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ABSTRACT

Reward-based crowdfunding is an emerging financing channel for entrepreneurs to raise money for their innovative projects. How to screen the crowdfunding projects is critical for crowdfunding platform, project founder, and potential backers. This study aims to investigate whether backers' word-of-mouth (WOM) is a valuable input to generate collective intelligence for project screening. Specially, we answer three questions. First, is backers' WOM an effective signal for implementation performance of crowdfunding projects? Second, how do the WOM help screen projects during the fund-raising process? Third, which kind of comments (positive or negative) is more effective in screening crowdfunding projects? Research hypotheses were developed based on theories of collective intelligence and WOM communication. Using a cross section dataset and a panel dataset, we get the following findings. First, backers' negative WOM can effectively predict project implementation performance, however positive WOM does not have that prediction power. The prediction power of positive and negative WOM differs significantly. One possible reason is that negative WOM does contain more information of project quality. Second, project with more accumulative negative WOM tend to attract fewer subsequent backers. However, accumulative positive WOM is not helpful for attracting more potential backers. We conclude that negative WOM is useful for project screening project, because it is a signal of project quality, and meanwhile it could prevent backers make subsequent investments.

Keywords: Reward-based crowdfunding, word-of-mouth, project screening, collective intelligence

INTRODUCTION

Traditionally the best fund-raising options for start-ups in the seed or early stage are business angel and their family members or friends (Tomczak and Brem, 2013). However, only a very small percent of entrepreneurs can actually get funds from angel investors (Pope, 2011). Crowdfunding, a novel financing channel based on the Internet and online social network, to somewhat extent has filled the gap of traditional business angels (Zheng et al., 2014a). According to the return forms to investors, crowdfunding includes diverse models, such as donation-, lending-, equity-, and reward-based crowdfunding (Ahlers et al., 2015; Belleflamme et al., 2014). This study focuses on reward-based crowdfunding in which backers get product or service produced by the founder as rewards for their investments. The report released by Massolution in 2015 stated that reward-based crowdfunding is one of the primary crowdfunding models with a growth of 84 percentages in 2014, and that reward-based crowdfunding is the largest category in terms of overall number of platforms. . The statistics on Kickstarter, a famous reward-based crowdfunding platform in US, show that 100,386 projects have received 2.21 billion dollars from 10,313,215 backers in the Kickstarter platform by February 17, 2016.

Although crowdfunding has gained rapid growth, it has its own challenges and drawbacks. For instance, some projects show higher level of challenges or risk of failure in the implementation process. Mollick (2014) found that complex projects are more likely to deliver rewards late, and large-scale crowdfunding projects with high funding targets often experienced delays. For the founders, testing products and getting feedback from potential backers is one of their motivations to start a crowdfunding project. Thus, how to screen the right projects is critical for platforms, founder, and backers. Collective intelligence embedded in the crowds themselves is widely recognized as the power to screen projects. For example, Mollick and Nanda (2016) found that the backers in crowdfunding platform and offline experts make similar funding decisions.

Except funding decisions, other input such as electronic comments also contribute to screening the right projects. To facilitate backers' comments, most of crowdfunding platforms build online community for backers to post their comments. Active participation could enable backers to enjoy the fun of belonging to a crowdfunding community (Gerber et al., 2012), called community benefit (Belleflamme et al., 2014). In addition, studies in marketing and electronic commerce indicate that online word-of-mouth (WOM), a signal of product quality, could help consumers make better choices (Wang and Yu, 2015). From backers' WOM, we could derive their ratings of the crowdfunding projects. The research on collective intelligence also found that crowds' rating is a one effective approach to filter ideas (Klein and Garcia (2015). However, the value of backers' electronic WOM gains little attention in crowdfunding filtering. To investigate the role of backers' WOM in screening projects, this study aims to answer three questions: 1) Is backers' WOM an effective signal for implementation performance of crowdfunding projects? 2) How does the WOM help screen projects during the fund-raising process? And 3) Which kind of comments (positive or negative) is more effective in screening crowdfunding projects?

