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Scarcity Strategy in Crowdfunding: An Empirical Exploration

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Completed Research Paper

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Abstract

Scarcity-based marketing strategy has been increasingly adopted in reward-based crowdfunding in the form of reward limits, whereby project creators are able to restrict the quantity of contributors in each reward tier. This study uncovers the effect of reward limits in eventual and concurrent funding performance. Specifically, we performed campaign and campaign-day level analysis. At the campaign level, we find that setting reward limit at the beginning of a campaign is beneficial for final funding outcomes across four different performance measures. The number of limited reward tiers is shown to have an inverted U-shaped relationship with fundraising performance. Potential endogeneity issues are addressed with propensity score matching and the Heckman selection model. At the campaign-day level, we find incorporating new limited reward tiers is helpful for attracting new backers, but having reward tiers being "sold out" will demotivate subsequent backers to contribute thus lead to lower funding speed in subsequent days.

Keywords: scarcity strategy, reward limit, crowdfunding, exclusivity, empirical study

Introduction

One of the major obstacles typically faced by entrepreneurs is the sourcing of financial capital (Burtch et al. 2015; Mollick and Nanda 2016; Wetzel 1987). The recent emergence of crowdfunding eases the fundraising process by directly tapping the general public for needed capital (Agrawal et al. 2013; Kim and Hann 2015). Online crowdfunding, defined as "a collective effort by individuals who network and pool their money together, usually via the Internet, to invest in or support the efforts of others" (Ordanini et al. 2011, p.443), has garnered substantial attention from both researchers and practitioners. Among the various forms of crowdfunding (i.e., reward-, equity-, lending- and donation-based), the reward-based model provides a unique funding mechanism, which allows project founders to presale their deliverables and gives funders more tangible returns for their support. It has taken a considerable proportion of the whole online crowdfunding market and has become the channel of choice for numerous startups. As of April 2017, influential reward-based crowdfunding platforms such as *Kickstarter.com* and *IndieGoGo.com* have involved more than 500,000 projects and 20 million backers.

In reward-based crowdfunding, the reward scheme is an essential aspect of campaign design (Wang et al. 2016; Xiao et al. 2014), as it is the major channel through which project creators convey to backers what kinds of rewards they will receive by supporting their project. It entails creators' marketing efforts; creators can adopt various strategies in designing their reward scheme to attract potential backers (Wang et al. 2016). Recently, one of the strategies that has become increasingly prevalent is to incorporate a reward limit[1] – i.e., creators can artificially constrain the quantity of backers in each reward tier, the aim of which is to engender a sense of urgency via scarcity (Fortune 2005). These limited rewards typically come with price discount, limited edition products or early access to the product.

However, there are some doubts as to whether using reward limits ultimately helps or hurts crowdfunding outcomes. On the one hand, limiting the availability of certain rewards could signal higher project quality (Stock and Balachander 2005) and satisfy early backers' desire to be exclusive and distinctive (Balachander and Stock 2009; Brown 2001; Snyder and Fromkin 1980). If so, reward limits will attract more prospective backers to a project. On the other hand, reward limits may also refrain backers from supporting the project at a lower price or with special values. Backers, as consumers in reward-based crowdfunding, also prefer exclusivity (Balachander and Stock 2009) and would like to acquire a reward at a lower price (Hu et al. 2015). Once the limited rewards have been depleted, it may become more difficult to attract additional backers. If so, such a scarcity strategy can have a negative impact on later backers' willingness to contribute. Overall, its overall impacts still remain enigmatic.

In order to resolve this tension, we empirically explore the role of reward limits in crowdfunding. More specifically, we examine 1) *the effectiveness of the scarcity strategy (i.e., reward limit) on crowdfunding campaign performance* and 2) *how to effectively set reward limits to increase campaign performance*. Further, as the status of limited reward tiers can vary over time, we explore 3) *how the change in limited rewards dynamically influences the concurrent funding performance over the course of fundraising*.

We employ a comprehensive dataset from Kickstarter.com, the largest reward-based crowdfunding platform. Using daily records of seven months' live campaigns, we performed both campaign and campaign-day level analysis. For the campaign level analysis, we examined the effectiveness of setting reward limits and addressed potential endogeneity concerns by implementing propensity score matching and the Heckman selection model. Incorporating limited rewards in a project is shown to be beneficial for funding performance across four different measures. Interestingly, the number of limited reward tiers was shown to have an inverted U-shaped relationship with campaign performance. For campaign-day level analysis, we constructed a two-way fixed effects panel model to test the dynamics of reward limit during the course of fundraising. Although introducing a new limited reward tier within the fundraising process increases subsequent day's performance, having rewards that are "sold out" will demotivate following backing behaviors and result in lower funding speed. Our findings not only confirm that the aggregated impact of reward limit is positive but also identify both directions in the tension of including limited rewards.

