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The Dynamics of Funding Behaviors in Reward-Based Crowdfunding Projects

(Work in Progress)

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ABSTRACT

With the growing popularity of crowd-funded markets, smaller manufactories and entrepreneurs are regarding crowdfunding as their main venue of financing. To better understand the dynamic behaviors of participants (i.e. backers) and supplement existing works in crowdfunding research, the paper studies how early backers' funding decisions influence the later participants in a special reward-based crowdfunding projects. By using vector autoregressive models, we plan to find empirical evidence for the existence of herding and bystander effects in our research context while controlling for strong signals of founders' quality. With this research-in-progress, preliminary results and discussion are provided.

Keywords: Crowdfunding, reward-based, herding effect, bystander effect, vector autoregressive models

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INTRODUCTION

Over the past decade, many companies, entrepreneurs and charity organizations have been using crowd-funded markets as one of their main sources for fundraising, leading to an explosive attention from academia to crowdfunding platforms. Early works in the area studied factors influencing the success of crowdfunding projects, such as interface element designs (Beier & Wagner, 2015; Simons, Weinmann, Tietz, & vom Brocke, 2017; Tietz, Simons, Weinmann, & vom Brocke, 2016), the language of project descriptions (Kim, Cho, & Lee, 2016; Mitra & Gilbert, 2014; Xu et al., 2014), and founders' characteristics (Hou, Wang, & Ge, 2015; Lin & Viswanathan, 2015).

More recent work have shown strong interests in the funding dynamics of participants (i.e. funders or backers), particularly, how early contributions influence the subsequent backers' behaviors. However, many of them study the issue for charity projects (Burtch, Ghose, & Wattal, 2013; Solomon, Ma, & Wash, 2015), leaving backer behaviors for reward-based projects less investigated despite its popularity (Mollick, 2014).

Behaviors for charity-based projects and for reward-based projects could be very different. For the former, backers perceive themselves as contributing towards a greater social good (Aitamurto, 2011; Solomon et al., 2015) and the projects involve backers' altruistic motivation. However, founders of reward-based projects often use crowdfunding to raise capitals for start-ups or finance their creative ideas (Roma, Gal-Or, & Chen, 2018). Hence reward-based projects motivate backers with tangible, non-financial rewards or pre-purchasing opportunities. For such projects, to understand when and how backers decide to fund their projects is vitally important to adjust their attempts in posting innovative products.

To study the dynamics of pledge performances, we collected data of crowdfunding projects from a very special platform called iZhongchou, which is affiliated to Taobao.com, a well-known B2C online market. The platform is unique in a way that project founders are all required to be good sellers on Taobao. With the existing signals on Taobao, backers' behaviors in such crowdfunding projects may show special patterns comparing to those on other platforms.

Our data collection is not only on crowdfunding projects but also on founders' shop performance on Taobao. Together, the dataset contains 2,421 weekly observations for 470 projects during Sep 2017 to May 2018. By using vector autoregressive models with exogenous covariates (VARX), we plan to estimate the long-term and accumulative effects of prior backers' behaviors.

Findings of the work could bring insights to both research and practices. The funding dynamics on the special platform joins the literature on online marketing and sheds light upon studies in entrepreneur innovation. The paper can also provide strategies for founders on the platform to adjust or manage their crowdfunding campaigns so that they be most benefited from the campaigns.

RELATED LITERATURE

Funding behaviors in crowdfunding projects

Studies on the funding behaviors in crowdfunding are many. Some of them focuses on the design of projects or funding platforms to investigate their impact on the project success and funding behaviors. For example, Roma et al. (2018) studies how the design of projects influence the subsequent VC funding behaviors. Chakraborty and Swinney (2019) focused on the funding target and found that founders should signal high quality to investors by setting a high target. Bi, Geng, and Liu (2019) investigates the differences in fixed and flexible funding mechanisms and provides pledging strategies for both backers and prediction for founders.

There are also studies working on the dynamics of backers' funding behaviors. Among them, two specific funding periods particularly stand out in existing works – early stage of the entire funding period, and the threshold timing of achieving the funding goal. Colombo, Franzoni, and Rossi–Lamastra (2015) investigates one of the determinants for early pledges – internal social capital. They also find a positive relationship between early pledges and the project success. Crosetto and Regner (2018) further examine the situations when projects lack early pledges and find projects' communication plays an important role in projects' final success. For the goal-reaching timing, Li and Wang (2019) find special patterns in the backers' pledging and sharing behaviors for both public-good and private-good projects.

