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The Bandwagon Effect in Digital Environments: An Experimental Study on Kickstarter.com

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Abstract

Online investment decision behavior in crowdfunding projects is characterized by a lack of information and a comparatively high risk. Although crowdfunding has achieved notable attention from the general public in the last years, the academic research on this fast-growing market remains rather limited until today. This paper investigates how users behave when making risky online investment decisions in crowdfunding. How are they influenced by information on the choices of earlier funders on a web-based platform? These questions are evaluated using an online experiment based on kickstarter.com. We show that crowdfunding supporters follow the signal of previous users, even when this is associated with a higher monetary commitment. Based on these findings, implications for crowdfunding project creators and platform operators are discussed.

1 Introduction

Crowdfunding platforms are virtual marketplaces where any individual can pitch a project idea and interested others can invest in the proposed idea, often with direct or indirect benefits for the funders (Burtch 2011). Almost 1.5 billion US Dollars were raised via crowdfunding world-wide in 2011 and the total funding volume is expected to have doubled in 2012 (Esposti 2012). The fast-growing but early-stage industry has achieved notable attention from the general public, but academic research on crowdfunding is rather limited until today (Gerber et al. 2012; Mollick 2012). Only little is known (Zhang and Liu 2012) about how funders are and can be influenced in their decision on the funding amount and in their selection of the rewards they receive in return for their contribution in crowdfunding. Research on crowdfunding has mainly focused on the online and offline links between funders and funded such as geographical proximity (e.g., Agrawal et al. 2011; Lin and Viswanathan 2013). We will close this research gap by focusing on one possible factor: the investment choices of previous supporters in the crowdfunding context of Kickstarter.com.

When the behavior of people is influenced by actions of other individuals, this is described as herding behavior or as the bandwagon effect (Leibenstein 1950). Such situations can be found in political campaigns, fashion, dining, financial investment, or technology adoption. It is argued that online environments are particularly susceptible to herding as it is much easier to inform about and perceive previous decisions. This holds true in particular for crowdfunding markets, as the available information about a project is fairly limited and the risk involved is comparatively high, what makes people even more prone to herding (Duan et al. 2009).

Based on these considerations we will investigate the question '*how are online investment decisions influenced by information on choices of earlier funders?'* The influences and interrelationships of these factors are investigated using an online experiment.

The remainder of this paper is structured as follows: Next, we discuss related literature streams and develop our research hypotheses. We then outline the design of our experiment and present the results of our research. Finally, we discuss theoretical and managerial implications and highlight limitations of our research as a guide for future work.

2 Background and Theoretical Foundations

Crowdfunding is widely seen as a type of crowdsourcing (Howe 2006; Kleemann et al. 2008). The basic idea of crowdfunding is to finance projects or organizations by a large group (the crowd) instead of only a few sophisticated investors. Crowdfunding is defined as "an open call, essentially through the internet, for the provision of financial resources either in form of donation or in exchange for some form of reward and/or voting rights in order to support initiatives for specific purposes" (Lambert and Schwienbacher 2010, p. 6).

Kickstarter.com is a well-known American crowdfunding platform (CFP) which gained a lot of media attention during the last years, mostly due to extremely successful projects that collected several million dollars (e.g. Lindvall 2012; Strickler 2012). Crowdfunding on Kickstarter proceeds as follows: In order to request funds, a creator sets up a project page on kickstarter.com. Creators offer different rewards to their funders in return for, and depending on, the amount of their contribution. When a funder decides to support a project, he selects a funding amount and an associated reward. Crowdfunding on Kickstarter is all-or-nothing, which means all funders get their money back when the funding goal is not reached in time. At the end of a successful funding period, Kickstarter transfers the money to the project creator who starts to implement his idea.