[1] In our data, 58% of projects have some form of reward limits.

This research makes several contributions. We extend the boundary of crowdfunding literature by documenting the positive and negative effects of scarcity strategy in project design. We offer one of the first studies to delve into the dynamics arising from project attribute changes within campaign durations. Additionally, our research contributes to the marketing literature by empirically examining the role of product scarcity in a crowd-based setting. We also offer practical implications for project creators on how to strategically design crowdfunding projects.

Related Literature

Crowdfunding

Given our focus on the role of scarcity strategy (i.e., reward limit) in funding performance, particularly relevant is the stream of research that deals with the relationship between project design strategy and crowdfunding campaign performance. Extant crowdfunding research examines the design implications from multiple aspects (Short et al. 2017). For instance, the effects of campaign description (Beier and Wagner 2015; Bi et al. 2017; Parhankangas and Renko 2017), introduction video (Liu et al. 2014; Thies et al. 2016), update posting (Xu et al. 2014), goal setting (Li and Jarvenpaa 2016) and project reward scheme (Xiao et al. 2014) have thus far been investigated.

There appears to be two lacunae in the literature. First, although rewards are considered to play a dominant role in backer's decision making, empirical evidence to implicate the effective design in reward tiers has been limited. Since the reward scheme is the primary channel through which project creators convey to backers the returns to supporting the project, its design strategies deserve further exploration. Second, prior studies focus on the influence of project final state, such as the final project reward scheme, during their examinations largely due to data limitations. However, project creators do adjust project attributes, including the reward scheme, to promote superior fundraising outcomes. Accordingly, the present study contributes to crowdfunding literature by closing these two gaps. We explore the strategies to effectively set the reward limits and uncover the dynamics of change in limited rewards during crowdfunding process.

Scarcity-based Marketing Strategy

Scarcity appeals are widely implemented by retailers to make the product more desirable (Balachander et al. 2009). Using such strategy, brands typically convey scarcity messages to consumers in two manners – limited-time scarcity and limited-quantity scarcity (Jang et al. 2015), both of which communicate a certain or potential unavailability of a product in the future. Past research in marketing suggests that there are merits to inducing product scarcity by limiting the quantity of product or the duration of selling a product. Based on the commodity theory (Brock 1968), "any commodity will be valued to the extent it is unavailable" (p. 246). In other words, consumers tend to value a commodity more when there is a high difficulty in obtaining it.

More recently, DeGraba (1995) shows that intentionally limiting product availability may induce a buying frenzy among consumers, especially those who rush to buy before they are sufficiently informed to fully evaluate the product. In so doing, firms are likely to increase sales. Generally, using such a marking strategy induces scarcity effects – i.e., customers may develop positive perceptions toward a product when purchasing a scarce commodity, in that the purchase satisfies their desire for exclusivity and distinctiveness (Balachander and Stock 2009; Brown 2001; Snyder and Fromkin 1980), which promotes a sense of bandwagon reasoning[2] (Worchel et al. 1975) or a feeling of being chosen (Brock and Mazzocco 2004). In addition, Stock and Balachander (2005) suggest that marketers' scarcity strategy may also signal higher product quality to uninformed consumers; observing product scarcity and the purchasing

[2] The bandwagon reasoning refers to the perception that "if everyone is trying it, it must be good" (Worchel et al, 1975, p.911). For example, the experiment in Worchel et al (1975) suggests that subjects perceived cookie tastier (e.g., high quality) when there were only few cookies left than when there were abundant.

behavior of informed consumers, uninformed consumers would infer that the product must be of high quality (Balachander et al. 2009).

