How to Design Your Project in the Online Crowdfunding Market? Evidence from Kickstarter

Research-in-Progress

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Abstract

Raising money in the online crowdfunding market is an important way for start-up enterprises to start their entrepreneurial projects. However, how to help creators design their projects in this market is still an open and very realistic issue. In this study, we collect a unique dataset from Kickstarter (a leading crowdfunding platform in the U.S.) to examine the impacts of reward scheme related and unrelated factors on projects' crowdfunding performance based on solid theories. We use a Heteroscedasticity-based instrument method to solve the endogeneity of backing price. We found that a project creator can raise more money in the crowdfunding market if he/she sets a bit higher maximum backing price; lists relative fewer reward tiers in their reward schemes; publishes well designed project homepage; and communicates with backers as much as possible during the project's survival time. We also discuss the implications for project design in this market.

Keywords: project design; reward scheme design; price endogeneity; crowdfunding

Introduction

With the rapid development of web 2.0 and other information technologies, online crowdfunding has been developed as a mechanism to raise funds for start-ups, to support micro-financing in less developed countries, and to generate donations for not-for-profit organizations (Szaky 2011). As the economic potential of this mechanism has recently become more apparent, the crowdfunding industry has experienced tremendous growth in recent years. Marketplaces like Kickstarter and Indiegogo are beginning to facilitate greater transactions, both in terms of volumes and amounts. A recent report from "Kickstarter Stats" shows that by the end of May 1st 2014, 144,585 projects had been launched on the

Kickstarter platform, among which 60,902 projects had been successfully funded, and $1,093,026,057 dollars had been raised. With the passing in the US of the Jumpstart Our Business Start-ups (JOBS) Act in September 2013, the crowdfunding industry acquired legitimacy and is expected to lead a new era of entrepreneurship (Wortham 2013).

In this study we consider the project design problem in the online crowdfunding market. We focus on the case where project creators raise money from backers to start their ventures within a limited time window and in return the creators provide backers with different rewards. When raising money in this case, project creators are required to provide a reward scheme (a menu of reward offering including reward items and backing prices) for backers; interested backers choose appropriate reward items and pay the backing prices to support these projects. A project will be successfully funded if the total money of committed purchases from backers exceeds a specified goal within a predetermined time window. The objective of the current research is to empirically examine the impacts of reward scheme-related and reward scheme-unrelated factors on projects' crowdfunding performance by using an explanatory empirical framework based on a unique dataset from Kickstarter.

Our empirical analysis yields four major findings. First, these well described projects and projects featured by the crowdfunding platforms are intend to raise more money in the crowdfunding market; Second, more communications between backers and creators will help creators raise more money; Third, the backing price of the top reward item in a reward scheme is a good signal for the value of a project, and a relatively higher maximum backing price also has positively and significant influence on projects' crowdfunding performance; Fourth, unlike what conventional wisdom would suggest, a relatively less reward item in a reward scheme will help project creator raise more money. In the remainder of this paper, we review related literature and develop our hypotheses based on solid theories in Section 2. Section 3 describes our dataset and variables, and Section 4 provides the econometric analysis and discusses the results. Section 5 concludes the paper and points out our future research directions.

Literature Review and Hypotheses

We review crowdfunding-related empirical studies and propose our hypotheses in this section.

Extant empirical studies on crowdfunding: Our study makes contribution to the emerging literature on reward-based crowdfunding mechanisms by focusing on the reward scheme design problem. In fact, the emergences of different kinds of crowdfunding platforms have already attracted the attentions of researchers and practitioners. A number of researchers have empirically investigated these factors that influence project successes or performances (Agrawal et al., 2011; Mollick, 2014; Marom and Sade, 2013; Calvin, 2013; Colombo, et al., 2013; Belleflamme, 2013, 2014) When summarizing the aforementioned literature, we will find that they actually examine projects' crowdfunding performance from backer-side, creator-side, and project description-side separately. However, in the online crowdfunding market, backers support crowdfunding projects by choosing appropriate reward items in the reward schemes. Project backers and creators are actually linked together by the reward scheme in each project, and the reward scheme plays a vital role in influencing projects' success and performances. Different form extant studies, we develop an empirical model based on solid theories to analyze the impacts of both reward scheme related and unrelated factors on project's crowdfunding performance. Next, we will develop our hypotheses based on two solid theories.