Harvey Leibenstein in 1950 introduced *bandwagon effects* as situations "where an individual will demand more (less) of a commodity at a given price because some or all other individuals in the market also demand more (less) of the commodity" (Leibenstein 1950, p. 190). Until today, the term attracts attention in marketing and economics literature, most of the time described as *social learning*. Social learning is defined as "mechanisms through which individuals may learn from others" (Cai et al. 2009, p. 864). This includes, inter alia, *observational learning*, where individuals are influenced by the information that is contained in other people's action. The theory of informational cascades is used to explain observational learning and is based on the idea, that social and economic actions are influenced by the actions and experiences of other individuals (Welch 1992). An informational cascade takes place, when it's rational for an individual to ignore his private information and to imitate the behavior of its predecessors (Bikhchandani et al. 1998). An informational cascade can arise "when decision makers have imperfect knowledge of the true value of a product so they infer its utility from observing actions of their predecessors." (Duan et al. 2009). Once a cascade has started, the private information of the decision maker does not join the common knowledge pool, as his observable action does not convey any information about it. Later decisions are not improved due to this reason. Ignoring his private information and joining the herd is thus described as a negative *herd externality* on the rest of the population (Banerjee 1992; Burtch 2011).

Researchers document evidence of bandwagon effects in online environments due to observational learning (Chen et al. 2011). Salganik et al. (2006) created an artificial music download platform and analyzed the influence of knowledge about the previous participants' choice on download behavior. Tucker and Zhang (2011) find that displaying previous numbers of clicks attracts visitors to popular vendors. Chen et al. (2011) examine the differential and interaction effects of word-of-mouth (Arndt 1967; Bowman and Narayandas 2001) and observational learning in a natural experiment on Amazon.com. Simonsohn and Ariely (2008) find evidence of observational learning in online auctions on Ebay.com. Based on these strong theoretical foundations of informational cascade theory and the presented empirical findings, we posit:

h1: *A funders' preference for a crowdfunding reward is positively related to its popularity compared to other alternative crowdfunding rewards.*

The basic model of informational cascades assumes an equality in signal strength, but we can also consider a setting in which heterogeneity between the individuals is allowed (Bikhchandani et al. 1992, 1998). When more informed individuals decide first, novices may imitate the behavior of experienced decision makers, so that an informational cascade could start even easier. But when a fashion leader appears later in a sequence he can break an existing cascade by following his private signal as he will be more certain about his choice. One group, which could be described as fashion leaders in crowdfunding settings, are of more experienced crowdfunders that may be able to better estimate the strengths, weaknesses and risks of a crowdfunding project. Hence, we suggest:

h2: Experienced crowdfunders will be less influenced by the choice of earlier decision makers.

3 Methodology

To test our hypotheses we conduct an online experiment. Our experiment uses between-subject design, crossing the amount of supporters (popular vs. unpopular), which leads to two different experimental groups. Two crowdfunding rewards at different prices of $19.59 (low-priced reward) and $19.79 (high-priced reward) are presented and the participants are asked to decide between the two rewards. The descriptions of the rewards are completely identical except for the price and the experimental treatments. The rewards are both introduced as “One Square. Shipping included in the US. International, please add $15.” An overview of the experimental groups and treatments is given in Table 1.

An exemplary crowdfunding project from *kickstarter.com*, which offers a reinvented, squared water bottle, is used as the basis of our stimuli in order to meet a realistic scenario and assure typical wording and common practices of crowdfunding projects (Mayer 2012). The exemplary project was successfully funded on October 11, 2012 with more than 1700 supporters reaching 600% of its funding goal of $20.000.

During the experiment, the participants choose between the rewards by stating their preference on a scale from 1 (low-priced reward) to 7 (high-priced reward). To get a deeper inside in their thoughts and feelings about the rewards, the *willingness to buy* and the *perceived value* scales are adapted from Dodds et al. (1991) with only limited changes. As described, we expect that crowdfunding experts will be less influenced by a cascade than inexperienced crowdfunders. To test this hypothesis we adopt a three-item scale to measure the crowdfunding expertise of the participants (Lambert-Pandraud et al. 2005).