Even though research has investigated limited products in traditional markets, reward limits in the crowdfunding context are characterized by at least the following distinctive features. First, rewards in crowdfunding are usually novel or innovation-oriented. That is, the limited rewards in our context are for new (usually innovative) products that only emerge after the project is launched. On the contrary, traditional limited product is usually part of existing product line (Balachander and Stock 2009), and the introduction of such product is predetermined. Thus, consumers' perception of such limited rewards may be different since the product will be both new and limited. Second, consumers also act as supporters in crowdfunding, where their backing utility is decided not only by the returns but also by the project's outcome. In other words, backers in crowdfunding also take into account how their contribution affects the success of the project (Hu et al. 2015). The limited rewards in such a scenario may play a different role compared to traditional market. Third, reward limit in crowdfunding is constrained by both predetermined project duration and product quantity, combining both limited time and limited quantity (Cialdini 2009), which may intensify the urgency of selling and purchasing limited products. However, as discussed in literature, traditional limited products typically carry only one type of scarcity message. These differences make it hard to apply the findings from the traditional market to online crowdfunding.

Further, researchers have primarily employed analytical modeling approaches to analyze firm's scarcity strategy for introducing limited edition product. Even though there are some studies examining this issue in experimental settings (e.g., Amaldoss and Jain 2010), they focus on the effect of firm's strategy on consumers' purchase intention, which is distinct from firm level performance (i.e., campaign performance in crowdfunding). Thus, extending this stream of literature, our study employs an empirical approach to examine the implications of scarcity strategy in crowdfunding and its dynamics during fundraising process. Examining this effect at aggregate campaign and fine-grained daily levels facilitates a broader understanding of scarcity strategy on firm performance.

Reward Limit in Crowdfunding

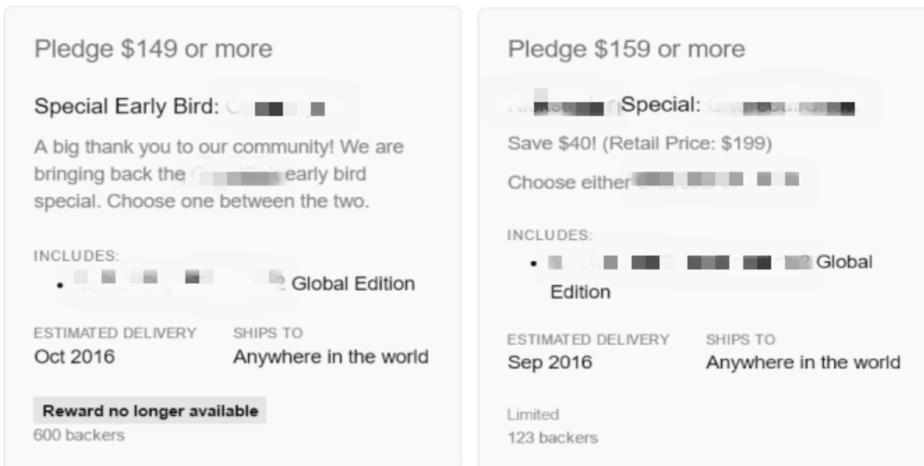
In reward-based crowdfunding, project creators need to specify a set of reward tiers. The reward tiers present the items backers will receive by supporting the project at various pledge levels. Rewards are typically items produced by the project itself – e.g., a limited edition of the comic book, a copy of the album or a ticket for the performance. Each reward tier includes the description of the items, minimum pledge amount and estimated delivery date. One essential function of reward tiers is that project creators are able to limit the quantity of each reward (see Figure 1), such that only a predefined number of backers can choose the reward tier when contributing to the project. The reward limits typically come with early delivery, price discount, or specialized version of the produced product. For example, the Tic Interactive Smart Watch, a project launched in 2016 on Kickstarter, offers multiple limited reward tiers for backers with different levels of discounts.[3] Another distinctive feature of project reward is that it can be adjusted during the course of fundraising. Creators may add new or remove existing reward limits, so that the reward scheme may change dynamically during the fundraising campaign.

Although limited products could result from supply constraints, it could arise strategically via intentional manipulation (Amaldoss and Jain 2010). In crowdfunding, the latter is more dominant, as the product is typically in pre-production or even pre-development stages. Thus, setting reward limits can be considered as a strategy to engender product scarcity. Drawing upon the product scarcity literature, it is reasonable to expect that setting limits could satisfy backers' desire to be exclusive and unique (Balachander and Stock 2009; Brown 2001; Snyder and Fromkin 1980) and/or signal the project's higher quality to prospective backers (Stock and Balachander 2005). Following the two mechanisms, reward limits may increase backers' utility for a project and in turn evoke a sense of urgency to support the project. On the other hand, different with other contexts, the crowdfunding process is bounded by a predefined duration. Ensuing backers may no longer participate after the campaign deadline. The reference group effects suggest that later backers may desire to follow early backers, especially those who are able to get the

