richness (Model 2 vs. 17: ΔR^2=0.001, p<0.05). The results in Model 17 do not lend much support for H4 given the insignificant coefficient for *CreatingDiversity* (β=0.179, ns) and negative and significance coefficient for *BackingDiversity* (β=-0.406, p<0.01). Since the majority of the serial entrepreneurs have just two entrepreneurship-related founding experiences in our sample, we conduct further analysis by distinguishing those entrepreneurs who have completed two entrepreneurship projects from those that have completed more than two such projects (see Model 18). To do this, the diversity variables are interacted with an indicator variables (*>2Exp*) denoting whether the entrepreneurs more than 2 entrepreneurship campaigns. The results for Model 18 still show the insignificant impact of *CreatingDiversity* for both groups of serial entrepreneurs. This result may be due to the limited variability in creating diversity (mean=0.0116 and st.dev=0.0553; see Table 1). That said, we do observe that the negative impact of *BackingDiversity* is primarily for those entrepreneurs who have more than two entrepreneurship-related founding experiences (*BackingDiversity*×*>2Exp*: β=-0.764, p<0.01). When we compare the number of backed categories, those serial entrepreneurs who created many entrepreneurial-related projects (i.e., *>2Exp*=1) are more likely to back projects in more diverse categories (t=15.58, p<0.00). This means when keeping the number of backing experience controlled, having more diverse backing experiences can impede learning and the effects of positive direct and indirect learning may be mitigated. When entrepreneurs engage in diverse new tasks through exploration, if they do not have adequate opportunity to apply the existing body of knowledge, the subsequent performance improvement may not follow suit (Narayanan et al. 2009).

Conclusions and Contributions

In this study, entrepreneurial learning effects in IT-enabled crowdfunding are empirically investigated with six years of panel data involving 3,525 serial entrepreneurs. We find empirical evidence of learning effects from several fine-gained experience dimensions. Serial entrepreneurs not only learn directly by launching their own projects but also indirectly by funding 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 both of these experiences co-occur, their interactive effect on subsequent performance is of much greater significance than the sum of their independent effects. Further, we find that successful founding experiences may have a detrimental effect on subsequent success, whereas successful funding experiences have 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 replicate similar strategies with an expectation of continued success, but instead they end up with less than ideal outcomes. In addition, richness and diversity of experiences were found to not

[10] When we investigate the actual contents of the updates and comments posted after the campaign deadline, we observe that many of these post-deadline posts are related to delayed product delivery or (replies to) complaints about delivered products.

always be beneficial. Only timely efforts in direct experiences are shown to be beneficial, and too much diversity in indirect experiences can also hurt subsequent projects.

Some of these findings are in stark contrast to the existing results in the organizational learning literature, which predominantly documents positive impacts of successful experiences (e.g., Greve 2003b; Kim et al. 2009) and of experience diversity (e.g., Boh et al. 2007; Graydon and Griffin 1996). Specifically, prior research argues that organizations (and individuals) can learn fruitfully from their own successful experiences, since success helps them to develop a more comprehensive and richer repertoire of appropriate strategies (March 1991). Similar strategies will be embraced for future tasks. Furthermore, the learning effects are stronger when there is a variety of experiences accumulated, because this facilitates obtaining knowledge from a broader schema (Paas and Van Merriënboer 1994). Nevertheless, for entrepreneurial ventures in IT-enabled crowdfunding contexts, where entrepreneurs need to develop fledging and innovative ideas every time, this may not be the case. Instead, this study shows that there is strong evidence that past successful founding experience and past backing diversity are *negatively* associated with subsequent entrepreneurial success. Entrepreneurs are likely to fixate their strategies on previously successful ones, rather than exploring situational actions given the emergent 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 an inherently 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. Finally, the negative impact of backing diversity suggests that having indirect experiences in too many different domains can actually inhibit (indirect) learning as well. Indirect experiences were found to facilitate learning but too much diversity weakens this effect.

