

Cues or Content? Examining the Moderating Role of Crowdfunder Experience

Full Paper

Yan Lin

Nanyang Business School
Nanyang Technological University
Liny0065@e.ntu.edu.sg

Wai Fong Boh

Nanyang Business School
Nanyang Technological University
awfboh@ntu.edu.sg

Abstract

Crowdfunders face information asymmetry problems when making funding decisions. How crowdfunders overcome this problem has become a centerpiece of crowdfunding research. We examine how crowdfunder experience might affect crowdfunder reliance on various types of information provided on the crowdfunding page. Drawing on the Elaboration Likelihood Model, we find that experienced crowdfunders are more likely to pay attention to the content of the information, whereas less experienced crowdfunders are more likely to pay attention to simple cues. Our study highlights the important role of crowdfunder experience in crowdfunding research. We also discuss the implications of this study for various participants of the crowdfunding platform.

Keywords

Experience, Elaboration Likelihood Model, Information Asymmetry, Crowdfunding, Signaling, Observational Learning

Introduction

Crowdfunding refers to efforts initiated by individuals as open calls, usually through the Internet, to fund initiatives by drawing on small contributions from the crowd (Mollick 2014). Crowdfunders are often faced with severe information asymmetry problem when making decisions (Ahlers et al. 2015). How crowdfunders overcome the information asymmetry problem and make funding decisions has attracted wide attention among crowdfunding researchers. So far, prior research has started to address this question from the perspectives of either the project creator or the crowdfunder. From the project creator's perspective, prior research has focused on signaling theory (Spence 1973) and seeks to identify project attributes that serve as effective signals used by project creators to communicate project quality in order to reduce crowdfunders' uncertainty and thus increase their fundraising success (Ahlers et al. 2015; Lin et al. 2013). From the crowdfunder's perspective, using observational learning theory (Bikhchandani et al. 1992), much of the attention has been given to how crowdfunders rely on previous crowdfunders' decisions in making decisions (Herzenstein et al. 2011; Zhang and Liu 2012). Both sets of literature that focus on overcoming the information asymmetry problem assume that all crowdfunders are homogeneously influenced by a set of project information and do not consider that individuals might interpret project information differently (Zhu and Zhang 2010).

We explore how different crowdfunders overcome information asymmetry by relying on various information available about projects by focusing on crowdfunder experience because it has been shown to be one of the most important and visible dimensions characterizing the heterogeneity of crowdfunders (Herzenstein et al. 2011; Yang and Hahn 2015). For example, Yang and Hahn (2015) find that experienced crowdfunders are more likely to succeed when launching their own projects. In the literature review section, we first introduce the elaboration likelihood model as our theoretical lens. We then apply it to explain how a crowdfunder's experience might affect how s/he rely on the information in making decisions.

Literature and Hypotheses

To explain how a crowdfunder's experience affects his or her reliance on the project information available to crowdfunders, we draw upon the Elaboration Likelihood Model (ELM) as our theoretical lens (Petty and Cacioppo 1986). The ELM distinguishes between two routes in which information is processed: the central route and the peripheral route. When taking the central route, individuals engage in detailed information processing by carefully scrutinizing available information, inferring relevance of the content, and forming a critical judgment. When taking the peripheral route, individuals rely on cues and simple heuristics in making decisions. The difference between the two routes lies in the depth of information processing (i.e. elaboration). One of the most important factors determining which information processing route individuals are likely to take is individuals' ability to process information, which is often operationalized as prior experience or expertise (Bhattacharjee and Sanford 2006). Applied to the context of crowdfunding, we argue that experience in the crowdfunding domain increases an individual's ability to process information, thus increasing the elaboration likelihood. Hence, experienced crowdfunders will pay more attention to the content of the information, whereas less experienced crowdfunders will rely on simple cues in decision making.

The crowdfunding literature on how crowdfunders make funding decisions has focused on two sets of information a potential crowdfunder can rely on in making decisions: the project information provided by project creator to "signal" potential crowdfunders (Ahlers et al. 2015) and the social information derived from observing other crowdfunders (Zhang and Liu 2012). In the next part, we develop our hypotheses on how crowdfunder experience might affect their reliance on these two types of information.

Crowdfunder Experience and Project Information

Literature suggests that insiders have the incentive to obfuscate information by strategically hiding adverse information (Bloomfield 2002) or making it more difficult to comprehend (Li 2008). In crowdfunding, the amount of information revealed might serve as a signal of project quality, as the more information the project creator is willing to disclose, the more confident the project creator is in the project. This is evident in Michels (2012)'s study of loan listings in *Prosper.com*. He finds that the effects of voluntary, unverifiable disclosures reduce the cost of debt. For a potential crowdfunder, a simple heuristic would be the amount of information disclosed by the project, which is reflected in the number of pictures and videos provided on the project page, as videos and pictures are highly visible, and contain significant amount of information (Pieters and Wedel 2004). However, simply the number of pictures and videos may convey limited information, if one does not look at the actual content of the information. According to the ELM, individuals who lack the ability are more likely to rely on non-content cues in making decisions. Hence, we expect experienced crowdfunders to rely less on such simple cues:

H1a: When backing projects, experienced crowdfunders are less likely than inexperienced crowdfunders to rely on information about the number of pictures embedded in the project description.