[3] See: https://www.kickstarter.com/projects/mobvoi/ticwatch-2-the-most-interactive-smartwatch

product at a discounted price or as a special edition (Amaldoss and Jain 2008), but such effects may not arise immediately after the project launch. It would take a certain amount of time for following backers (especially for uninformed ones) to notice the value and exclusivity of backing a project, and as a result, the reference group effects may not arise before the crowdfunding deadline. Furthermore, backers would prefer getting the same product at a lower price (Hu et al. 2015) or with special utility. Hence, they would be less likely to support a project when the limited reward tiers (especially those with discounted prices) have been depleted by leading backers. Based on the two opposing predictions, the effect of having reward limits on campaign performance remains unclear.

Figure 1. Reward Limit in Crowdfunding Platforms



Note: The left reward is marked with "Reward no longer available" to indicate "sold out" status, while backers can still choose the right one. (Product names have been disguised to preserve anonymity)

We also propose that the improper use of limited rewards (e.g., overuse of reward tiers with limit) will play a role in funding performance. As noted earlier, leading consumers desire to distinguish themselves from the mass (Mussweiler et al. 2004). Therefore, having a greater number of limited reward tiers may reduce the exclusivity for leading backers. In general, the number of limited reward tiers may affect funding performance by diminishing leading backers' exclusivity and evaluation of the project.

In addition, as previously discussed, project reward schemes may change over time when new backers join the project or new limited rewards are introduced (or existing limits are removed). The varying availability of limited rewards may exert an effect on concurrent funding performance, leading to temporary acceleration or deceleration in funding speed.

The Empirical Study

We employ an exploratory approach to answer our research questions by investigating the effect of reward limits in crowdfunding from three aspects: 1) the aggregate effectiveness of reward limits on funding outcomes, 2) the influence of the number of limited reward tiers on funding outcomes, and 3) the concurrent effect of changes in limited rewards on funding performance.

Data

Data was retrieved from Kickstarter.com, one of the largest reward-based crowdfunding platforms currently in operations. On this platform, project creators are able to set reward limits on any reward they prepare for backers within the fundraising process, allowing us to investigate both the effectiveness and dynamics of reward limit. The detailed information about rewards in each project was collected at the daily level. Our dataset contains all the 48,862 projects within a seven-month window across the 15 categories[4]. We excluded those projects with incomplete daily information (i.e., left or right censored) from our analysis. This resulted in a sample of 31,919 projects with daily snapshot available. Tables 1 and 2 present descriptive statistics and correlations.

Among all projects in our sample, one third of them (33.3%) were successfully funded; while more than a half of the projects (58%) offered at least one limited reward tier, suggesting that limited rewards are common. Moreover, in the campaigns that set reward limits, most (>95%) implemented it at the beginning of the campaign. On average, projects in our dataset have 6.77 reward tiers of which 2.28 have some form of limits. These observations support the significance of investigating reward limit in crowdfunding and the adequacy of our dataset for such analysis.

Table 1. Descriptive Statistics and Correlation Matrix of Campaign Analysis (*N*=31,919)

	Mean	Std. Dev	4	5	6	7	8	9	10	11	12	13
1. Success	0.333	0.471										
2. Pledged	10,575	101,497										
3. Backers	112.8	957.6										
4. HasLimit	0.560	0.496	1									
5. LimitProportion	0.291	0.336	0.77***	1								
6. Goal	66,916	1,649,336	-0.02**	-0.01	1							
7. ImageCount	6.313	9.932	0.27***	0.13***	-0.01*	1						
8. HasVideo	0.619	0.486	0.21***	0.07***	-0.01*	0.26***	1					
9. CampaignDuration	32.69	11.18	-0.03***	-0.02***	0.02***	0.02**	-0.01**	1				
10. DescriptionLength	2,980	3,155	0.24***	0.10***	-0.00	0.54***	0.31***	0.01	1			
11. RiskLength	656.3	578.8	0.15***	0.07***	0.01	0.24***	0.21***	0.01*	0.37***	1		
12. NumReward	6.772	5.270	0.37***	0.18***	-0.01**	0.42***	0.36***	-0.01	0.42***	0.25***	1	
13. AvgRewardPrice	371.6	916.1	0.06***	0.04***	0.05***	0.03***	0.06***	0.05***	0.08***	0.07***	0.11***	1