To answer these questions, we developed research hypotheses based on research on collective intelligence and WOM communication, and conducted an empirical study in Demehour which is a famous crowdfunding platform in China. As positive and negative WOM are typical valences, we ignore the neutral comments. Project implementation performance was measured as delivery timeliness (Mollick, 2014) and product quality (Zheng et al., 2014b). Firstly, we conducted a cross-section data analysis on logistic regression to see whether backers' WOM works as a signal of project implement performance. Secondly, a fixed-effect regression model was used to analyze the approach in which WOM screens projects in the fund-raising step. In both cross-section and panel data analyses, we compared the different roles of positive and negative WOM to answer the third question.

The structure of the paper is as follows. First, we review the relevant literature in crowdfunding. Second, we then develop the research hypotheses. Third, we present the research design, data, and results. Finally, we discuss the implications for research and practice, and conclude the study.

LITERATURE REVIEW

Crowdfunding was initially coined by Howe (2008) as a kind of crowdsourcing, which refers to utilizing the power of crowd to get ideas, feedback, and solutions to solve business problems (Belleflamme et al., 2014). Crowdfunding is defined by Belleflamme et al. (2014) as "involving an open call, mostly through the Internet, for the provision of financial resources either in form of donation or in exchange for the future product or some form of reward to support initiatives for specific purposes". This concept covers several kinds of crowdfunding models including reward-, equity-, donation-, and lending-based crowdfunding.

Compared with traditional business angel investment, reward-based crowdfunding has its own characteristics. First, the capital raised by crowdfunding is relatively smaller (Belleflamme et al., 2013). Second, the backers or investors in crowdfunding are often active to contribute time and expertise which allow entrepreneurs to extract more value (e.g., comments or constructive ideas) in crowdfunding community (Belleflamme et al., 2013; Zheng et al., 2015). Third, crowdfunding often takes the form of pre-ordering (i.e., advanced purchase) model although most of the products are not completely developed. The entrepreneurs describe the products and list the rewards for the backers who would like to obtain the products before they are released to market (Belleflamme et al., 2014). Forth, the backers pay more in the pre-ordering process than the traditional consumers who wait and buy the final products in the market (Belleflamme et al., 2014). These characteristics show that backers' participation, especially their constructive ideas, is valuable for founders. However, the role of backers' electronic WOM in project screening does not gain enough attention.

The research on backers' collective intelligence, fund-raising performance, and project implementation in crowdfunding are closely related to this study. The theoretical studies have debuted in academia (e.g., Mollick and Nanda, 2016). The widely accepted idea is that collective intelligence in the crowds helps screen the projects. The focus variable of collective behaviour is funding decision. However, there is a dearth of studies concerning the other inputs such as electronic WOM.

A variety of studies have shed light on the fund-raising stage for additional insights. For instance, entrepreneur's social capital plays an important role in fund-raising process (e.g., Mollick, 2014; Zheng et al., 2014a). Crowdfunding project difficulty, team experience, and project planning were found play important roles in improving project implementation performance (Zheng et al., 2014b). The number of an entrepreneur's fans or friends in online social networks is a significant predictor for funding success (Mollick, 2014; Zheng et al., 2014a). Compared to fund-raising process, fewer studies have focused on project implementation (Mollick, 2014; Zheng et al., 2014b). We posit that projects screening is prerequisite for funding success and product quality. Thus it is critical to explore how to filtering crowdfunding projects.

THEORETICAL HYPOTHESES

The online community in crowdfunding platform is one kind of consumer community in which backers expresses their feelings, provide ideas, and seek information from founder. We focus on two categories of backers' comments – positive and negative WOM - as positive and negative are important attributes values of WOM valence. Most of the studies in WOM have investigated the impact of extremely positive or extremely negative WOM (Cheung and Thadani, 2012). Backers' positive WOM in crowdfunding emphasizes or praises the strength of crowdfunding project, whereas their negative WOM highlights or criticizes the weakness of the product or service. Except valence, volume (information quantity) also has received much attention in WOM research (Cheung and Thadani, 2012). Marketing research found that the number of reviews (volume) is significantly associated with product sales (Duan et al., 2008).