This research also extends the organizational learning literature by providing some nuanced insights derived from the unique context of *IT-enabled* entrepreneurship. Specifically, information transparency of the IT-enabled crowdfunding context facilitates our examination of learning from several dimensions: direct vs. indirect experiences and successful vs. failed experience. This enable us to respond to calls from prior organizational learning research (Argote et al. 2003; Argote and Todorova 2007) to characterize experience at a fine-grained level to develop nuanced theoretical insights into the learning effects. Consistent with the literature, we found strong empirical evidence of both *experiential* (Schilling et al. 2003) and *vicarious* learning (Bandura and McClelland 1977) in entrepreneurial activities. However, in contrast to prior research, where routinized tasks were typically investigated, entrepreneurs, especially in the IT-enabled crowdfunding context, seem to benefit from their own failures and others' success. Their own successful experiences may confine them into "early success traps" (Kim and Rhee 2009; Rhee and Kim 2015). This finding is consistent with entrepreneurship literature which states that entrepreneurs tend to be overconfident (Camerer and Lovallo 1999; Moore and Cain 2007), meaning they are inclined to overestimate their likelihood of success and erroneously expect success for themselves. 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). Additionally, 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 extent of involvement in each of the experiences (i.e., richness) that can also be important. Timely and deep involvement seems to improve learning effectiveness.

Finally, this research contributes to the nascent IS literature on crowdfunding by studying the dynamics of entrepreneurial actions across campaigns, which has yet to be investigated. Existing studies have been largely devoted to exploring the potential drivers of contribution intention (e.g., Burtch et al. 2013; Zhang and Liu 2012) or crowdfunding projects success (e.g., Koch and Siering 2015; Marom 2013; Mollick 2014; Qiu 2013; Xiao et al. 2014; Zvilichovsky et al. 2013). Those studies (implicitly) assume that projects even if initiated by the same entrepreneur are independent, neglecting the notion that entrepreneurs develop competencies in entrepreneurship over time. We utilize a panel-level analysis approach, from serial entrepreneurs' perspective and find that serial entrepreneurs accumulate experience-based knowledge, which in turn can be leveraged to facilitate subsequent performance improvements.

From the practitioners' perspective, we provide guidance to entrepreneurs in IT-enabled crowdfunding platforms on how to design experience to promote learning that may help to ultimately lead to entrepreneurial success. Specifically, entrepreneurs should avoid overconfidence, especially when they experience early success. Rather than merely fixating themselves to existing seemingly successful strategies, they are recommended to explore new strategies that fit well with their new innovative ideas. Moreover, when they launch their own projects, they will benefit more if they have timely interactions with their (potential) backers, than engagement afterwards. In addition, our research offers implications for the design of crowdfunding platforms, to induce more successful strategies from entrepreneurs. The crowdfunding operators are encouraged to create a recommendation system to entrepreneurs and backers, where some relevant projects rather than a large variety of unrelated projects are recommended according to their backing history. Also, interactive communication forums can be constructed to facilitate experience sharing among entrepreneurs.

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References

Agrawal, A., Catalini, C., and Goldfarb, A. 2010. "Entrepreneurial Finance and the Flat-World Hypothesis: Evidence from Crowd-Funding Entrepreneurs in the Arts." NET Institute.

Allison, P.D. 2005. *Fixed Effects Regression Methods for Longitudinal Data Using SAS*. Sydney, Australia: SAS Institute.

Argote, L. 2012. *Organizational Learning: Creating, Retaining and Transferring Knowledge*. New York: Springer.

Argote, L. 2013. "Organization Learning: A Theoretical Framework," in *Organizational Learning*. New York: Springer, pp. 31-56.

Argote, L., Beckman, S.L., and Epple, D. 1990. "The Persistence and Transfer of Learning in Industrial Settings," *Management Science* (36:2), pp. 140-154.

Argote, L., and Ingram, P. 2000. "Knowledge Transfer: A Basis for Competitive Advantage in Firms," *Organizational Behavior and Human Decision Processes* (82:1), pp. 150-169.

Argote, L., McEvily, B., and Reagans, R. 2003. "Managing Knowledge in Organizations: An Integrative Framework and Review of Emerging Themes," *Management Science* (49:4), pp. 571-582.