Note: Only correlations among core independent variables are presented.
Significance: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2. Descriptive Statistics and Correlation Matrix of Campaign-Day Analysis (*N*=602,166)

	Mean	Std. Dev	3	4	5	6	7	8
1. Pledged	283.0	3808						
2. Backers	2.995	40.36						
3. NumLimitReward	2.448	3.896	1					
4. NumLimitRewardGone	0.236	1.106	0.50***	1				
5. CumRatio	3.857	267.1	0.02***	0.06***	1			
6. ImageCount	6.819	10.72	0.26***	0.25***	0.01***	1		
7. HasVideo	0.630	0.4828	0.19***	0.12***	0.00	0.28***	1	
8. DescriptionLength	3110	3321	0.24***	0.17***	0.00	0.52***	0.30***	1

Note: Only correlations among core independent variables are presented.
Significance: * $p < 0.05$, ** $p < 0.01$, *** $p < 0$

[4] The 15 categories include: art, comics, crafts, dance, design, fashion, film & video, food, games, journalism, music, photography, publishing, technology and theater.

Campaign Level Analysis

Model Specification

In campaign level analysis, we intend to answer our first two research questions by investigating the effects of reward limits. We first test the impact of having reward limits on project performance. Then we examine the effects of reward limit setting to explore how to set reward limits.

Effects of Reward Limits. To assess the effectiveness of having reward limits, we construct a set of campaign level econometric models with campaign performance as the dependent variables. As suggested by the crowdfunding literature (Mollick 2014), we adopt *Success* (whether funding goal was reached), *Pledged* (amount of funds received in USD) and *Backers* (number of backers supporting the project). Besides these commonly used measures for campaign performance, we include another measure – *DaysToSuccess* (the number of days to reach funding goal for successfully funded project, or campaign duration if not successfully funded). Since projects can continue to get additional funding from backers even after they have achieved the original funding goal, project creators who get funded earlier would have more room to set higher level goals (e.g., stretch goals), which has been shown to further increase the funding performance (Li and Jarvenpaa 2016). Thus, this measure not only captures the campaign performance but also provides important implications for understanding the fundraising process and momentum.

The key independent variable is *HasLimit*, which is coded 1 if a project has at least one limited reward tier. To account for other confounding factors, we include a series of control variables including *Goal* (the project's funding goal), *ImageCount* (number of images in the project story), *HasVideo* (whether a video is provided), *CampaignDuration* (total time for seeking funds), *NumReward* (total number of reward tiers), *AvgRewardPrice* (average price across all reward tiers), *NumCreated* (number of past projects by the creator) and *NumBacked* (number of projects the creator has backed) (Yang and Hahn 2017). We also include category, year and month fixed effects in all the models.

We apply different specifications in our analysis. Logit model is used for Success, while OLS is applied for log-transformed Pledged and Backers. For *DaysToSuccess*, we employ the Proportional Hazards model[5] (Helsen and Schmittlein 1993) by treating success (funding amount > goal) as the "failure" event and estimate a survival model with right-censored duration (since failed projects did not experience the "failure" event).

Identification Strategy. In addition to the regression analysis, to establish the causal effect of having reward limits, we implement two approaches for identification. First, in our regression models, we construct all the independent variables using the *first day snapshot of each campaign*. This will help us to rule out the reverse effects caused by possible changes in reward limits during the campaign. Second, we apply the propensity score matching (PSM) approach (Heckman et al. 1998; Rosenbaum and Rubin 1983) to construct a control group similar to the projects in treatment group (Rubin 2008). We regard *HasLimit* as a treatment, and estimate the propensity score in a Probit model by including a series of factors that affect not only the treatment but also the project outcome (Caliendo and Kopeinig 2008). Empirically, we include all the control variables used in regression except *ImageCount* and *HasVideo* which we believe are not likely to affect the treatment. We use both propensity score matching and Mahalanobis distance-based matching (which uses both the propensity score and covariates) (Rubin and Thomas 2000) to obtain robust results.[6] All four dependent variables in regression analysis are used to estimate the Average Treatment Effect on the Treated (ATT) (Caliendo and Kopeinig 2008).

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[5] Weibull distribution was selected as the hazard function distribution in our presented results by comparing AIC and BIC with exponential and log-logistic distribution. Accelerated Failure Time and Cox model specifications were also tested for all survival models and the results are similar.