Signaling theory and hypotheses: The signaling theory is fundamentally concerned with reducing information asymmetry between two parties (Spence 2002), and usually includes three primary actors: signaler, receiver and signal itself. Signalers are insiders who obtain information about an individual (Spence 1973) and product (Kirmani and Rao 2000) that is not available to outsiders. This private information provides insiders with a privileged perspective regarding the underlying quality of some aspect of the individual, product. Receivers are outsiders who lack information but would like to receive this information. They usually have partially conflicting interests such that successful deceit would benefit the signaler at the expense of the receiver (BliegeBird, Smith et al. 2005). Signal is the third element and it is always raftered to the action that insiders take to intentionally communicate with the outsiders. Efficacious signal usually has two characteristics: observability and cost. The former refers to the extent to which outsiders are able to notice the signal and the later refers to the price that insiders have to pay for showing this signal (BliegeBird, Smith et al. 2005). Spence (1973) is the first researcher who utilized the labor market to model the signaling function of education. Currently it has been widely used (Kirmani et al., 2000; Certo 2003; Busenitz et al., 2005; Lester et al., 2006; Zhang et al., 2009; Ahlers et al., 2012).

In our research context, project creators are first required to provide a project homepage and a reward scheme (a menu of reward offering including reward items and its backing price) to introduce their projects and to attract backers. Backers choose reward item to support the projects according to their own preferences. Obviously, the information between project creators and backers is asymmetric (creators know the real quality of their projects, while backers don't know). To realize their funding goals, creators have to show the backers more information about their projects. Generally speaking, They have three ways to send their project signals to backers: 1) Provide a well designed project homepage (i.e., use more words to descript their projects, post more videos.); (2) Communicate with backers as much as possible, and update project information quickly; (3) Provide a well designed reward scheme. The project's homepage is the main channel for backers to learn about the project, hence a well designed homepage are intend to attract more backers and likely raises more money. Furthermore, if project creators communicate with customer actively, they will leave the backers a good image and reassure them to some extent. Being consistent with signaling theory, we propose our first two hypotheses:

Hypothesis 1: The elements on the homepage of a project that can well describe the project are positively associated with its crowdfunding performance.

Hypothesis 2: The number of communication activities between project creators and backers are positively associated with project's crowdfunding performance.

Excepting the project description, the value of reward items in each project, especially the value of the top tier reward item, is another very important signal for creators to show the project quality. That's because, they represent the value, especially the highest value that a creator can provide to the backers. If their values are too low, it will easily leave bad image to the backers. Since the value of the top tier reward item is always correlated with its backing price, we propose:

Hypothesis 3: A relative higher maximum backing price in a project's reward scheme will have a positive effect on its crowdfunding performance.

Choice overload theory and hypotheses: Unlike signaling theory, the choice overload theory here is used to explain backers' information overload situation. This theory can be traced back to the French philosopher Jean Buridan (1300–1358), who theorized that an organism faced with the choice of two equally tempting options, such as a donkey between two piles of hay, would delay the choice; this is sometimes referred to as the problem of "Buridan's ass" (Zupko and Buridanus 2003). In the twentieth century, Miller (1944) reported early experimental evidence that relinquishing an attractive option to obtain another (a situation he referred to as "double approach avoidance competition") may lead to procrastination and conflict. Lewin (1951) and Festinger (1962) further proposed that choices among attractive but mutually exclusive alternatives lead to more conflict as the options become more similar. Lipowski (1970) extended their arguments by proposing that choice conflict further increases with the number of options. After that, this theory becomes very common in the economics and management literature (Iyengar et al., 2000; Mogilner et al., 2008; Reutskaja et al.,2009; Goldreich et al., 2013).

In our study, a reward scheme is a reward menu provided by the creators and there is inherent order of reward items. In particular, reward items are indexed such that the item listed on a toper position of a reward scheme usually has lower value and backing price. In reality, backers' evaluations of reward items are different. Furthermore, because many projects in the crowdfunding market are relative new, many backers (even experienced one) are lack of familiarity with the reward item listed in the reward schemes. As a result, backers may face the choice overload effect when choosing the reward items to support these projects. In line with the choice overload effect, we propose the following hypothesis:

Hypothesis 4: The number of reward tier in a project's reward scheme will have a negative effect on its crowdfunding performance.