Dynamics in contribution behaviors

Regarding how early contributions influence later contribution behaviors, papers studying different crowdfunding projects conclude with different findings.

Herding effect has been found in projects for equity-, lending- and charity-based crowdfunding (Agrawal, Catalini, & Goldfarb, 2011; Herzenstein, Dholakia, & Andrews, 2011; Zhang & Liu, 2012). The theoretical support of herding behaviors is rooted in signaling theory – early contributions, acting as quality signals, trigger the subsequent contribution behaviors (Burtch et al., 2013; Zhang & Liu, 2012). Additionally, rational herding behaviors are found in crowd-lending markets that backers observe early contributions and use observable founder features to moderate their inferences (Zhang & Liu, 2012).

Another opposing phenomenon is the bystander effect, i.e. potential backers decide not to contribute as the project has already been receiving a great deal of support (Kuppuswamy & Bayus, 2017) and they feel less important of their own contributions (Burtch et al., 2013). The bystander effect (also crowd-out effect) has been documented in charity-based (Burtch et al., 2013) and reward-based crowdfunding projects (Kuppuswamy & Bayus, 2017). And the focuses of the two papers are the amount of monetary contribution and number of funders respectively.

STUDY CONTEXT & METHOD

Our study context is iZhongchou, a crowdfunding platform affiliated to Taobao.com, which is one of the biggest e-commerce platforms in China. The platform is specialized on reward-based crowdfunding campaigns. iZhongchou follows the dominant approach of crowdfunding, the "all for nothing" model, which means that the collected money is only given to the project initiator if the target fund of the campaign is achieved within the campaign duration.

Project founders on the platform are unique. Regulated by the iZhongchou, project founders must have opened their shops on Taobao.com already and performed well in their past transaction history. Therefore, the founders have already signaled their quality through the performance in the Taobao shops.

The projects we targeted on are from two categories, Technology and Design, which are typically more risky and require large amount of capital (Hogg, 2014; Roma et al., 2018). Founders of such projects normally use the crowdfunding to pre-sell their innovative products and assess the market potential (Crosetto & Regner, 2018).

To test the existence of herding or bystander effect, we constructed a dataset by weekly crawling and collecting data from iZhongchou. Our dataset contains project records collected during September 6th 2017 – May 2nd 2018 in the two categories, In total, there are records for more than 500 projects. We further filtered them, keeping those that started and ended within our collection window.

After processing, we have 2,421 project-week observations for 470 distinct projects, among which 18 projects were not funded successfully (the funding goal were not reached when the project ended). The projects duration vary from one to eight weeks.

Besides, in our data collection, we were able to collect information on founders experience in funding the projects. The 470 projects in our dataset were conducted by 303 distinct founders. There were 230 out of 470 projects were founders' first attempts during our collection period, while 240 projects were founders' further attempts.

Measurements

A list of all variables included in the VARX models is provided in Table 1. Our focal variables are the funding status of a project *i* at time *t*, including *Raised funding*, measured by the ratio of the current funding over the funding goal, and *Number of funders*, measured by the current number of accounts contributing to the project. Noted that following the all-or-nothing model, a project succeeds when *Raised funding* reaches or high than 1. If a project yields a *Raised funding* lower than 1 when the campaign ends, the project is unsuccessful.

We control the length of project description and the minimum price of the project's reward choices. Particularly, on iZhongchou platform, description of all projects are delivered with images. Therefore, the description length is the summation of images' length (in pixels).

Table 1: Descriptive Statistics of Variables

Variable	Mean	Std.dev.	Max	Min
RaisedFunding	4.365226	7.344317	0	95.03399
NumberofFunders	3267.019	7624.671	0	111423
DesLength	21709.15	10584.9	1161	87024
MinPrice	296.2028	531.713	0.1	3599
Score	4.880837	0.1320316	4.4	5
Size	56.96575	522.2116	1	12647
Sales	7620.204	49988.11	1	689184

To account for other founder signals such as credibility and experience in e-commerce, we control for the founders' shop *Score* (average review rating from previous buyers), *Size* (number of products being posted in its own shop), and its *Sales* data (number of previous orders).