Argote, L., and Miron-Spektor, E. 2011. "Organizational Learning: From Experience to Knowledge," *Organization Science* (22:5), pp. 1123-1137.

Argote, L., and Todorova, G. 2007. "Organizational Learning: Review and Future Directions," in *International Review of Industrial and Organizational Psychology*. New York: John Wiley & Sons, pp. 193-234.

Audia, P.G., Locke, E.A., and Smith, K.G. 2000. "The Paradox of Success: An Archival and a Laboratory Study of Strategic Persistence Following Radical Environmental Change," *Academy of Management Journal* (43:5), pp. 837-853.

Bandura, A., and McClelland, D.C. 1977. "Social Learning Theory," G.L. Corporation (ed.). pp. 305-316.

Baumol, W.J. 1993. "Formal Entrepreneurship Theory in Economics: Existence and Bounds," *Journal of Business Venturing* (8:3), pp. 197-210.

Bayus, B.L. 2013. "Crowdsourcing New Product Ideas over Time: An Analysis of the Dell Ideastorm Community," *Management Science* (59:1), pp. 226-244.

Belsley, D.A., Kuh, E., and Welsch, R.E. 2005. *Regression Diagnostics: Identifying Influential Data and Sources of Collinearity*. New York: John Wiley & Sons.

Berger, S.M. 1961. "Incidental Learning through Vicarious Reinforcement," *Psychological Reports* (9:3), pp. 477-491.

Boh, W.F., Slaughter, S.A., and Espinosa, J.A. 2007. "Learning from Experience in Software Development: A Multilevel Analysis," *Management Science* (53:8), pp. 1315-1331.

Bosma, N., van Praag, M., and De Wit, G. 2000. "Determinants of Successful Entrepreneurship," EIM Zoetermeer.

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

Burtch, G., Ghose, A., and Wattal, S. 2014. "An Empirical Examination of Peer Referrals in Online Crowdfunding," *Thirty Fifth International Conference on Information Systems*, Auckland.

Camerer, C., and Lovallo, D. 1999. "Overconfidence and Excess Entry: An Experimental Approach," *American Economic Review* (89:1), pp. 306-318.

Cohen, J., Cohen, P., West, S.G., and Aiken, L.S. 2013. *Applied Multiple Regression/Correlation Analysis for the Behavioral Sciences*. New York: Routledge.

Cohen, M.D., and Bacdayan, P. 1994. "Organizational Routines Are Stored as Procedural Memory: Evidence from a Laboratory Study," *Organization Science* (5:4), pp. 554-568.

Cope, J. 2005. "Toward a Dynamic Learning Perspective of Entrepreneurship," *Entrepreneurship Theory and Practice* (29:4), pp. 373-397.

Cyert, R.M., and March, J.G. 1963. "A Behavioral Theory of the Firm," *Englewood Cliffs, NJ* (2).

Darr, E.D., Argote, L., and Epple, D. 1995. "The Acquisition, Transfer, and Depreciation of Knowledge in Service Organizations: Productivity in Franchises," *Management Science* (41:11), pp. 1750-1762.

Dutton, J.M., and Starbuck, W.H. 1979. *Diffusion of an Intellectual Technology*. New York University, Graduate School of Business Administration.

Fiol, C.M., and Lyles, M.A. 1985. "Organizational Learning," *Academy of Management Review* (10:4), pp. 803-813.

Gino, F., Argote, L., Miron-Spektor, E., and Todorova, G. 2010. "First, Get Your Feet Wet: The Effects of Learning from Direct and Indirect Experience on Team Creativity," *Organizational Behavior and Human Decision Processes* (111:2), pp. 102-115.

Gompers, P., Kovner, A., Lerner, J., and Scharfstein, D. 2006. "Skill Vs. Luck in Entrepreneurship and Venture Capital: Evidence from Serial Entrepreneurs," National Bureau of Economic Research, Cambridge, MA.

Gray, C., and Gonsalves, E. 2002. "Organizational Learning and Entrepreneurial Strategy," *The International Journal of Entrepreneurship and Innovation* (3:1), pp. 27-33.