H1b: When backing projects, experienced crowdfunders are less likely than inexperienced crowdfunders to rely on information about the number of videos embedded in the project description.

By contrast, the content of the textual project description may provide useful information to potential crowdfunders. Research has shown that venture capitalists do look for information embedded in business plans when making funding decisions (Chen et al. 2009). The content of the project description might also convey complex signals information about the project quality. In studying the impact of electronic word-of-mouth, Chevalier and Mayzlin (2006) find evidence that consumers do read review text rather than rely on summary statistics. Compared to simple signals like the number of videos and photographs, textual descriptions are more time consuming and difficult to process. But experienced crowdfunders will rely on contain detailed information in their analysis. Processing and analyzing the content of the information demand a significant amount of cognitive effort. We expect that experienced crowdfunders are more likely to read the content of project description and be influenced by the complex signals embedded in it. The effects of these signals are likely to be correlated with the length of the description. According to Chevalier and Mayzlin (2006), the length of the review "is correlated with the enthusiasm of

the review in ways that are not captured by the star measures” (pp. 350). Following them, we expect the length of the project content will be stronger for the experienced crowdfunders:

H2: When backing projects, experienced crowdfunders are more likely than inexperienced crowdfunders to rely on the amount of textual information embedded in the project description.

Crowdfunder Experience and the Reliance on Social Information

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

Research has found that there is often a herding effect in crowdfunding platforms, such that crowdfunders are more likely to back projects that have a large number of existing crowdfunders (Herzenstein et al. 2011; Zhang and Liu 2012). The number of existing crowdfunders for each project is usually observable in most crowdfunding platforms, which typically provides such a summary statistic for each project. It is thus a readily available cue that crowdfunders often rely on for their decision making. However, the number of existing crowdfunders might be of poor informational quality, as it suffers from potential informational cascades, which leads to wrong decisions and poor information aggregation when subsequent individuals discard their private information (Bikhchandani et al. 1992). Studies have suggested that experienced individuals are less likely to herd (Simonsohn and Ariely 2008), whereas the observational learning effect is stronger for less experienced individuals (Cai et al. 2009). In fact, Simonsohn and Ariely (2008) have found that experienced bidders are less likely to herd into *eBay* auctions with lower starting prices, as it is a mistake that experienced bidders have learned to avoid. Similarly, Clement and Tse (2005) find that experienced analysts are more likely to issue “bold” forecasts (which turn out to be more accurate) rather than forecasts that are consistent with the rest of the analyst herd. Hence, we hypothesize:

H3: When backing projects, experienced crowdfunders are less likely than inexperienced crowdfunders to rely on information about the number of crowdfunders that have backed the project.

In addition to the number of existing crowdfunders, crowdfunding platforms also disclose the identity of crowdfunders who have backed each project. In this regard, the endorsement of some crowdfunders might provide more valuable information than simple information on the number of crowdfunders. Several studies have shown that a small group of individuals (e.g. opinion leaders, or fashion leaders) are more influential than others. Recent studies on opinion leadership also suggest that opinion leaders act as key intermediates in forming public opinions (Godes and Mayzlin 2009; Watts and Dodds 2007). In the crowdfunding context, Kim and Viswanathan (2014) show that experts including app developer and experienced backers are likely to influence *the crowd* and that *the crowd* is able to identify experts in the market and follow their decisions accordingly. Experienced crowdfunders might possess more valuable information than the ordinary crowd. Hence, following the “experts” might be a wiser strategy for a potential crowdfunder who rely on others’ decisions. Identifying the experts in the existing crowdfunder list require the potential crowdfunder to closely scrutinize the crowdfunder list, and identify who are the experts. According to ELM, this requires a higher level of elaboration and is likely to take place for those who are capable of processing the information extensively and suffer less from cognitive overload (Park and Lee 2008). Hence, we expect that the experienced crowdfunders are more likely to back projects that have been backed by “experts” in the market.

H4: When backing projects, experienced crowdfunders are more likely than inexperienced crowdfunders to rely on information about the number of experienced crowdfunders that have backed the project.