Data and Variable

We collect our dataset from Kickstarter. It includes 802 projects over a period from April 2009 to July 2012. These projects cover three categories: Hardware (22.82%), Open Software (30.92%), and

Technology (46.26%) and raised \$ 129, 484, 820. We opt to study these projects because they are good represents for projects that produce both tangible and intangible products. The dataset includes an exhaustive list of project description-related information and its reward-related information. We also collected project update-related information, which captures the communications between backers and creators on Kickstarter. To get rid of the reward updating effect (Xu et al., (2014)), we use text mining technologies to discard 65 projects whose reward schemes have been modified. We also removed 22 projects that can be identified as outliers in our dataset. Since the total amount of money that each project raised in the crowdfunding market can directly reflect project crowdfunding performance, it is treated as dependent variable in our study. We use its log form due to its skewed nature. Based on extant empirical studies, reward scheme-related and unrelated variables are constructed as Independent Variable (Table 1).

Table 1. Variables and Explanations

Variable	Explanation	Obs.	Min	Max	Mean	Std.
lnpledge	log(total amount pledged)	715	0	13.80	6.86	2.86
ta1, ta2	Dummy variable (project category)	715	1	3	2.25	0.79
duration	Project' survival time	715	7	91	40.91	17.30
ln_goal	Log (the amount of money want to raise)	715	3.91	13.53	9.10	1.39
lncomment	Log (# of comments in each project)	715	0	7.44	1.50	1.64
lnupdate	Log (# of updates in each project)	715	0	4.86	1.33	1.15
imag	# of image used in each project	715	1	45	3.30	4.12
lnFacebook	Log (creator's Facebook friends)	715	0	8.54	2.46	2.98
lnplength	Log (length of project description)	715	0	13.13	6.86	2.86
featured	Indicate Kickstarter's mention (1=yes)	715	0	1.00	0.06	0.24
comp_index	projects in the same class at the same time	715	2	112	33.85	23.10
levelnumber	# of reward tier/level	715	0	9.21	6.69	1.70
lnminpledge	Log (the minimum backing price)	715	0	6.91	1.26	1.22
lnmaxpledge	Log (the maximum backing price)	715	0	9.21	6.69	1.70
lnrlength	Log (average length of reward description)	715	2.49	6.74	5.13	0.53
above_stra	Whether using "above all strategy" [1]	715	0	1.00	0.33	0.47
limit_ratio	(# of reward tier that limits the number of backer)/(# of reward tier)	715	0	1.00	0.18	0.24

Econometrical Model and Analysis

To test our hypotheses, the regression model in which we are most interested is of the following form:

$$\text{lnpledge}_i = \alpha_0 + \sum_{j=1}^{k} \alpha_j x_{ij}^{\text{reward-unrelated}} + \sum_{l=1}^{k'} \beta_j x_{il}^{\text{reward-related}} + \varepsilon_{i0} \tag{1}$$

Where, $x_{ij}^{\text{reward-unrelated}}$ (for j=1,2,...,k) refers to the k non-reward scheme related variables, while $x_{il}^{\text{reward-related}}$ (for l=1,2...,k') refers to the *k'* reward scheme-related variables in a project (lnminpledge,

[1] The "above all strategy" is a reward design strategy. If it is used in a reward tire, it means that the backers who have chosen this reward tier can get all the reward items that are listed above this reward tier.

lnmaxpledge, levelnumber, above_stra, limit_ratio, the average length of reward description). We first check the Heteroscedasticity and multi-collinearity issues in regression model (1). We performed a White test and Breusch-Pagan test for our simple regression model (1). Both the White test statistic ($\chi^2_{(132)}$=255.46 with p-value=0.00) and the Breusch-Pagan statistic ($\chi^2_{(1)} = 133.06$ with p-value=0.00) indicate the existence of Heteroscedasticity. To control the Heteroscedasticity, we have to use robust standard errors(Baltagi, Bresson et al. 2006) in the following econometric analysis. The elements in the correlation matrix of variables in formula (1) are small and all the variables' variance inflation factors (VIF) are less than 10 (the highest is 2.59, and the average is 1.52). Therefore, we don't need to worry about the multi-collinearity issue in model (1). Next, we have to solve the endogeneity of backing price in regression model (1). Specifically, there are two potential endogenous variables in our model (1): lnminpledge and lnmaxpledge. As a result, we have to use other method rather than OLS to estimate regression our model.