Graydon, J., and Griffin, M. 1996. "Specificity and Variability of Practice with Young Children," *Perceptual and Motor skills* (83:1), pp. 83-88.

Greenberg, M.D., and Gerber, E.M. 2014. "Learning to Fail: Experiencing Public Failure Online through Crowdfunding," *Proceedings of the 32nd annual ACM conference on Human factors in computing systems*: ACM, pp. 581-590.

Greve, H.R. 1998. "Performance, Aspirations and Risky Organizational Change," *Academy of Management Proceedings*: Academy of Management, pp. 224-228.

Greve, H.R. 2003a. "A Behavioral Theory of R&D Expenditures and Innovations: Evidence from Shipbuilding," *Academy of Management Journal* (46:6), pp. 685-702.

Greve, H.R. 2003b. *Organizational Learning from Performance Feedback: A Behavioral Perspective on Innovation and Change*. Cambridge, UK: Cambridge University Press.

Haas, P., Blohm, I., and Leimeister, J.M. 2014. "An Empirical Taxonomy of Crowdfunding Intermediaries," *Thirty fifth International Conference on Information Systems*, Auckland, New Zealand.

Hahn, J., and Lee, G. 2013. "Archetypes of Crowdfunders' Backing Behaviors and the Outcome of Crowdfunding Efforts: An Exploratory Analysis of Kickstarter," in: *Conference on Information Systems and Technology*. Minneapolis, MN.

Harrison, D.A., and Klein, K.J. 2007. "What's the Difference? Diversity Constructs as Separation, Variety, or Disparity in Organizations," *Academy of Management Review* (32:4), pp. 1199-1228.

Harrison, R.T., and Leitch, C.M. 2005. "Entrepreneurial Learning: Researching the Interface between Learning and the Entrepreneurial Context," *Entrepreneurship Theory and Practice* (29:4), pp. 351-371.

Holcomb, T.R., Ireland, R.D., Holmes Jr, R.M., and Hitt, M.A. 2009. "Architecture of Entrepreneurial Learning: Exploring the Link among Heuristics, Knowledge, and Action," *Entrepreneurship Theory and Practice* (33:1), pp. 167-192.

Howe, J. 2008. *Crowdsourcing: How the Power of the Crowd Is Driving the Future of Business*. New York: Crown Publishing Group.

Hsu, D.H. 2007. "Experienced Entrepreneurial Founders, Organizational Capital, and Venture Capital Funding," *Research Policy* (36:5), pp. 722-741.

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

Huber, G.P. 1991. "Organizational Learning: The Contributing Processes and the Literatures," *Organization Science* (2:1), pp. 88-115.

Hwang, E., Singh, P., and Argote, L. 2014. "Jack of All, Master of Some: The Contingent Effect of Knowledge Breadth on Innovation," *Thirty fifth International Conference on Information Systems*, Auckland, New Zealand.

Ingram, C., Teigland, R., and Vaast, E. 2013. "Is Crowdfunding Doomed in Sweden? When Institutional Logics and Affordances Collide, (Re-)Design Matters," *Thirty Fourth International Conference on Information Systems*, Milan, Italy.

Jung, E.J., Susarla, A., and Sambamurthy, V. 2014. "Evolutionary Fundraising Patterns and Entrepreneurial Performance in Crowdfunding Platforms," *Thirty fifth International Conference on Information Systems*, Auckland, New Zealand.

Kang, K., and Hahn, J. 2009. "Learning and Forgetting Curves in Software Development: Does Type of Knowledge Matter?," *Thirtieth International Conference on Information Systems*, Phoenix, United States, p. 194.

Kim, J.-Y., Kim, J.-Y., and Miner, A.S. 2009. "Organizational Learning from Extreme Performance Experience: The Impact of Success and Recovery Experience," *Organization Science* (20:6), pp. 958-978.

Kim, K., and Hann, I.-H. 2014. "Crowdfunding and the Democratization of Access to Capital: A Geographical Analysis." Available at SSRN: http://ssrn.com/abstract=2334590.

Kim, T., and Rhee, M. 2009. "Exploration and Exploitation: Internal Variety and Environmental Dynamism," *Strategic Organization* (7:1), pp. 11-41.