Similar to other online platforms, crowdfunding platforms also display comments contributed by existing crowdfunders in addition to the number of existing backers and the identity of existing backers (Chen et al. 2011; Godes et al. 2005). So far, prior research has not explored the effects of backers’ comments on crowdfunders’ decision making in the crowdfunding context. In other online contexts, online feedback or word-of-mouth has been shown to influence consumer decision and product (Chevalier and Mayzlin 2006; Duan et al. 2008; Liu 2006). Different from the online review system found in many other electronic word-of-mouth platforms, the comment system provided by crowdfunding platforms does not have summary statistics such as star rating. Hence, if potential crowdfunders’ decisions do incorporate information derived from the comments, such information is likely to be derived from the actual content

of the comments. We also expect that negative comments are more influential than positive comments. This is because most crowdfunding platforms allow only existing backers (those who have already pledged their money) to post comments. These people are more likely to feel positive about the project before providing funds to the project. In fact, many positive comments are only expressions of excitement, encouragement, and congratulation such as “good Job”, “well done” etc. Such information is less likely to provide additional information to a potential crowdfunder, especially when one can already observe other crowdfunders’ decisions. On the other hand, negative comments are more informative, as they can indicate problems from continued project monitoring and information search about the project by the existing backers (Ito et al. 1998; Rozin and Royzman 2001). Reading the content of the comments involves extensive information processing. Therefore, crowdfunders who are more able to elaborate on and process the information are more likely to be influenced by the content of the comments (Lee et al. 2008). Hence, we expect that experienced crowdfunders have the ability to scrutinize the content of the reviews posted by existing backers and rely on the information available in them:

H5: When backing projects, experienced crowdfunders are more likely than inexperienced crowdfunders to rely on negative comments posted by existing crowdfunders of the project.

Methodology

We used a discrete choice model to test our hypotheses (McFadden 1973). For a backer i , faced with choice set C_i of J_i choices, the utility of choice $j \in C_i$ is:

$$U_{ij} = V_{ij} + \varepsilon_{ij} \quad (1)$$

where V_{ij} is a linear combination of the independent variables with their interaction terms with experience (Gu et al. 2014), plus control variables:

$$\begin{aligned} V_{ij} = & \beta_{1,i} \text{Log Num Content Pic}_j + \beta_{2,i} \text{Log Num Cotent Video}_j + \beta_{3,i} \text{Log Cotent Length}_j \\ & + \beta_{4,i} \text{Log Num Backer}_j + \beta_{5,i} \text{Per Expert}_j + \beta_{6,i} \text{Neg Comment}_j \\ & + \sum_{k=1}^K \beta_k \text{Control}_{k,j} \\ & \beta_{l,i} = \alpha_l \text{exp}_i + \theta_l, \quad l = 1, 2, \dots, 6 \end{aligned} \quad (2)$$

And ε_{ij} is a random error. If we further assume that ε_{ij} follows type I extreme value distribution, as shown in McFadden (1973), the probability of choice $j \in C_i$ being chosen by backer i can be written as:

$$P(Y_{ij} = 1) = \frac{\exp(V_{ij})}{\sum_{k=1}^{J_i} \exp(V_{ik})} \quad (3)$$

Equation (3) is effectively a conditional logistic model with interactions. Our dataset comprises technology projects collected from *Kickstarter* from April 1, 2013, to December 31, 2014. As *Kickstarter* did not disclose the time when a crowdfunder pledges his or her money, we constantly updated the backer (crowdfunders who have backed the project) information and used these multiple snapshots to work out an estimation of the time when a backer backs a project. In total, 753 projects were captured. We further split the backing decisions into two parts: decisions made from April 2013 to August 2013 was used for determining who were the experienced crowdfunders and decisions made from September 2013 to December 2013 was used for hypothesis testing. The empirical analysis was based on 87,396 decisions made by 70,612 crowdfunders during September 1, 2013, to December 31, 2013. Modeling all the backing decisions would require extensive computational power unavailable to us. We thus randomly sampled 9,000 decisions for hypothesis testing.

Constructing the Choice Set. For each project-backing instance, we constructed a set of projects as alternatives for the crowdfunder. We considered all the projects that were open for funding at the time when the decision was made (Gompers et al. 2016). To deal with the excessive choice set and reduce the computational burden, we followed the procedure described by McFadden (1978) by randomly sampling 39 choices together with the project chosen as the choice set. Changing the sampling number does not affect the results.

For each crowdfunder i and the choice j , we constructed the following variables.

Crowdfunder Experience. We counted the number of technology projects backed as the crowdfunder's experience. To calculate the number, we used the data we collected after the website change from January 2014, when all the projects were revealed, including projects with less than 10 backers (backer information was previously not available for projects with less than 10 backers). For each backing decision made, we counted how many technology projects the crowdfunder had backed prior to this project as the crowdfunder's experience (using natural logarithm): **Log Exp**.