Crowdfunding community could be seen as an information or intelligence aggregation tool about project quality (Zwass, 2010). By analyzing the information in the community, backers could infer the success possibility of crowdfunding project, and the founder could receive useful market information about the product or service. Thus, backers' electronic WOM is an effective signal for the implementation performance of crowdfunding projects. In addition, more volume of information makes WOM more credible and powerful (Duan et al., 2008) to predict implementation performance which was measured with complaints of product quality and delivery timeliness. Thus, we propose that

H1a: a project with more positive WOM tends to receive fewer complaints of product quality and delivery timeliness.

H1b: a project with more negative WOM tends to receive more complaints of product quality and delivery timeliness.

From a co-creation perspective, crowdfunding is one approach for founder to utilize crowd intelligence for beta testing of their

products in their early stages (Zwass, 2010). Compared with positive WOM, negative WOM is more useful for crowdfunding projects which need negative feedbacks to identify limitation or solutions. Klein and Garcia (2015) also found that crowds are better at eliminating bad ideas than identify good ideas, which suggests that crowds' criticism is one important approach to generate collective intelligence. In addition, the backers who have close relationships with the founder are less likely to criticize the project, and the strangers may post negative WOM when they found weak points of crowdfunding projects. Jeppesen and Lakhani (2010) found that in crowdsourcing solvers with high technical and social marginality may be good at solving problems as they have different perspectives and heuristics. As for crowdfunding, the backers who are social distant from the founder might provide better feedbacks though they are negative WOM in most cases. Thus, we propose that negative WOM contains more information about project quality, which could make better prediction of implementation performance.
H2: compared with positive comments, negative WOM has more prediction power for the complaints of product quality and delivery timeliness.

As the second research question is how the WOM help screen projects, one possible approach is that the negative (positive) WOM could impede (motive) subsequent investments during the fund-raising process. Studies on the adoption of WOM have shed much light on the effects of WOM on consumers purchase decisions (e.g., Cheung and Thadani, 2012; Wang and Yu, 2015). For instance, Wang and Yu (2015) found that positive WOM will have a strong positive effect on a consumer's purchasing intention, and negative WOM will have a strong negative effect on intention to purchase. It is proper to identify the effects of WOM in dynamic approach by investigating the effects of accumulative WOM on investments in subsequent periods (e.g., next day). Based on the prior studies on individual level (Cheung and Thadani, 2012), we could derive the aggregate effect of WOM on project level so we hypothesize that:

H3a: a project with more accumulative positive WOM tends to attract more subsequent investments.

H3b: a project with more accumulative negative WOM tends to attract fewer subsequent investments.

Marketing research on WOM communication found that consumers tend to weight negative information more than positive information (Cheung and Thadani, 2012). The rule of "bad is stronger than good" works across a broad range of psychological phenomena as bad impressions and bad stereotypes are quicker to form (Baumeister et al., 2001). Park and Lee (2009) found that compared with positive WOM, negative WOM has a stronger effect. In crowdfunding, backers also react more strongly to the negative WOM. Thus, we propose that
H4: compared with positive comments, negative WOM has a stronger effect on subsequent investments.

RESEARCH CONTEXT AND DATA

We conducted an empirical study on Demohour (www.demohour.com), which is the first popular reward-based crowdfunding platform in China. One of the famous projects in Demohour is animation movie "big fish begonia" which hit the screen in 2016 and earned 0.55 billion Chinese Yuan (approximately 0.09 billion dollars) at the box office. From 2011 to 2014, Demohour operated as an integrated platform covering diverse categories of crowdfunding projects such as arts, technology, food, movie, publication, etc. Then, Demehour transformed from an integrated website to a vertical platform which focuses on the area of smart hardware.

When posting their projects in Demohour, founders are required to describe their projects and set a list of reward (investment) options. All of the backers are allowed to comment on any project that draws their attention. If backers favor one project, they can choose one reward option and transfer money to the platform. The crowdfunding model in Demohour works in an All-or-Nothing way – pledge will be transferred to the founder if and only if the total amount of money pledged by the backers is larger than or equal to the fund-raising goal. If one project failed to reach its goal, all the pledged money will be refunded to the backers. If one project is successfully funded, the founders will start their projects and deliver the products or service to the backers according to their reward options once the project is completed. If the backers cannot receive the reward on time as promised by the founders, or receive defective products, they are free to comment or complain in the crowdfunding community.