We recruit participants of our survey via the micro-task platform Amazon Mechanical Turk (MTurk). Although micro-task markets lower “the cost of recruiting participants and offer research immediate access to hundreds of users”(Heer and Bostock 2010), researchers report issues with random answers and spammers on Mturk. Therefore, a verification mechanism is needed to make sure that workers answer our survey accurately (Downs et al. 2010; Kapelner and Chandler 2010). To block low performance workers and spammers, several additional measures are implemented in our questionnaire (Schulze et al. 2011).

The questionnaire is tested in three qualitative pretests with university students. While answering the questions, pretesters are able to write down everything that they notice. When having finished the survey, every participant describes his decision process and influential factors in a personal interview. The questionnaire is refined based on the feedback. Afterwards a quantitative pretest with participants from MTurk is performed.

In order to validate our research instrument we follow the approaches of Straub (1989) and MacKenzie et al. (2011) to assure content validity, construct validity and reliability. First, content validity is defined as “the degree to which items in an instrument reflect the content universe to which the instrument will be generalized” (Straub et al. 2004, p. 424). Literature reviews and expert judges are suggested to assure content validity. After a literature review on every construct, experts from different fields such as IS, marketing and crowdfunding evaluate our questionnaire. Second, “construct validity is an issue of operationalization or measurement between constructs. The concern is that instrument items selected for a given construct are, considered together and compared to other latent constructs, a reasonable operationalization“ (Straub et al. 2004). A high correlation between items of the same scale (convergent validity) and a low correlation between items of constructs that are expected to differ (discriminant validity) is assured by a exploratory factor analysis based on the final survey data (Straub 1989). Finally, to estimate internal reliability Cronbach’s alpha has traditionally been used with an acceptance level of .70 or above (MacKenzie et al. 2011, p. 314). All constructs reach Cronbach’s alpha above .80.

Table 1. Experimental Groups and Treatments

	low-priced reward ($19.59)	**high-priced reward ($19.79)**
group 1	79 supporters	9 supporters
group 2	9 supporters	79 supporters

We published our survey on October 24, 2012 at 3:15 p.m. on Mturk with a reward of $0.35. We preselected workers according to their qualifications (Geiger et al. 2011) and made a geographical restriction and allowed only US citizens to take our survey. 366 responses were collected until November 9, 2012 with an average response time of 11 minutes and an effective hourly rate of $1.89. We had to reject a certain number of assignments due to quality issues. In total, 144 questionnaires were usable for this project. The characteristics of the respondents indicate that 57% of the respondents are female. Average age is 36,49 years. 38% of the participants have a bachelor degree, 30% attend college at the moment. 41% reported an annual household income between $35.000 and $75.000, 29% between $15.000 and $35.000. More than two thirds heard about crowdfunding before taking our survey. This is way higher than our experience during the pretests with German students, providing support for our decision to conduct the survey with US participants on MTurk. Moreover, 23% had already supported a crowdfunding initiative in the past.

4 Results

In this section, we report our main findings, which demonstrate that popularity has a significant effect on funders' reward decision. We present the results from an analysis of variance between all experimental groups and test for the influence of consumers' need for uniqueness and crowdfunding knowledge via a multiple regression in a second step. Figure 1 summarizes the reward decisions in the two experimental groups. In the first experimental group, nearly 71% of the funders decide in favor of the low-priced reward ($19.59) over the high-priced reward ($19.79) and follow the decision of their predecessors. When the popularity is shifted from low-priced reward to the high-priced reward, only a third of the funders decide in favor of the low-priced reward. The hypotheses regarding the two main effects are tested first by an analysis of variance. Table 2 presents the mean of the preferences indicated by the participants. It is measured on a 7-point scale, where 1 indicates a preference for the low-priced reward and 7 for the high-priced reward. The results of the one-way independent ANOVA show that the mean differences between the experimental groups are significant.