[6] Given that there are more than half projects in the treatment group in our sample, we implement a 1-to-1 nearest neighbor matching procedure with replacement, which allows projects without treatment to be matched more than once into control group.

Effective Reward Limit Setting. To further investigate the effective ways of setting reward limits, we consider the variable *LimitProportion*, which captures the proportion of limited reward tiers in the reward scheme. We fit a non-linear curve by including both the linear and quadratic terms using all the projects that have limited reward tiers at the beginning of the campaign. Thus, the model is specified given the decision of including reward limits to test how to set the limited rewards. To account for potential sample selection bias, we build a Heckman selection model in our estimation (Heckman 1979):

$$Pr(HasLimit = 1) = \Phi(Z\gamma)$$

$$Outcome = X\beta + \lambda + \varepsilon$$

In the two-stage model, we first estimate a Probit model by introducing a set of identification variables and then include the inverse mill ratio λ in the second stage to correct for selection bias. Specifically, in the selection equation, besides all the covariates in our regressions except *ImageCount* and *HasVideo* (same covariates as in the PSM), we introduce two additional variables that affect the decision of having reward limits but not the project outcome: *AvgDelivery* (average duration in month to deliver the rewards) and *OtherLimit* (number of projects that have reward limits and launched within one week before the focal project) to meet the *exclusion restriction* condition (Wooldridge 2010). These variables will affect creator's decision to include reward limits, but should not have direct effects on project outcomes. In the second stage, we incorporate the correction term for selection bias with the reward limit proportion terms as well as all the control variables and dummies. We estimate the models with all four dependent variables as before using Probit, OLS and Proportional Hazard models, respectively.

Results

Table 3 presents the results of the regression analysis. The estimates of *HasLimit* on all four campaign performance measures are positive and significant. The results suggest that having reward limits at the first day will increase the likelihood of final success, total funds received and number of contributors (see Models 1-3). The results in Model 4 (β=0.191, Hazard Ratio=1.211, $p<0.01$) imply that projects with reward limits are more likely and quicker to become successful within the campaign duration. For further insights, we plotted the Kaplan-Meier Survival estimates (Kaplan and Meier 1958) for projects with and without reward limits. Figure 2(a) shows that projects with reward limits exhibit lower "survival" rate (i.e., higher probability to transfer to success state) consistently across the project duration, indicating better campaign performance.

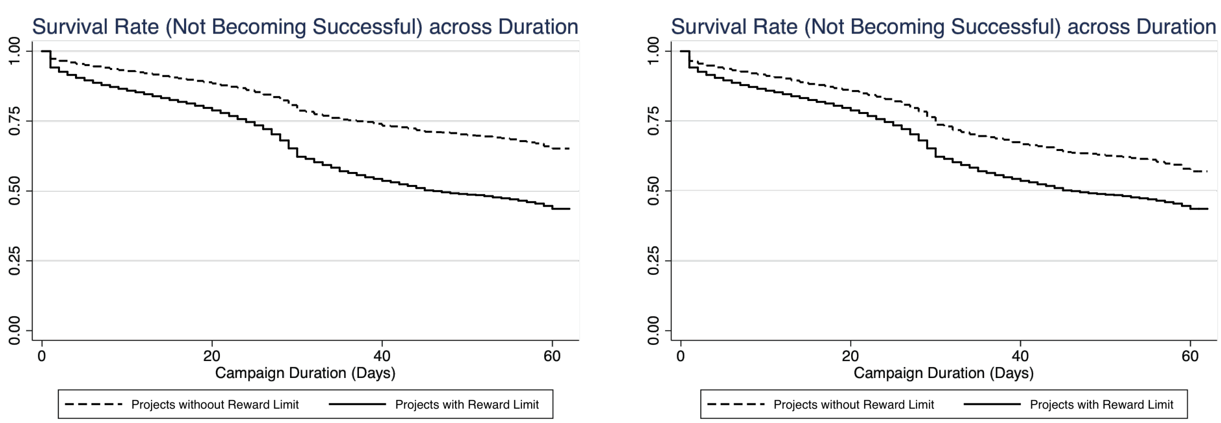
To provide stronger support for the causality of this effect, Table 4 presents the results using the matching approaches on the ATT values for the unmatched sample, the propensity score matched sample, and the Mahalanobis distance matched sample. Compared with the unmatched sample, the estimated ATTs (difference between treatment and control group) on the propensity score matched sample and the Mahalanobis distance matched sample are still positive and significant, albeit smaller in magnitude. In addition, we compared the covariates in treatment and control group in the three samples (see Table 5). The standardized bias (in percentage) (Caliendo and Kopeinig 2008; Rosenbaum and Rubin 1985) is reduced significantly into acceptable magnitudes in the two matched samples and the covariates are quite similar across treatment and control groups after matching. The results suggest that our findings are robust after accounting for the systematic difference between projects with and without reward limits. Moreover, the Kaplan-Meier estimates on propensity score matched sample in Figure 2(b) exhibit less but significant difference in "survival" rate across treatment and control groups.