The dataset used in this study falls into the period in which Demohour operated as an integrated platform. The funding records in our dataset started from July 1, 2011 and ended on July 2, 2014. The dataset includes detailed information about project, founder, investment, backers' electronic WOM during the fund-raising step, and backers' WOM regarding project implementation performance. All of backers' WOMs are in text format. We coded the textual WOM as the following categories – positive WOM, negative WOM, delivery late, and defective product. Project performance was measured with delivery late and defective product. Two researchers were trained as data coders by following procedures suggested by Maxwell (2008) to ensure inter-rater reliability. After the two coders finished the independent coding, the research team met to discuss disagreements between the two coders and chose a mutually agreeable coding mechanism (Qu et al., 2008). We excluded the projects which did not complete the fund-raising step. At last, the resulting sample included 845 projects among which 396 projects failed to reach the fund-raising goal. Table 1 presents the summarized statistics for all projects. Except binary variable and title length, all the other variables were log transformed as they are highly skewed.

Table1. Descriptive statistics of sample projects

Variable	Observations	Mean	Std. Dev.	Min	Max
goal (Yuan RMB)	822	17616.06	62421.13	200	1208130
pledge (Yuan RM)	845	26743.22	115331	17	1709502
fund_ratio	845	4.307503	59.36567	0	1709.5
positive WOM	845	43.71243	127.4155	0	2063
negative WOM	845	1.957396	5.563769	0	86
delivery late	845	0.247337	1.614253	0	38
defective product	845	0.697041	2.904165	0	34
reward categories	845	7.363314	3.805936	1	35
project description length	845	1772.075	1114.722	128	13589
reward options	845	7.363314	3.805936	1	35
project title length	845	19.35621	6.677381	1	38
		percentage			
funding success					
fail	396	46.86			
success	449	53.14			
colon					
No	800	94.79			
Yes	44	5.21			

METHOD AND RESULTS

Empirical model

To answer the first question, we built a logistic regression model as follows to test whether WOM works as an effective signal for implementation performance.

*(1)*The dependent variable refers to whether or not one project gets a complain of delivery timeliness and/or product quality. and are the key variables, i.e., number of positive and negative WOM. Mollick (2014) found that product delivery would be more likely to delays if one project is excessively overfunded. So, the ratio of pledge over goal was included in model 1. At last, we posited that fund-raising goal and description length are proxy variables of project complexity which may lead to failure of project implementation. So, we included fund-raising goal and project description length .

To approach the second question – how the negative (positive) WOM impede (motive) subsequent investment during the fund-raising process, we developed regression equation 2.

(2)The dependent variable in model 2 is the number of backers who pledged in project i on day t. refers to the accumulative numbers of backers who pledged in project i before day t. are the time varying attributes of project i. Except $PastPositiveWOM_{i,t-1}$ and $PastNegativeWOM_{i,t-1}$, other time varying attributes come from Kuppuswamy and Bayus (2013). We also included time invariant variables such as goal, reward categories, and project description length and title length. The error term is decomposed as time invariant part and time varying part . The key variables used in this study were summarized in Table 2.

Table 2 key variables in empirical model

Category	Variable	Brief description
	$BackersAdded_{it}$	Number of backers who pledge in project I on day t
	$PastBackers_{i,t-1}$	The numbers of backers of project i before day t
	$PastBackers\,Relative_{i,t-1}$	the ratio of the cumulative number of backers bakcing project i before day t to the total number of backers required to reach project i's goal
Time varying attributes	$PastPositiveWOM_{i,t-1}$	The cumulative number of positive word of mouths for project i before day t
	$PastNegativeWOM_{i,t-1}$	The cumulative number of negative word of mouths for project i before day t
	$PosFunded_{i,t-1}$	1 if the project i is fully funded before day t and 0 otherwise
	$DayofWeek_{it}$	Day in the week, 1 is Monday, 2 is Tuesday, …, and 7 is Sunday
	$FundingTime_{i,t-1}$	Ratio of the cumulative number of days that have elapsed for project i up to day t to the length of project i's funding cycle in days
	FirstWeek	1 if project i is in the first week of its funding cycle on day t (0 otherwise)
	LastWeek	1 if project i is in the final week of its funding cycle on day t (0 otherwise)
	$PastProjectUpdates_{i,t-1}$	The cumulative number of project updates for project i before day t
Time invariant variables	$Goal_i$	Fund-raising goal (Yuan RMB)
	$Duration_i$	Fund-raising duration (Day)
	$TitleLength_i$	The number of words in the title
	$Colon_i$	1 if the title of a project has a colon, 0 otherwise
	$DescriptionLength_i$	The number of words in the project description
	$RewardOptions_i$	The number of reward categories
	$FundRatio_i$	The ratio of total pledge over goal
	$Complain_i$	1 if backers complain about delivery or product quality, and 0 otherwise
	$DeliveryLate_i$	1 if backers complain about delivery, and 0 otherwise
	$DefectiveProduct_i$	if backers complain about product quality, and 0 otherwise