Kirzner, I.M. 1978. *Competition and Entrepreneurship*. Chicago: University of Chicago press.

Koch, J.-A., and Siering, M. 2015. "Crowdfunding Success Factors: The Characteristics of Successfully Funded Projects on Crowdfunding Platforms," *Twenty-Third European Conference on Information Systems*, Münster, Germany.

Lant, T.K., and Mezias, S.J. 1990. "Managing Discontinuous Change: A Simulation Study of Organizational Learning and Entrepreneurship," *Strategic Management Journal* (11:5), pp. 147-179.

Lehman, D.W., and Hahn, J. 2013. "Momentum and Organizational Risk Taking: Evidence from the National Football League," *Management Science* (59:4), pp. 852-868.

Levinthal, D.A., and March, J.G. 1993. "The Myopia of Learning," *Strategic Management Journal* (14:S2), pp. 95-112.

Levitt, B., and March, J.G. 1988. "Organizational Learning," *Annual Review of Sociology* (14:1), pp. 319-338.

Lin, Y., Boh, W.F., and Goh, K.H. 2014. "How Different Are Crowdfunders? Examining Archetypes of Crowdfunders and Their Choice of Projects." Available at SSRN: http://ssrn.com/abstract=2397571.

Lippman, S.A., and Rumelt, R.P. 1982. "Uncertain Imitability: An Analysis of Interfirm Differences in Efficiency under Competition," *The Bell Journal of Economics* (13:2), pp. 418-438.

Malone, T.W., Laubacher, R., and Dellarocas, C. 2010. "The Collective Intelligence Genome," *IEEE Engineering Management Review* (38:3), p. 38.

March, J.G. 1991. "Exploration and Exploitation in Organizational Learning," *Organization Science* (2:1), pp. 71-87.

March, J.G., Sproull, L.S., and Tamuz, M. 1991. "Learning from Samples of One or Fewer," *Organization Science* (2:1), pp. 1-13.

Marom, D. 2013. "Crowd-Empowered Microfinance," in: *Microfinance in Developing Countries: Issues, Policies and Performance Evaluation*. pp. 127-151.

Minniti, M., and Bygrave, W. 2001. "A Dynamic Model of Entrepreneurial Learning," *Entrepreneurship Theory and Practice* (25:3), pp. 5-16.

Mollick, E. 2013. "The Dynamics of Crowdfunding: An Exploratory Study," *Journal of Business Venturing* (29:1), pp. 1-16.

Mollick, E. 2014. "The Dynamics of Crowdfunding: Determinants of Success and Failure," *Journal of Business Venturing* (29:1), pp. 1-16.

Moore, D.A., and Cain, D.M. 2007. "Overconfidence and Underconfidence: When and Why People Underestimate (and Overestimate) the Competition," *Organizational Behavior and Human Decision Processes* (103:2), pp. 197-213.

Mumford, A. 1999. *Effective Learning*. London, England: Chartered Institute of Personnel and Development.

Narayanan, S., Balasubramanian, S., and Swaminathan, J.M. 2009. "A Matter of Balance: Specialization, Task Variety, and Individual Learning in a Software Maintenance Environment," *Management Science* (55:11), pp. 1861-1876.

Paas, F.G.W.C., and Van Merriënboer, J.J.G. 1994. "Variability of Worked Examples and Transfer of Geometrical Problem-Solving Skills: A Cognitive-Load Approach," *Journal of educational psychology* (86:1), p. 122.

Politis, D. 2005. "The Process of Entrepreneurial Learning: A Conceptual Framework," *Entrepreneurship Theory and Practice* (29:4), pp. 399-424.

Qiu, C. 2013. "Issues in Crowdfunding: Theoretical and Empirical Investigation on Kickstarter," in: *(October 27, 2013)*. Available at SSRN: http://ssrn.com/abstract=2345872

Radner, R. 1975. "A Behavioral Model of Cost Reduction," *The Bell Journal of Economics* (6:1), pp. 196-215.

Rae, D. 2005. "Entrepreneurial Learning: A Narrative-Based Conceptual Model," *Journal of Small Business and Enterprise Development* (12:3), pp. 323-335.