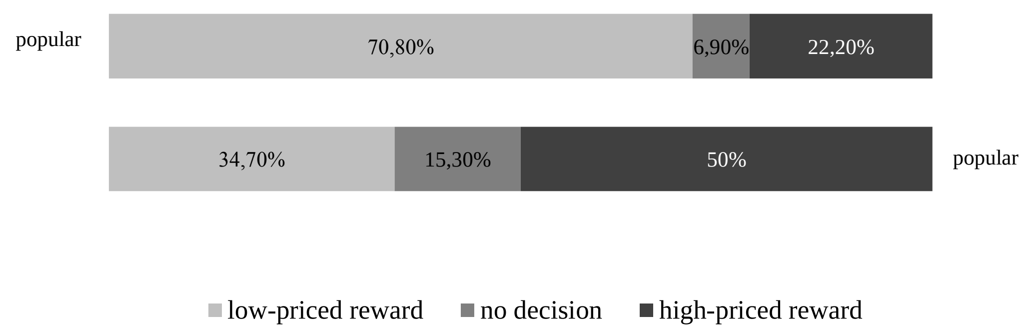

Figure 1. Reward Decisions in Experimental Groups

Table 2. Result of one-way independent ANOVA

	Group 1 (n=72)	Group 2 (n=72)
Popularity	low-priced reward	high-priced reward
Preference		
Mean[a]	2.74	4.24
Standard Deviation	2.25	2.41
	$F_{(3,284)} = 13.89$ ($p < .001$), $r = .357$ LSD Test: Group1 < Group2***	

[a] Mean value on a 7-point scale, where 1 indicates low-priced reward and 7 indicates high-priced reward
* p < .05; ** p < .01; *** p < .001;

In a second step of our analysis, we use a multiple regression with the reward preference as dependent variable. We create a dummy variable as predictor: it indicates if the low-priced reward is more popular (0) or if more predecessors chose the high-priced reward (1). The coefficients for the effects of popularity are shown to be highly significant and positive as summarized in Table 3. We do not find crowdfunding knowledge to be a significant moderator of the popularity effect as assumed in hypothesis h2. However, when looking at the direct effects on the choice of the higher priced reward, we find a negative significant effect. We control for demographics and some additional variables that potentially might influence funder’s choice. Only if funders show characteristics of experiential thinking in their decision style, we find a significant effect on the choice of the higher priced reward.

Table 3. Result of Multiple Regression

Variables	Coefficients	Std. Err.
Popularity	1.647***	.372
Crowdfunding Knowledge	-.244 ns	.127
Interaction Effect Popularity x Crowdfunding Knowledge	-.071 ns	.244
Controls		
Product Involvement	-.002 ns	.174
Product Quality	-,260 ns	.201
Experiential Thinking	.507***	.119
Education	.074 ns	.146
Sex	.253 ns	.393
Age	.027 ns	.016
Income	.041 ns	.182
Others		
R^2	.257	2.180
Sample Size	144	
ns= not significant; *p < .05; **p < .01; ***p < .001		

5 Discussion

We find that funders are significantly influenced by information on preceding funders' reward decisions. This is consistent with previous findings in offline (e.g. Cai et al. 2009; van Herpen et al. 2009) as well as online settings (e.g. Chen et al. 2011; Simonsohn and Ariely 2008). However, previous studies did not take a financial perspective into account, analyzing for example only the popularity of free software downloads or songs with only a single price (Duan et al. 2009; Salganik et al. 2006). We contribute to this literature stream with the striking result that observational learning even takes place when following the decision of previous others is associated with a higher monetary commitment. Similar results can be found in the literature on charitable giving, where donors changed their contribution in the direction of social information (Croson and Shang 2008). Interestingly, we did not find crowdfunding knowledge to be a moderator (interaction effect) of the observational learning effects but could see an overall negative trend on the preference for the high-priced reward along experienced crowdfunders in groups. It seems that this type of funders pays more attention to project characteristics and reward descriptions and therefore notices the high similarity between the offered rewards. We controlled for the decision thinking style and found a significant effect if funders make their decisions experiential, i.e. in a rather spontaneous manner. They significantly tend to spend more money.

Existing crowdfunding literature focuses mainly on the categorization of crowdfunding initiatives, the motivation of crowdfunding participants (Gerber et al. 2012; Ordanini et al. 2011) and success drivers of crowdfunding campaigns (Lambert and Schwienbacher 2010; Mollick 2012). We contribute to this literature stream as we show two influence factors for funders' decisions about their funding amount and their selection of rewards, which they receive in return for their support.