Table 3. The Effect of Reward Limit on Campaign Performance

VARIABLES	Model1 *Success*	Model2 *ln(Pledged)*	Model3 *ln(Backers)*	Model4 *DaysToSuccess*
HasLimit	**0.192***	**0.407***	**0.273***	**0.191***
	(0.033)	(0.035)	(0.018)	(0.024)
ln(Goal)	-0.624***	-0.135***	-0.051***	-0.422***
	(0.013)	(0.010)	(0.005)	(0.013)
ImageCount	0.036***	0.060***	0.042***	0.018***
	(0.002)	(0.003)	(0.002)	(0.002)
HasVideo	0.887***	1.628***	0.813***	0.586***
	(0.036)	(0.037)	(0.019)	(0.028)
CampaignDuration	-0.016***	-0.005***	-0.004***	-0.050***
	(0.001)	(0.001)	(0.001)	(0.001)
ln(DescriptionLength)	0.213***	0.340***	0.158***	0.180***
	(0.022)	(0.020)	(0.011)	(0.019)
ln(RiskLength)	0.283***	0.479***	0.230***	0.196***
	(0.025)	(0.026)	(0.014)	(0.018)
NumReward	0.056***	0.118***	0.063***	0.016***
	(0.004)	(0.006)	(0.003)	(0.002)
ln(AvgRewardPrice)	0.186***	0.160***	0.022***	0.121***
	(0.013)	(0.012)	(0.006)	(0.011)
ln(NumCreated)	0.138***	-0.022	0.028	0.195***
	(0.029)	(0.030)	(0.018)	(0.020)
ln(NumBacked)	0.601***	0.748***	0.545***	0.315***
	(0.020)	(0.018)	(0.012)	(0.011)
Constant	-0.755***	-2.764***	-1.549***	-4.077***
	(0.267)	(0.295)	(0.155)	(0.211)
R^2	0.283	0.464	0.498	-
Model Fit (χ^2)	6441.27***	-	-	8384.56***
Observations	31,919	31,919	31,919	31,919

Note: Model 1 uses Logit model; Model 2 and 3 use OLS; Model 4 uses Proportional Hazard model with Weibull distribution (coefficients are presented); Category, month and year dummies are included; Robust standard errors in parentheses.
Significance Levels: *** p<0.01, ** p<0.05, * p<0.1

Figure 2. Survival Estimates on Unmatched and Propensity Score Matched Sample



(a) Unmatched Sample **(b) Propensity Matched Sample**

Note: Some of the censored observations were cut due to its limitation of estimating some incomplete data.

Table 4. The Treatment Effect of Reward Limit using Propensity Score Matching

Outcomes	Metrics	Unmatched	PSM	Mahalanobis
Success	ATT	0.177***	**0.051***	**0.035***
	t-value	33.85	4.93	4.49
Pledged	ATT	13311.3***	**8740.5***	**9912.4***
	t-value	11.65	6.33	9.08
Backers	ATT	125.4***	**71.7***	**89.81***
	t-value	11.64	3.62	6.23
DaysToSuccess	ATT	1.983***	**1.539***	**1.538***
	z-value	32.90	17.26	18.08

Note: Hazard ratio is used for the ATT of DaysToSuccess; All the category, month and year dummies are included to estimate propensity score; Heteroskedasticity-consistent robust standard errors are used to obtain t-values.
Significance Levels: *** p<0.01, ** p<0.05, * p<0.1