Hypotheses testing

Based on the dataset of projects which were successfully funded, we ran model 1 three times with binary variables: Complaini, DeliveryLatei, and DefectiveProducti. The results are listed in Table 3. We found that positive WOM does not significantly predict implementation regardless of whether one project receives at least one complaint about delivery timeliness or product quality. Thus, H1a is not supported. The results indicate that project with more negative WOM would be more likely to receive complains of implementation performance, suggesting that H1b is supported. To test hypotheses 2, we compared the absolute values of the coefficients by conducting Wald Tests. The result shows a significantly different effects between positive and negative WOM (chi square (1) = 22.1, p<0.001). So H2 is supported - compared with positive comments, negative WOM has more prediction power for implementation performance. As for the control variable, we found projects with high fund ratio and fund-raising goal would be more likely to receive complains on implementation performance. To check the robust of the findings, we ran ordinary least square models with complains number as dependent variables. The results of OLS confirmed the findings of logistic regressions.

Table 3 logistic regression result

	(1) Complain	(2) DeliveryLate	(3) DefectiveProduct
LN_PWOM	0.0419 (0.37)	0.0647 (0.49)	-0.00682 (-0.06)
LN _NWOM	0.911^{***} (5.43)	0.487^{**} (2.80)	0.850^{***} (4.96)
LN _fund_ratio	0.563^{**} (2.86)	0.720^{***} (3.56)	0.709^{***} (3.52)
LN _goal	0.198 (1.80)	0.244 (1.88)	0.241^{*} (2.03)
LN _project_description_len	0.141 (0.71)	0.0990 (0.44)	0.291 (1.37)
Constant	-5.293^{**} (-3.15)	-6.088^{**} (-3.14)	-7.083^{***} (-3.89)
N	449	449	449

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Based on a Hausman type test (Allison 2005), the fixed-effects model is preferred for our dataset. In addition to fixed effects regression, we also ran an OLS regression using the pool data as a comparison. To check the robust, we replaced PastBackers with PastBackersrelative and ran another fixed effects regression (Kuppuswamy and Bayus, 2013). All the results of panel data analysis are listed in Table 4. Because OLS regression cannot exclude the confusing effects of unobserved project heterogeneity, the results of OLS about positive and negative WOM cannot answer the second question. Thus, we turn to fixed effects regression which could remove any unobserved, time-invariant heterogeneity across projects. The results indicate that accumulative positive WOM does not help attract more subsequent backers. So H3a is not supported. However, negative WOM will prevent subsequent backers from making investments. Thus, H3b is supported. To test the different effects, we found that negative WOM has a stronger effect on subsequent investments ($F(1, 817) = 8.9$, $p<0.01$). Thus, H4 is supported. Additionally, we also found the diffusion of responsibility effects – the negative effects of accumulative backers (Kuppuswamy and Bayus, 2013). Control variables in the first week and last week also have significant effects on subsequent investment, which could lead to a bathtub shaped pattern of backer support over the funding cycle (Kuppuswamy and Bayus, 2013). Finally, we found that on weekends backers are less likely to make investments.