Our findings have important implications for the different players in the crowdfunding environment. From a project creators' perspective, herding is considered to be beneficial for the success of crowdfunding initiatives as it helps projects to keep their funding drive (Burtch 2011). However, we find that it also can be obstructive to the funding success as it could discourage funders to support with a higher funding amount.

Platform operators should carefully decide if they offer information about the reward decisions of previous funders. On the one hand, it offers some insights in how much financial risk previous supporters are willing to take. Hence, the information assists potential funders in their decision-making. On the other hand, the characteristics of an informational cascade are that people ignore their private information and follow the signal of the herd. In this way, funders could be influenced to spend more money than they planned taking a higher risk than they can manage. Platform operators should notice that "herding is associated with poorer decision-making for investors [funders]" (Burtch 2011).

Finally, we want to outline possible limitations of our approach and will draw a picture of possible future research that could overcome these drawbacks and further contribute to a deeper understanding of crowdfunding in general and the selection of rewards and funding amounts in detail. As this is the first academic research that focuses on the reward decision of funders and the influences on the amount of financial support in crowdfunding campaigns, further research in this area seems beneficial. While popularity information of a reward are only one important factor, other influences such as the type of reward (e.g. material vs. immaterial), scarcity, the delivery date, or project and reward descriptions could be subjects of future investigations. The results of our pretests highly suggest that future research should investigate funders' reactions to different levels of popularity and - most important - price differences to achieve a deeper understanding of our findings. A dynamic approach observing the development of rewards' popularity during the investment path of a crowdfunding campaign could offer valuable new insights too. In our experiment, funders had to decide only between two different rewards. In a real world setting, most creators of crowdfunding projects will offer far more than this. However, informational cascade theory can also be applied to settings with more than two alternatives. In these situations cascades "tend to take longer to form and aggregate more information" (Bikhchandani et al. 1998). Our experimental setting is somewhat similar to online environments such as online-shops, mobile application markets or micro-lending platforms. Future research endeavors could investigate if our findings are adaptable to these markets.

6 Conclusion

Although crowdfunding has achieved notable attention from the general public, this fast-growing market is being researched to a very limited extend only. Existing literature mainly focuses on motivation factors for crowdfunding participants and on success factors for funding initiatives. Little is known about how crowdfunding supporters set their funding amount and how they select rewards, which they receive in return for their financial support. Therefore, we investigate '*how are online investment decisions influenced by information on choices of earlier funders?'* based on observational learning and informational cascade theory.

We perform an online experiment based on the platform kickstarter.com where participants select between two rewards at different funding amount levels to test our hypotheses. We contribute to the literature stream of observational learning and are able to show that online funders even follow the decision of previous others when a higher financial commitment is associated. Experienced crowdfunders are less prone to herding effects and pay more attention on characteristics of rewards. We discuss these results in the light of the informational cascade theory that suggests such a change in the payoff structure as a possible way to reduce or even eliminate socially inefficient herding

(Banerjee 1992). To the best of our knowledge, this is the first study that confirms this suggestion empirically.

Our results have implications for project creators as well as platform operators. Creators should keep in mind that herding can not only lead to a stronger financial support, but can also be obstructive to funding success when funders gather together on a low-priced reward. Hence, first funders might be the most important funders of a project based on our results. This might also be explained through a path dependency perspective. Countering these effects might be, to encourage friends and family to be first funders or to advertise for the higher rewards through additional incentives for first funders. From a platform operator's perspective, information on previous decisions can be offered to their users serving as signals about how much risk others are willing to take. However, funders could be provoked to take a higher financial risk than they can manage.

Future research might further investigate on other influence factors such as different types of rewards, delivery date, scarcity, and the general project description. Moreover, other levels of price differences and popularity of a reward might be of interest to understand our results in more detail possibly together with alternative theoretical perspectives such as signaling or path dependency theory. Finally, future research endeavors could investigate if our findings are adaptable to other online contexts such as online shopping platforms, mobile application markets or P2P lending.

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