Model specification

The following VARX model is built:

$$Y_t = \mu + \sum_{j=1}^{q} A_j Y_{t-j} + BX + \varepsilon_t$$

where t represents time, j is lag length and the q is maximum lags. The lag order is selected by Bayesian information criterion (BIC), Akaike information criterion (AIC), and the Quinn information criterion (QIC). The optimal lag order was two according to the criterions. $Y_t = (RaisedFunding, NumberofFunders, DesLength, MinPrice)^T$, $X_t = (Score, Size, Sales)^T$.

PRELIMINARY RESULTS

To check of collinearity and multicollinearity exist, we analyzed the correlation and variance inflation factor (VIF). The mean VIF did not exceed 1.02. We conclude that no such issues exist in our data given the low correlation value (as shown in Table 2) and the VIF value.

Table 2: Correlation Matrix

		1	2	3	4	5	6	7
1.	RaisedFunding	1						
2.	NumberofFunders	0.5455	1					
3.	DesLength	-0.0271	-0.0206	1				
4.	MinPrice	0.0028	-0.0339	0.047	1			
5.	Score	-0.0072	0.0051	-0.0681	-0.0509	1		
6.	Size	-0.0049	-0.0141	0.074	0.0528	-0.0915	1	
7.	Sales	-0.1903	-0.0411	0.0337	0.0036	-0.0088	0.0826	1

To run the VARX model, we first check whether the variables were evolving stationary by conducting unit-root test using an augmented Dickey-Fuller test with 1 lags. The result rejected the null hypothesis of a unit root with a 95% confidence level.

We run Hausman test to determine the existence of fixed or random effect in our panel, and find the presence of fixed effect in both of our focal variables. Therefore, correlation issues between variables might occur. Overcome its influence, the VARX is estimated by the Generalized Method of Moments (GMM), with the lags of the regressors as instrumental variables (Holtz-Eakin, Newey, & Rosen, 1988).

Exogenous variables

As shown in Table 3, the quality scores of the shops are negatively associated with description lengths of the crowdfunding projects, indicating that quality sellers on Taobao are not paying as much efforts as others would do in marketing their projects. Also, the past sales of founders' shops have a negative relationship with the RaisedFunding. The counter-intuitive results might be caused by two reasons, one is the rational herding behaviors previously found in microloan markets (Zhang & Liu, 2012), i.e. people uses the observable variables to make inferences; the other possible reason is on the founders' side – their less attention on the crowdfunding projects may also cause the effect.

Table 3: Coefficients of Exogenous Variables

Variables	RaisedFunding	NumberofFunders	DesLength	MinPrice
Score	-6.835 (-0.46)	-5101.163 (-0.54)	-58847.28 (-2.09) **	115.275 (1.63)
Size	0.00046 (0.69)	0.244 (0.52)	1.979 (1.59)	-0.005 (-1.72) *
Sales	-0.00037(-2.44) **	-0.577 (-1.57)	-0.572 (-1.38)	0.00008 (0.07)

Note: Coefficients and t-values (in parenthesis) are reported in the table. ** and * denote statistical significance of 5% and 10% level.

Further analyses

We plan to conduct Granger Causality tests (Abrigo & Love, 2016; Granger, 1969) to understand the (granger) causality direction of our focal relationships. We will further compute the impulse response functions (IRFs) for better interpretation of the results. The IRF exhibits a variable's behavior faced with a shock in another variable. The function also helps to understand the time needed for variables to go back to equilibrium after shock.

For robustness checks, additional VARX models for each project categories will be tested to assess the consistency of the results. Other adjustment of the model and plan for further analysis are introduced in the Discussion section below.

DISCUSSION

With the growing popularity of crowd-funded markets, smaller manufactories and entrepreneurs are regarding crowdfunding as their main venue of financing. Our work joins the discussion of backers' funding dynamics by conducting analysis on the special crowdfunding platform affiliated to a well-known online market. The finding of the work could help understand the backers' behavior and provide strategies for project founders to manage their projects, by which the work may contribute to current studies of both online marketing and entrepreneur innovation.

The current work has a few limitations. First, the current VARX model does not consider the effect of the reward design. According to prior studies (Chakraborty & Swinney, 2019; Roma et al., 2018), the design might influence backers contribution decisions at the early stage of the funding period. Second, our model does not account for further analysis on the current performance of exogenous variables. We plan to look deeper into the above issues and adjust our models accordingly. In addition, we do not investigate the potential impact of crowdfunding success on the performance of Taobao shops in future, for which later research may wish to investigate empirically.

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