Heteroscedasticity-based Instruments Estimation Method and Estimation

To solve the endogeneity of backing price, we have to find instrument variables. Because of the difficulties in finding external and efficient instrument variables, we use the Heteroskedasticity based method to estimate parameters in model (1). This approach has been developed by Rigobon (2003) and Lewbel (2012) and has been widely used in a variety of real data settings where traditional instrument variables are not available (Kelly and Markowitz 2007; Sabia 2007; Giambona and Schwienbacher 2008; Shahe Emran and Hou 2008). We use $x_{il}^{\text{reward-related 2}}$ (for l=3,4,5,6) to represent the *levelnumber*, *above_stra*, *limit_ratio*, *lnrlength* in each project, and assume the backing price are the only exogenous variables. Then we can decompose regression model (1) as follows:

$$\text{lnpledge}_{\text{i}} = \alpha_0 + \sum_{j=1}^{k} \alpha_j x_{ij}^{\text{reward-unrelated}} + \beta_1 \cdot \text{lnminpledge}_{\text{i}} + \beta_2 \cdot \text{lnminpledge}_{\text{i}} + \sum_{l=3}^{6} \beta_j x_{il}^{\text{reward-related 2}} + \varepsilon_{i1} \quad (2)$$

$$\text{lnminpledge}_{\text{i}} = \gamma_{01} + \sum_{j=1}^{k} \gamma_{j1} x_{ij}^{\text{reward-unrelated}} + \sum_{j=k+1}^{k+4} \gamma_{j1} x_{il}^{\text{reward-related 2}} + \varepsilon_{i2} \quad (3)$$

$$\text{lnmaxpledge}_{\text{i}} = \gamma_{02} + \sum_{j=1}^{k} \gamma_{j2} x_{ij}^{\text{reward-unrelated}} + \sum_{j=k+1}^{k+4} \gamma_{j2} x_{il}^{\text{reward-related 2}} + \varepsilon_{i3} \quad (4)$$

In (3) and (4), both ε_{i2} and ε_{i3} are standard error terms. If the errors $\boldsymbol{\varepsilon_1}$, $\boldsymbol{\varepsilon_2}$ and $\boldsymbol{\varepsilon_3}$ are all uncorrelated with each other, equation (2) is actually a recursive system and parameters in this system would be identified. Alternatively, parameters in (2) can also be estimated by using exogenous instrument variables (standard IV estimation method). However, In our study, $\boldsymbol{\varepsilon_1}$, $\boldsymbol{\varepsilon_2}$ and $\boldsymbol{\varepsilon_3}$ are correlated with each other because of the endogenous backing price. Lewbel (2012) has shown that, in the presence of heteroskedastic disturbances in Equation (3) and (4), identification of equation (2) can be achieved by using two exclusion restrictions: $[Z\text{-}\bar{Z})]\widehat{\boldsymbol{\varepsilon_2}}$and $[Z\text{-}\bar{Z})]\widehat{\boldsymbol{\varepsilon_3}}$ (where *Z* is a vector of observed exogenous variables that can be a subset of the exogenous variables *X* or can equal *X*, and its elements can be discrete or continues). In our study, we let Z comprise of all the exogenous variables in model (2). The Breusch-Pagan statistics of equation (3) and (4) are $\chi^2_{(1)} = 27.73$ with p-value=0.00 and $\chi^2_{(1)} = 6.14$ with p-value=0.0132. When considering $[Z\text{-}\bar{Z})]\widehat{\boldsymbol{\varepsilon_2}}$and $[Z\text{-}\bar{Z})]\widehat{\boldsymbol{\varepsilon_3}}$, the Hansen J statistic is $\chi^2_{(28)} = 27.430$ with p-value=0.4950. These results indicate the efficiencies of these two instrument variables. Parameters in regression model (2) can be estimated by 2SLS. In addition, considering all the moment restrictions mentioned above, we can also use GMM method to estimate these parameters. Specifically, if we define *S* to be the vector of *Y* and exogenous variables *X*, let $\mu = \text{E}(\text{Z})$, $\theta = \{\gamma_1, \gamma_2, \eta, \beta_1, \beta_2, \mu\}$ (where $\eta = (\boldsymbol{\alpha}, \beta_3, \beta_4, \beta_5, \beta_6)$) and let