Cues. We measured two simple cues associated with project information provided by the project creator: (1) the natural logarithm of the number of content pictures embedded in the project description: **Log Num Content Pic**; and (2) the natural logarithm of the number of content videos embedded in the project description: **Log Num Content Video**. For the simple cue associated with social information available on projects, we used the natural algorithm of the number of existing crowdfunders cumulated for each project choice when the crowdfunder made the project backing decision: **Log Num Backer**.

Content of the Information. The length of project description was measured as the word count of the project description, and we took the natural logarithm of the original variable: **Log Content Length**. In order to determine who the experienced crowdfunders were, we split the data into two parts: data from April 2013 to August 2013 was used for determining who the experienced crowdfunders were, and data from September 2013 to December 2013 was used for hypothesis testing. Tabulation of backer experience showed that about 10% of the crowdfunders had backed more than three projects as of August 2013. We thus considered these crowdfunders as the experienced crowdfunders in the dataset. For all the existing crowdfunders cumulated for each project choice, we calculated the percentage of experienced crowdfunders and named the variable: **Per Expert**. To measure the negative comments provided by other backers, we used a text analysis software called *Linguistic Inquiry and Word Count* (LIWC) to analyze the comments posted by existing crowdfunders (Pennebaker et al. 2015). Following Yin et al. (2014), we focused on two negative emotions embedded in the comments: anxiety and anger. The *Anxiety* word category includes 116 words such as "worried", "fearful" etc. The *Anger* word category includes 230 words such as "hate", "kill", "annoyed" etc. (Pennebaker et al. 2015). The negative score for each comment was calculated as the percentage of total words made up by anxiety and anger words. For each project choice, the measure of negative comments was the average negative scores of all comments posted prior to the time when the crowdfunder made the project backing decision: **Neg Comment**.

Control Variables. We also included several control variables in our models based on prior research. First, we controlled for several project static measures that have been found to affect project funding success (Mollick 2014). **Hardorsoft** indicated whether the project was a "Hardware" project or a "Software" project. **Duration** was the number of days of the project duration. **Log Goal** was the natural logarithm of the project goal amount. **Video Exist** indicated whether the project creators used a video to describe the project. **Num Created** was the number of projects the project creators had created prior to creating the focal project. **Log Num Creator Backed** was the number of projects backed by the project creator. **Log Num Update** was the number of updates (natural logarithm) the project creator had provided. **Log Num Categories** was the number of different reward categories (natural logarithm), assuming that more prepared project creators would create more types of rewards that cater to different crowdfunders. **Recommended** was a dummy variable indicating if the campaign was featured in the projects recommended by Kickstarter. **Successful** was a dummy variable indicating if the choice had met its funding goal by the time the backer made his or her backing decision (Herzenstein et al. 2011). **Stage** was the percentage of the funding period that had elapsed since the project was launched. The correlation coefficients among variables (not produced here) are all below 0.6. We also calculated variance inflation factor (VIF) for all the variables in our models including the interaction terms. All the VIFs were below 3, indicating that multicollinearity was not a serious concern.

Results

The regression results are reported in Table 1. Like many other non-linear models, the marginal effects are dependent on the estimated coefficients and the specific data point (Ai and Norton 2003). To make the interpretation more informative, we used a hypothetical case to calculate and plot probabilities at different data points using Equation (3). Consider a case where all alternatives are identical with all attributes set at the sample mean. In this case, the probability of any choice being chosen is 2.5% for all

the 40 choices. Holding the remaining 39 choices constant, we then varied the attributes of the first choice and examined how the probability of it being chosen changed with the attribute of interest.