Rae, D. 2006. "Entrepreneurial Learning: A Conceptual Framework for Technology-Based Enterprise," *Technology Analysis & Strategic Management* (18:1), pp. 39-56.

Reagans, R., Argote, L., and Brooks, D. 2005. "Individual Experience and Experience Working Together: Predicting Learning Rates from Knowing Who Knows What and Knowing How to Work Together," *Management science* (51:6), pp. 869-881.

Reber, A.S. 1989. "Implicit Learning and Tacit Knowledge," *Journal of experimental psychology: General* (118:3), p. 219.

Rhee, M., and Kim, T. 2015. "Great Vessels Take a Long Time to Mature: Early Success Traps and Competences in Exploitation and Exploration," *Organization Science* (26:1), pp. 180-197.

Rosenbaum, M.E., and Hewitt, O.J. 1966. "The Effect of Electric Shock on Learning by Performers and Observers," *Psychonomic Science* (5:2), pp. 81-82.

Schilling, M.A., Vidal, P., Ployhart, R.E., and Marangoni, A. 2003. "Learning by Doing Something Else: Variation, Relatedness, and the Learning Curve," *Management Science* (49:1), pp. 39-56.

Schwienbacher, A., and Larralde, B. 2010. "Crowdfunding of Small Entrepreneurial Ventures." Available at SSRN: http://ssrn.com/abstract=1699183.

Simon, H.A. 1991. "Bounded Rationality and Organizational Learning," *Organization Science* (2:1), pp. 125-134.

Stuart, R.W., and Abetti, P.A. 1990. "Impact of Entrepreneurial and Management Experience on Early Performance," *Journal of Business Venturing* (5:3), pp. 151-162.

Surowiecki, J. 2005. *The Wisdom of Crowds*. New York: Random House LLC.

Szulanski, G. 1996. "Exploring Internal Stickiness: Impediments to the Transfer of Best Practice within the Firm," *Strategic Management Journal* (17:Winter Special Issue), pp. 27-43.

Thies, F., Wessel, M., and Benlian, A. 2014. "Understanding the Dynamic Interplay of Social Buzz and Contribution Behavior within and between Online Platforms–Evidence from Crowdfunding," *Thirty Fifth International Conference on Information Systems*, Auckland, New Zealand.

Ward, C., and Ramachandran, V. 2010. "Crowdfunding the Next Hit: Microfunding Online Experience Goods," *Workshop on Computational Social Science and the Wisdom of Crowds at NIPS2010*.

Wooldridge, J. 2012. *Introductory Econometrics: A Modern Approach*. Boston: Cengage Learning.

Wulf, G., and Schmidt, R.A. 1997. "Variability of Practice and Implicit Motor Learning," *Journal of Experimental Psychology: Learning, Memory, and Cognition* (23:4), p. 987.

Xiao, S., Tan, X., Dong, M., and Qi, J. 2014. "How to Design Your Project in the Online Crowdfunding Market? Evidence from Kickstarter," *Thirty Fifth International Conference on Information Systems*, Auckland, New Zealand.

Xu, A., Yang, X., Rao, H., Fu, W.-T., Huang, S.-W., and Bailey, B.P. 2014. "Show Me the Money!: An Analysis of Project Updates During Crowdfunding Campaigns," *Proceedings of the 32nd Annual ACM Conference on Human Factors in Computing Systems*: ACM, pp. 591-600.

Zahra, S.A. 2007. "Contextualizing Theory Building in Entrepreneurship Research," *Journal of Business venturing* (22:3), pp. 443-452.

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

Zvilichovsky, D., Inbar, Y., and Barzilay, O. 2013. "Playing Both Sides of the Market: Success and Reciprocity on Crowdfunding Platforms," *Thirty Fourth International Conference on Information Systems*, Milan, Italy.

Zvilichovsky, D., Inbar, Y., and Barzilay, O. 2014. "Playing Both Sides of the Market: Success and Reciprocity on Crowdfunding Platforms." Available at SSRN: http://ssrn.com/abstract=2304101