$$Q_1(\theta, S) = X \cdot \boldsymbol{\varepsilon_1} \quad (5)$$

$$Q_2(\theta, S) = X \cdot \boldsymbol{\varepsilon_2} \quad (6)$$

$$Q_3(\theta, S) = X \cdot \boldsymbol{\varepsilon_3} \quad (7)$$

$$Q_4(\theta, S) = Z - \mu \quad (8)$$

$$Q_5(\theta, S) = (Z - \mu)\boldsymbol{\varepsilon_1}\boldsymbol{\varepsilon_2} \quad (9)$$

$$Q_6(\theta, S) = (Z - \mu)\boldsymbol{\varepsilon_1}\boldsymbol{\varepsilon_3} \quad (10)$$

Then, the parameters in model (2) can be estimated by using following formula:

$$\begin{pmatrix}\hat{\eta}\\ \widehat{\beta_1}\\ \widehat{\beta_2}\end{pmatrix} = \widehat{\Psi}_{ZX}\left(\widehat{\Psi}'_{ZX}\widehat{\Psi}_{ZZ}^{-1}\widehat{\Psi}_{ZX}\right)^{-1}\widehat{\Psi}'_{ZX}\widehat{\Psi}_{ZZ}^{-1}\begin{pmatrix}\overline{XY_1}\\ \overline{(Z-\bar{Z})\widehat{\varepsilon_2}Y_1}\\ \overline{(Z-\bar{Z})\widehat{\varepsilon_3}Y_1}\end{pmatrix} \quad (11)$$

Where $\widehat{\Psi}_{ZX}$ and $\widehat{\Psi}_{ZZ}$ are estimated value of Ψ_{ZX} and Ψ_{ZZ} ($\Psi_{ZX} = E\left[\begin{pmatrix}X\\ [Z-E(Z)]\varepsilon_2\\ [Z-E(Z)]\varepsilon_3\end{pmatrix}\begin{pmatrix}X\\ Y_2\\ Y_3\end{pmatrix}'\right]$, and $\Psi_{ZZ} = E\left[\begin{pmatrix}X\\ [Z-E(Z)]\varepsilon_2\\ [Z-E(Z)]\varepsilon_3\end{pmatrix}\begin{pmatrix}X\\ [Z-E(Z)]\varepsilon_2\\ [Z-E(Z)]\varepsilon_3\end{pmatrix}'\right]$).

Results and Evaluation of Hypotheses

We use both 2SLS method and GMM method to estimate parameters in equation (3), and the OLS method is treated as a bench method. In these models, the log-transformed funding pledge is dependent variable and the estimated coefficients are accordingly interpreted as the change in the log(pledged) when a variable change by one unit. The expected percentage change in funding pledge for a change in any of the regressors is defined as: $\%\widehat{\Delta y} = 100 * [\exp(\widehat{\Delta\beta_i}\Delta x_i) - 1]$, where y is the funding pledge, x_i is a regressor, and β_i is its coefficient (Wooldridge 2012). Positive regression coefficients signal improvement in the project crowdfunding performance. Regression results are reported in Table 2 (values in the parentheses are standard errors). In Table 2, project homepage-describing variables like *Featured*, *video* and *lnplength* have positive and significant influence on its crowdfunding performance. Variables describing the communication activities between creators and backers (i.e., *lnupdate* and *lncomment*) also have positively and significantly influences on project performances. *lnmaxpledge* has strong significant and positive effects on the project performance in all the three models, while *levelnumber* only has similar effect in the 2SLS and GMM model. The closeness of coefficients in 2SLS model and GMM model indicates the robustness of our results. Furthermore, after comparing the variances of coefficients in these two models, we find the GMM method is more efficient than the 2SLS method.