Table 1 Regression Results

	Model 1	Model 2	Model 3	Model 3
	Coef. (SE)	Coef. (SE)	Coef. (SE)	Coef. (SE)
Hardorsoft	-0.1202* (0.0589)	-0.1184* (0.0589)	-0.0461 (0.0602)	-0.0383 (0.0605)
Duration	-0.0382*** (0.0016)	-0.0383*** (0.0016)	-0.039*** (0.0016)	-0.0389*** (0.0016)
Video Exist	0.1908. (0.0985)	0.1896. (0.0987)	0.0834 (0.0989)	0.0779 (0.0987)
Log Goal	-0.1201*** (0.0121)	-0.1197*** (0.0122)	-0.1142*** (0.012)	-0.1138*** (0.0121)
Num Created	-0.1008*** (0.0203)	-0.0995*** (0.0203)	-0.1317*** (0.0201)	-0.1332*** (0.0202)
Log Num Creator Backed	-0.0321** (0.0123)	-0.0338** (0.0123)	-0.0356** (0.0124)	-0.0375** (0.0124)
Log Num Updates	-0.0098 (0.0262)	-0.0135 (0.0263)	-0.0178 (0.0265)	-0.0178 (0.0265)
Log Num Categories	-0.1737*** (0.0403)	-0.1787*** (0.0403)	-0.1621*** (0.0403)	-0.1716*** (0.0404)
Recommended	0.1385*** (0.0292)	0.1404*** (0.0293)	0.1309*** (0.0296)	0.1295*** (0.0297)
Successful	0.4115 (0.9992)	0.3793 (0.9964)	0.4814 (1.0153)	0.4691 (1.0156)
Stage	-2.2706*** (0.0618)	-2.2699*** (0.0617)	-2.2476*** (0.0622)	-2.2524*** (0.0623)
Log Num Content Pic	0.0947*** (0.0248)	0.0979*** (0.0247)	0.0883*** (0.0251)	0.0885*** (0.0251)
Log Num Content Video	0.0961*** (0.0223)	0.0995*** (0.0223)	0.0897*** (0.0224)	0.0957*** (0.0227)
Log Content Length	-0.0914** (0.0326)	-0.0919** (0.0326)	-0.0678* (0.0327)	-0.0694* (0.0328)
Log Num Backer	1.1443*** (0.0117)	1.1439*** (0.0117)	1.1522*** (0.0117)	1.1517*** (0.0117)
Per Expert	1.8905*** (0.0998)	1.8881*** (0.0999)	1.6831*** (0.0983)	1.6914*** (0.0984)
Neg Comment	-0.1548 (0.1024)	-0.1581 (0.1021)	-0.1221 (0.1052)	-0.1305 (0.1054)
Log Num Content Pic × Log Exp		-0.0504** (0.017)		-0.0123 (0.0174)
Log Num Content Video × Log Exp		-0.0843*** (0.0183)		-0.0530** (0.0178)
Log Content Length × Log Exp		0.0708** (0.0253)		0.0666** (0.0252)
Log Num Backer × Log Exp			-0.0559*** (0.0102)	-0.0511*** (0.0104)
Per Expert × Log Exp			1.2431*** (0.0795)	1.2657*** (0.0804)

	Model 1	Model 2	Model 3	Model 3
Neg Comment × Log Exp			-0.3111*** (0.0872)	-0.2988*** (0.0899)
AIC	39087.73	39050.86	38422.69	38415.1

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

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

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

The estimated results are highly consistent across different model specifications. Hence, the following analysis is based on results in the full model (Model 4). The main effects of *Log Num Content Pic* is positive and significant, showing that all crowdfunders do pay attention to the number of pictures embedded in the project description, but experienced crowdfunders are not less likely to pay attention to this information, as indicated by the insignificant coefficient of the interaction term *Log Num Content Pic*×*Log Exp* ($\alpha_1 = -0.123, p > 0.1$). Hence, *H1a* is not supported. The main effects of *Log Num Content Video* is positive and significant, showing that all crowdfunders also pay attention to the number of videos embedded in the project description, and as hypothesized, experienced crowdfunders are less likely to pay attention to this information, as indicated by the significant coefficient of the interaction term *Log Num Content Video*×*Log Exp* ($\alpha_2 = -0.0530, p < 0.01$), providing support for *H1b*.¹ With respect to the length of the textual project description, the main effects of *Log Content Length* is negative and significant, indicating that the longer the project description, the less likely crowdfunders will pay attention the project. Interestingly, however, it is the experienced crowdfunders who are more likely to pay attention to projects with longer project description ($\alpha_3 = 0.0666, p < 0.01$), which provides support for *H2*.²

Turning to the social information, the main effect of *Log Num Backer* is positive and significant, indicating that crowdfunders do pay attention to the number of existing backers on a project. However, the coefficient of the interaction term *Log Num Backer*×*Log Exp* is negative and significant ($\alpha_4 = -0.0511, p < 0.001$), showing that experienced crowdfunders are less likely than inexperienced crowdfunders to back projects that have already accumulated a large number of crowdfunders. This provides support for *H3*.³ Interestingly, the main effect of *Per Expert* is also positive and significant, indicating that crowdfunders, as a whole, pay attention to the percentage of expert backers on a project. Furthermore, the coefficient of the interaction term *Per Expert*×*Log Exp* is positive and significant ($\alpha_5 = 1.2657, p < 0.001$), indicating the experienced crowdfunders are even more likely to pay attention to expert backers, which provides support for *H4*.⁴ As to negative comments, the main effect is negative, although it is not significant ($\theta_6 = -0.1305, p > 0.1$), which indicates that crowdfunders generally do not pay attention to the negative comments provided by existing backers. However, the interaction term *Neg Comment*×*Log Exp* is negative and significant ($\alpha_6 = -0.2988, p < 0.001$), which indicates only the

¹ Our calculation shows that for a crowdfunder with zero prior experience, if *Log Num Content Video* increases from one standard deviation below the mean (-0.15) to one standard deviation above the mean (1.05), or from 1 video to 3 videos for the choice, the probability of it being chosen would increase from 2.36% to 2.64%, an increase by 11.9%. For a crowdfunder who has backed 7 projects (*Log Exp* = 2), the same increase of *Log Num Content Video* would slightly decrease the probability of the project being chosen from 2.52% to 2.48%, a decrease by 1.6%.