Table 4 results of panel data analysis

	(1) – OLS regression LN_backersaddedit	(2) – fixed effects regression LN_backersaddedit	(3) - fixed effects regression LN_backersaddedit
LN_pastpositivewomit1	0.0360^{***} (8.42)	-0.00233 (-0.12)	-0.0313 (-1.53)
LN_pastnegativewomit1	0.0744^{***} (9.46)	-0.127^{**} (-3.01)	-0.0947^{*} (-2.15)
LN_PastBackersit1	0.353^{***} (78.59)	-0.175^{***} (-8.40)	
LN_PastBackersrelativeit1			-0.260^{***} (-3.85)
firstweek	0.503^{***} (32.42)	0.132^{***} (5.35)	0.119^{***} (4.97)
lastweek	0.257^{***} (21.90)	0.250^{***} (14.05)	0.280^{***} (16.31)
postfundedit1	-0.0124 (-1.04)	-0.190^{***} (-4.40)	-0.171^{***} (-3.57)
LN_fundingtime	-0.371^{***} (-49.76)	-0.118^{***} (-6.16)	-0.190^{***} (-11.83)
LN_pastprojectupdatesit1	0.00143 (0.33)	0.00197 (0.08)	-0.00480 (-0.18)
weekDummy1	0.162^{***} (10.81)	0.124^{***} (11.68)	0.130^{***} (12.38)
weekDummy2	0.210^{***} (14.10)	0.153^{***} (13.90)	0.161^{***} (14.61)
weekDummy3	0.205^{***} (13.73)	0.159^{***} (14.02)	0.164^{***} (14.41)
weekDummy4	0.202^{***} (13.58)	0.167^{***} (14.53)	0.171^{***} (14.82)
weekDummy5	0.170^{***} (11.44)	0.142^{***} (12.87)	0.145^{***} (13.01)
weekDummy6	0.000705 (0.05)	0.000780 (0.08)	-0.000884 (-0.09)
LN_goal	-0.000807 (-0.22)		
Ln_project_description_len	-0.0583^{***} (-8.08)		
project_name_len	0.00150^{*} (2.44)		
colon	0.00839 (0.47)		
LN_rewardcategories	0.0669^{***} (7.05)		
Constant	-0.973^{***} (-17.38)	1.047^{***} (13.63)	0.579^{***} (11.67)
N	30695	30695	30695

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

CONCLUSION

In this study, we empirically investigated the value of backers' WOM in screening project in crowdfunding. We obtained two interesting findings, as follows. First, backers' negative WOM can effectively predict project implementation performance, however positive WOM does not have that prediction power. As such, the prediction power of positive and negative WOM differs significantly. One possible explanation for this finding is that negative WOM contains more information of project quality, as the negative WOM could help the founders find the limitations and improve their products. Second, projects with more accumulative negative WOM tend to attract fewer subsequent backers. However, accumulative positive WOM is not helpful for attracting more potential backers. In this approach, we could conclude that negative WOM is useful for project screening project, because it is a signal of project quality as it could prevent backers from making subsequent investments.

The findings of our study have several theoretical implications. First, we offer a new approach to screening project. Except the collective intelligence embedded in backers' funding behaviors (Mollick and Nanda, 2016), their WOMs are also helpful to generate wisdom of crowd. In particular, negative WOM includes more valuable information of project quality. This finding also confirmed that crowds are good at eliminating bad ideas (Klein and Garcia, 2015). Second, we extend the study on the dynamics of crowdfunding backers (Kuppuswamy and Bayus, 2013). Negative WOM was identified as one important factor affecting subsequent backers funding decisions. Third, we extend the research on WOM communications in the crowdfunding context. We confirmed that backers react more strongly to negative WOM.

The findings also provide substantial implications for practice. First, for crowdfunding platforms to reduce project failure, it is necessary to deeply leverage the value of backers' WOM which is useful for project screening. For instance, instead of just presenting textual WOM, platform could try to present the meaning and volume of WOM in a creative way (e.g., words cloud) which is easy for backer to understand. Second, as the negative WOM is closely related to implementation performance, the founder should pay more attention to negative WOM and find solutions to address backers' criticisms. Finally, for backers it is always an effective way to screen project by ignoring the project which has too much negative WOM.

There are several limitations in this study. First, we did not study the effect of WOM content which may be also influential for others' decisions (Wang and Yu, 2015). Second, as we could not obtain the project categories information, future research could test our findings by including project categories in the model.

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