Table 2. Parameter Estimation Results

	OLS	2SLS	GMM
	lnpledge	*lnpledge*	*lnpledge*
ln_goal	0.0644 (0.0649)	-0.0581 (0.0944)	-0.0692 (0.0861)
duration	-0.0022 (0.0045)	-0.0010 (0.0048)	-0.0009 (0.0044)
featured	0.3444** (0.1564)	0.2990* (0.1777)	0.3033* (0.1575)
imag	-0.0026 (0.0148)	0.0025 (0.0162)	0.0039 (0.0149)
video	1.0842*** (0.2228)	1.0967*** (0.2209)	1.0929*** (0.2117)
lnupdate	0.8388*** (0.0833)	0.8049*** (0.0912)	0.8022*** (0.0828)
lncomment	0.6222*** (0.0486)	0.6536*** (0.0553)	0.6628*** (0.0505)
lnplength	0.2999** (0.1241)	0.3191** (0.1280)	0.3534*** (0.1207)
comp_index	0.0053 (0.0044)	0.0061 (0.0045)	0.0040 (0.0041)
lnFacebook	0.0051(0.0042)	0.0058(0.0043)	0.0057(0.0042)
ca_1	0.1933 (0.2062)	0.2201 (0.2089)	0.0892 (0.1930)
ca_2	-0.2021 (0.2193)	-0.2131 (0.2207)	-0.2767 (0.2036)
levelnumber	-0.0277 (0.0231)	-0.0860* (0.0461)	-0.0831** (0.0375)
lnrlength	0.2204 (0.1491)	0.1767 (0.1523)	0.1280 (0.1403)

above_stra	0.1527 (0.1408)	0.0904 (0.1511)	0.0537 (0.1445)
limit_ratio	0.3284 (0.3123)	0.1681 (0.3246)	-0.0759 (0.3019)
lnminpledge	0.0799 (0.0581)	0.1117 (0.1810)	0.1997 (0.1461)
lnmaxpledge	0.1725*** (0.0587)	0.4262*** (0.1581)	0.4254*** (0.1291)
_cons	-1.4579 (0.9940)	-1.6358 (1.0090)	-1.5070 (0.9587)
N	715	715	715

Note: * $p < .1$, ** $p < .05$, *** $p < .01$

A summary of hypotheses evaluation results are provided in table 3. The regression results support hypothesis 1 investigating the significant and positive effects of project-description elements. This finding shows that (1) an increase in the number of video contributes to a better crowdfunding performance (109.67% and 109.29% improvement for each addition video in the 2SLS model and GMM model separately); (2) Being featured by the Kickstarter will positively increase its performance (29.90% and 130.33% improvement in the 2SLS and GMM model respectively); (3) More detailed description of project is also positively associated with better crowdfunding performance (0.32% and 0.35% improvement for additional 1% increase of project description in the 2SLS and GMM model). Hypothesis 2 is supported: (1) For each 1% additional updating in a project, the funding pledge increase by an additional nearly 0.80% in 2SLS and GMM model; (2) For each 1% additional comments in a project, its funding pledge increase by an additional 0.65% and 0.66% in the 2SLS and GMM Model. Hypothesis 3 is also supported: A relative higher backing price of the top reward tier does send a positive and significant signal to potential backers and drives funding pledge up (additional 1% increase of *lnmaxpledge* improves the crowdfunding performance by 0.4262% and 0.4254% in the 2SLS model and GMM model). The significant and negative coefficient of *levelnumber* indicates that our hypothesis 4 is also supported (an additional 8.31% decrease of funding pledge will be caused by an additional reward tier in a project's reward scheme).

Table 3. Summary of Hypotheses Results

Hypothesis	Test (expected effect)	Support
H1. The elements on the homepage of a project that can well describe the project are positively associated with its crowdfunding performance	a. # of *video* (+) b. *Featured* (+) c. *lnplength* (+)	Supported
H2. The number of communication activities between creators and backers are positively associated with the project's crowdfunding performance.	a. # of *updates* (+) b. # of *comments* (+)	Supported
H3. A relative higher maximum backing price in a project's reward scheme will have a positive effect on its crowdfunding performance.	a. *lnmaxprice* (+)	Supported
H4. The number of reward tier in a project's reward scheme will have a negative effect on its crowdfunding performance.	a. *levelnumber* (-)	Supported

Conclusion and Discussion

In this study, we empirically examine the impact of both reward scheme related and reward scheme-unrelated factors on project's crowdfunding performance and investigate the crucial roles of project design and reward scheme design based on solid theories. We also developed a model which can address several econometrics problems in crowdfunding studies. Particularly, we use a Heteroscedasticity based instrument method to solve the endogeneity problem of backing price. Compared with prior literature that was largely exploratory (Ordanini, Miceli et al. 2011; Mollick 2014) in crowdfunding market, we have conducted a confirmatory study based on a solid theoretical foundation to examine the effects of many factor, especially the scheme-related factors on projects' crowdfunding performance. In addition, we use a Heteroscedasticity based instrument method to solve the endogeneity problem of backing price. It provides crowdfunding researchers with a new method to get more efficient estimators when facing similar issues. Our research also sheds light on several practical implications for project creators.