² For a crowdfunder with zero prior experience, if *Log Content Length* increases from one standard deviation below the mean (6.55) to one standard deviation above the mean (7.79), or the length of the project description of a choice changes from 700 words to 2400 words, the probability of it being chosen would decrease from 2.61% to 2.40%, or an decrease by 8%. The effects, however, are the opposite for the experienced crowdfunders. For a crowdfunder who has backed 7 projects, the same change would actually increase from 2.41% to 2.60%, or an increase by 7.9%.

³ For a crowdfunder with zero prior experience, if *Log Num Backer* increases from one standard deviation below the mean (2.11) to one standard deviation above the mean (5.77), or the number of backers increases from 8 to 320, the probability of the project being chosen by the crowdfunder would increase from 0.31% to 17.42%. This suggests that the number of existing crowdfunders is an important factor affecting crowdfunders' decisions. For experienced crowdfunders, the effect is less strong. For a crowdfunder who has backed 7 projects (*Log Exp* = 2), the same increase would only increase the probability of the project being chosen by the crowdfunder from 0.37% to 14.89%.

⁴ For a crowdfunder with zero prior experience, if *Per Expert* increases from 2% to 52%, the probability of the project being chosen by the crowdfunder would increase from 1.65% to 37.7%, whereas for a crowdfunder who has backed 7 projects (*Log Exp* = 2) the same increase would increase the probability of the project being chosen from 0.88% to 68.3%.

experienced backers pay attention to negative comments from existing backers and avoid projects that have many such negative comments. This supports *H5*.⁵

Conclusion and Implications

Our research has several implications for research. First, this study highlights the importance of incorporating crowdfunder heterogeneity in theorizing on crowdfunder behavior. Prior studies on crowdfunder behavior tend to focus on the project level analysis, with the assumption that crowdfunders are homogeneous and rely on the same information in making funding decisions (Herzenstein et al. 2011; Zhang and Liu 2012). Our findings suggest that contextual factors, such as crowdfunder experience, might moderate the effects of the constructs of interest. In fact, this study shows that the number of videos and the length of the project description might have opposite effects on inexperienced crowdfunders and experienced crowdfunders.

Second, our research also contributes to the crowdfunding literature on the effects of crowdfunder experience. Although the effects of experience on decision tasks have been studied in the accounting and finance literature (e.g. Clement 1999; Ho 1994), there is still limited understanding about how experience might affect decision making in the crowdfunding context. In fact, differences between inexperienced and experienced individuals are more important in the context of crowdfunding, where a project's funding success is determined by both experienced and inexperienced crowdfunders, which is different from many accounting and investing tasks, where the investors are typically more experienced.

Third, our research also contributes to the literature on online comments. So far, literature on the effects of electronic word-of-mouth has mainly focused on consumer products such as movies (Duan et al. 2008) and books (Chevalier and Mayzlin 2006) through mechanisms of increasing awareness (Berger et al. 2010) and persuasion (Dellarocas et al. 2007). This study offers a different perspective that comments posted by existing crowdfunders during the campaign can provide further diagnostic information for potential crowdfunders in facing the information asymmetry problem. Furthermore, this study also points out one of the contingencies: that the effects of these comments are partially dependent on the crowdfunder's ability to analyze the comments.

Implications for Practice

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

Second, platform managers can develop different strategies depending on the crowdfunder composition. For a platform where the crowdfunders are relatively new to this new phenomenon, the managers should try to make summary statistics (e.g. number of backers) more visible to subsequent crowdfunders. They should also advise project creators to use a succinct textual description but embed more pictures and videos to illustrate their ideas. On the other hand, if the crowdfunding platform is reaching a mature stage where most of the crowdfunders are relatively experienced, managers should try to provide a large

⁵ For a crowdfunder with zero prior experience, if *Neg Comment* increases from 0 to 0.3, the probability of the project being chosen by the crowdfunder would slightly decrease from 2.52% to 2.43%. By contrast, for a crowdfunder who has backed 7 projects (*Log Exp* = 2), the same increase would decrease the probability of the project being chosen from 2.63% to 2.12%.

amount information for potential crowdfunders to make decisions, as these crowdfunders are more likely to pay attention to the details in the information. They can provide a summary of projects backed by the crowdfunder in order for potential crowdfunders to judge on the expertise of the crowdfunder.⁶ They may introduce a badge system showing who the most active crowdfunders are and who contribute the most.