Because online crowdfunding platform is actually a two sides market (Zvilichovsky, Inbar et al. 2013), in order to help project creators design their projects, we are considering using survey to collect the cost information of reward items from backers, and setting up a structural model like BLP model (Berry, Levinsohn et al. 1995) to derive more insights for reward scheme design and project design in the online crowdfunding market.

References

Agrawal, A., C. Catalini, et al. 2013. "Crowdfunding: Social Frictions in the Flat World?" http://funginstitute.berkeley.edu/sites/default/files/Crowdfunding_Social_Frictions_in_the_Flat_World_2013_10_05.pdf (accessed on May 1, 2014)

Agrawal, A. K., C. Catalini, et al. 2011. "The geography of crowdfunding," *National Bureau of Economic Research*, No. 16820.

Agrawal, A. K., C. Catalini, et al. 2013. "Some simple economics of crowdfunding," *National Bureau of Economic Research*, No. 19133.

Belleflamme, P., T. Lambert, et al. 2010. "Crowdfunding: An industrial organization perspective," *Workshop on Digital Business Models: Understanding Strategies*, Paris, France.

Belleflamme, P., T. Lambert, et al. 2014. "Crowdfunding: Tapping the right crowd," *Journal of Business Venturing* (29:5), pp.585-609.

Berry, S., J. Levinsohn, et al. 1995. "Automobile prices in market equilibrium," *Econometrica* (63:4), pp. 841-890.

Burtch, G., A. Ghose, et al. 2013. "An empirical examination of the antecedents and consequences of contribution patterns in crowd-funded markets," *Information Systems Research* (24:3), pp.499-519.

Calvin Q. 2013. "Issues in Crowdfunding: theoretical and empirical investigation on Kickstarter," Available at SSRN 2345872.

Colombo, M. G., C. Franzoni, et al. 2013. "Internal Social Capital and the Attraction of Early Contributions in Crowdfunding Projects," Available at SSRN 2319320.

Herzenstein, M., U. M. Dholakia, et al. 2011. "Strategic herding behavior in peer-to-peer loan auctions," *Journal of Interactive Marketing* (25:1), pp. 27-36.

Kuppuswamy, V. and B. L. Bayus 2013. "Crowdfunding creative ideas: the dynamics of projects backers in Kickstarter," Available at SSRN 22234765.

Marom, D. and O. Sade 2013. "Are the life and death of a young start-up indeed in the power of the tongue? Lessons from online crowdfunding pitches," Lessons from Online Crowdfunding Pitches.

Mollick, E. 2014. "The dynamics of crowdfunding: An exploratory study," *Journal of Business Venturing* (29:1), pp.1-16.

Smith, S., F. Windmeijer, and E. Wright. 2012, "The Effect of Social Information on Charitable Donations: Evidence from the (Running) Field," University of Bristol Working Paper, http://www.bristol.ac.uk/cmpo/events/2012/charitablegiving/smith.pdf (accessed on May 1, 2014).

Szaky, T. 2011. "Why start-ups need 'crowd-funding' ". *New York Times*, 5 Dec. 2011 http://boss.blogs.nytimes.com/2011/12/05/why-start-ups-need-crowd-funding/.

Ward, C. and V. Ramachandran. 2010. "Crowdfunding the next hit: Microfunding online experience goods, " *Workshop on Computational Social Science and the Wisdom of Crowds* at NIPS, Whistler, Canada.

Wortham, J. 2013. "Law opens financing of start-ups to crowds," *New York Times*, 22 Sep. 2013.

Xu, A., X. Yang, et al. 2014. "Show Me the Money! An Analysis of Project Updates during Crowdfunding Campaigns," *Proceedings of the ACM Conference on Human Factors in Computing Systems* (CHI), Toronto, Canada.

Zhang, J. and P. Liu. 2012. "Rational herding in microloan markets," Management science (58:5), pp. 892-912.

Zvilichovsky, D., Y. Inbar, et al. 2013. "Playing Both Sides of the Market: Success and Reciprocity on Crowdfunding Platforms," Available at SSRN 2304101.