Third, regarding comments, platform managers should realize that not all the crowdfunders have the cognitive ability to process the comments. Much like online word-of-mouth, backers are allowed to post comments freely. Potential crowdfunders might suffer from the overload of a large number of short comments and may not be able to derive useful information from these comments. Managers could introduce sorting mechanisms to identify the most valuable comments.

REFERENCES

- Agrawal, A., Catalini, C., and Goldfarb, A. 2015. "Crowdfunding: Geography, Social Networks, and the Timing of Investment Decisions," *Journal of Economics & Management Strategy* (24:2), pp 253-274.
- Ahlers, G., Cumming, D.J., Guenther, C., and Schweizer, D. 2015. "Signaling in Equity Crowdfunding," *Entrepreneurship Theory and Practice* (39:4), pp 955-980.
- Ai, C., and Norton, E.C. 2003. "Interaction Terms in Logit and Probit Models," *Economics Letters* (80:1), pp 123-129.
- Berger, J., Sorensen, A.T., and Rasmussen, S.J. 2010. "Positive Effects of Negative Publicity: When Negative Reviews Increase Sales," *Marketing Science* (29:5), pp 815-827.
- Bhattacharjee, A., and Sanford, C. 2006. "Influence Processes for Information Technology Acceptance: An Elaboration Likelihood Model," *MIS Quarterly* (30:4), pp 805-825.
- Bikhchandani, S., Hirshleifer, D., and Welch, I. 1992. "A Theory of Fads, Fashion, Custom, and Cultural Change as Informational Cascades," *Journal of Political Economy* (100:5), pp 992-1026.
- Bloomfield, R.J. 2002. "The "Incomplete Revelation Hypothesis" and Financial Reporting," *Accounting Horizons* (16:3), pp 233-243.
- Cai, H., Chen, Y., and Fang, H. 2009. "Observational Learning: Evidence from a Randomized Natural Field Experiment," *American Economic Review* (99:3), pp 864-882.
- Chen, X.-P., Yao, X., and Kotha, S. 2009. "Entrepreneur Passion and Preparedness in Business Plan Presentations: A Persuasion Analysis of Venture Capitalists' Funding Decisions," *Academy of Management Journal* (52:1), pp 199-214.
- Chen, Y., Wang, Q., and Xie, J. 2011. "Online Social Interactions: A Natural Experiment on Word of Mouth Versus Observational Learning," *Journal of Marketing Research* (48:2), pp 238-254.
- Cheung, C.M., Xiao, B.S., and Liu, I.L. 2014. "Do Actions Speak Louder Than Voices? The Signaling Role of Social Information Cues in Influencing Consumer Purchase Decisions," *Decision Support Systems* (65), pp 50-58.
- Chevalier, J.A., and Mayzlin, D. 2006. "The Effect of Word of Mouth on Sales: Online Book Reviews," *Journal of Marketing Research* (43:3), pp 345-354.
- Clement, M.B. 1999. "Analyst Forecast Accuracy: Do Ability, Resources, and Portfolio Complexity Matter?," *Journal of Accounting and Economics* (27:3), pp 285-303.
- Clement, M.B., and Tse, S.Y. 2005. "Financial Analyst Characteristics and Herding Behavior in Forecasting," *Journal of Finance* (60:1), pp 307-341.
- Dellarocas, C., Zhang, X.M., and Awad, N.F. 2007. "Exploring the Value of Online Product Reviews in Forecasting Sales: The Case of Motion Pictures," *Journal of Interactive Marketing* (21:4), pp 23-45.
- Duan, W., Gu, B., and Whinston, A.B. 2008. "Do Online Reviews Matter? — an Empirical Investigation of Panel Data," *Decision Support Systems* (45:4), pp 1007-1016.
- Godes, D., and Mayzlin, D. 2009. "Firm-Created Word-of-Mouth Communication: Evidence from a Field Test," *Marketing Science* (28:4), pp 721-739.
- Godes, D., Mayzlin, D., Chen, Y., Das, S., Dellarocas, C., Pfeiffer, B., Libai, B., Sen, S., Shi, M., and Verlegh, P. 2005. "The Firm's Management of Social Interactions," *Marketing Letters* (16:3-4), pp 415-428.
- Gompers, P.A., Mukharlyamov, V., and Xuan, Y. 2016. "The Cost of Friendship," *Journal of Financial Economics* (119:3).

⁶ *Kickstarter* used to provide such information, but the crowdfunder profile page is no longer available.

- Gu, B., Konana, P., Raghunathan, R., and Chen, H.M. 2014. "Research Note—the Allure of Homophily in Social Media: Evidence from Investor Responses on Virtual Communities," *Information Systems Research* (25:3), pp 604-617.
- Herzenstein, M., Dholakia, U.M., and Andrews, R.L. 2011. "Strategic Herding Behavior in Peer-to-Peer Loan Auctions," *Journal of Interactive Marketing* (25:1), pp 27-36.
- Ho, J.L. 1994. "The Effect of Experience on Consensus of Going-Concern Judgments," *Behavioral Research in Accounting* (6), pp 160-177.
- Ito, T.A., Larsen, J.T., Smith, N.K., and Cacioppo, J.T. 1998. "Negative Information Weighs More Heavily on the Brain: The Negativity Bias in Evaluative Categorizations," (75), pp 887-900.
- Kim, K., and Viswanathan, S. 2014. "The Experts in the Crowd: The Role of Reputable Investors in a Crowdfunding Market." Available at SSRN: <http://ssrn.com/abstract=2258243>.
- Lee, J., Park, D.H., and Han, I. 2008. "The Effect of Negative Online Consumer Reviews on Product Attitude: An Information Processing View," *Electronic Commerce Research and Applications* (7:3), pp 341-352.
- Li, F. 2008. "Annual Report Readability, Current Earnings, and Earnings Persistence," *Journal of Accounting and Economics* (45:2), pp 221-247.
- Lin, M., Prabhala, N.R., and Viswanathan, S. 2013. "Judging Borrowers by the Company They Keep: Friendship Networks and Information Asymmetry in Online Peer-to-Peer Lending," *Management Science* (59:1), pp 17-35.
- Liu, Y. 2006. "Word of Mouth for Movies: Its Dynamics and Impact on Box Office Revenue," *Journal of Marketing* (70:3), pp 74-89.
- McFadden, D. 1973. "Conditional Logit Analysis of Qualitative Choice Behavior," in: *Frontiers in Econometrics*. New York: Academic Press, pp. 105-142.
- McFadden, D. 1978. "Modelling the Choice of Residential Location," in: *Spatial Interaction Theory and Planning Models*. Amsterdam: North Holland, pp. 75-96.
- Michels, J. 2012. "Do Unverifiable Disclosures Matter? Evidence from Peer-to-Peer Lending," *The Accounting Review* (87:4), pp 1385-1413.
- Mollick, E. 2014. "The Dynamics of Crowdfunding: An Exploratory Study," *Journal of Business Venturing* (29:1), pp 1-16.
- Park, D.-H., and Lee, J. 2008. "Ewom Overload and Its Effect on Consumer Behavioral Intention Depending on Consumer Involvement," *Electronic Commerce Research and Applications* (7:4), pp 386-398.
- Pennebaker, J.W., Boyd, R.L., Jordan, K., and Blackburn, K. 2015. "The Development and Psychometric Properties of Liwc2015." Austin, TX: University of Texas at Austin.
- Petty, R.E., and Cacioppo, J.T. 1986. "The Elaboration Likelihood Model of Persuasion," *Advances in Experimental Social Psychology* (19:1), pp 123-205.
- Pieters, R., and Wedel, M. 2004. "Attention Capture and Transfer in Advertising: Brand, Pictorial, and Text-Size Effects," *Journal of Marketing* (68:2), pp 36-50.
- Rozin, P., and Royzman, E.B. 2001. "Negativity Bias, Negativity Dominance, and Contagion," *Personality and Social Psychology Review* (5:4), pp 296-320.
- Simonsohn, U., and Ariely, D. 2008. "When Rational Sellers Face Nonrational Buyers: Evidence from Herding on Ebay," *Management Science* (54:9), pp 1624-1637.
- Spence, M. 1973. "Job Market Signaling," *Quarterly Journal of Economics* (87:3), pp 355-374.
- Watts, D.J., and Dodds, P.S. 2007. "Influentials, Networks, and Public Opinion Formation," *Journal of Consumer Research* (34:4), pp 441-458.
- Yang, L., and Hahn, J. 2015. "Learning from Prior Experience: An Empirical Study of Serial Entrepreneurs in It-Enabled Crowdfunding," *Thirty Sixth International Conference on Information Systems*, Fort Worth.
- Yin, D., Bond, S.D., and Zhang, H. 2014. "Anxious or Angry? Effects of Discrete Emotions on the Perceived Helpfulness of Online Reviews," *MIS Quarterly* (38:2), pp 539-560.
- Zhang, J., and Liu, P. 2012. "Rational Herding in Microloan Markets," *Management Science* (58:5), pp 892-912.
- Zhu, F., and Zhang, X. 2010. "Impact of Online Consumer Reviews on Sales : The Moderating Role of Product and Consumer," *Journal of Marketing* (74:March), pp 133-148.