Table 5. Comparison between Treatment and Matched Control Group

Variable	Sample	Treated	Control	%bias
ln(Goal)	Unmatched	8.8551	8.6017	14
	PSM	8.8551	8.8474	0.4
	Mahalanobis	8.8551	8.8024	2.9
CampaignDuration	Unmatched	32.371	33.094	-6.4
	PSM	32.371	32.691	-2.8
	Mahalanobis	32.371	32.304	0.6
ln(DescriptionLength)	Unmatched	7.7318	7.1867	47.7
	PSM	7.7318	7.721	0.9
	Mahalanobis	7.7318	7.6741	5
ln(RiskLength)	Unmatched	6.3631	6.0758	41.7
	PSM	6.3631	6.3713	-1.2
	Mahalanobis	6.3631	6.3346	4.1
NumReward	Unmatched	8.5104	4.5565	82.9
	PSM	8.5104	8.6576	-3.1
	Mahalanobis	8.5104	7.9196	12.4
ln(AvgRewardPrice)	Unmatched	5.0828	4.2556	52.5
	PSM	5.0828	5.1289	-2.9
	Mahalanobis	5.0828	5	5.3
ln(NumCreated)	Unmatched	0.27763	0.20779	12.8
	PSM	0.27763	0.28332	-1
	Mahalanobis	0.27763	0.26884	1.6
ln(NumBacked)	Unmatched	0.64901	0.25049	44.4
	PSM	0.64901	0.58236	7.4
	Mahalanobis	0.64901	0.59368	6.2

Note: Unmatched: sample without matching; PSM: sample with propensity score matching; Mahalanobis: sample with propensity score and Mahalanobis matching.

Table 6 presents the results of Heckman selection model. Model 5 shows the Probit results on the selection equation where one of the two identification variables (*AvgDelivery*) show positive impacts, which suggest that those projects with greater delivery span are more likely to include limited rewards. The second stage analyses (Models 6-9) consistently exhibit an inverted U-shaped relationship between proportion of limited rewards and campaign performance.[7] The magnitudes of coefficients for the *LimitProportion* and its quadratic term indicate that the optimal proportion of limited reward tiers is around 0.5.[8]

Table 6. Heckman Selection Model on Reward Limit Setting Strategy

VARIABLES	Model 5 *HasLimit*	Model 6 *Success*	Model 7 *ln(Pledged)*	Model 8 *ln(Backers)*	Model 9 *DaysToSuccess*
LimitProportion		**0.492*****	**1.493*****	**0.946*****	**0.876*****
		(0.122)	(0.544)	(0.294)	(0.192)
LimitProportion^2		**-0.494*****	**-1.746*****	**-1.065*****	**-0.921*****
		(0.106)	(0.462)	(0.249)	(0.177)
ln(Goal)	-0.031***	-0.202***	0.125***	0.093***	-0.355***
	(0.005)	(0.008)	(0.031)	(0.017)	(0.016)
ImageCount		0.016***	0.057***	0.041***	0.020***
		(0.001)	(0.004)	(0.002)	(0.002)
HasVideo		0.311***	1.651***	0.858***	0.541***
		(0.021)	(0.080)	(0.043)	(0.037)
CampaignDuration	-0.003***	-0.004***	-0.001	-0.001	-0.045***
	(0.001)	(0.001)	(0.004)	(0.002)	(0.002)
ln(DescriptionLength)	0.044***	0.029***	0.072*	0.024	0.058***
	(0.008)	(0.008)	(0.043)	(0.023)	(0.019)
ln(RiskLength)	0.092***	0.024	0.062	0.013	0.039*
	(0.013)	(0.014)	(0.074)	(0.040)	(0.024)
NumReward	0.093***	-0.013***	-0.097***	-0.051***	-0.047***
	(0.002)	(0.002)	(0.018)	(0.010)	(0.007)
ln(AvgRewardPrice)	0.010***	-0.021***	-0.339***	-0.257***	-0.046**
	(0.006)	(0.008)	(0.048)	(0.026)	(0.018)
ln(NumCreated)	-0.073***	0.104***	0.239***	0.176***	0.278***
	(0.016)	(0.018)	(0.085)	(0.046)	(0.024)
ln(NumBacked)	0.156***	0.181***	0.199***	0.247***	0.127***
	(0.011)	(0.011)	(0.060)	(0.033)	(0.017)
ln(AvgDelivery)	**0.054*****				
	(0.015)				
ln(OtherLimit)	0.026				
	(0.037)				
Constant	-1.984***	1.987***	9.922***	5.085***	0.705*
	(0.150)	(0.169)	(1.840)	(0.640)	(0.427)
Model Fit (χ^2)	6681.29***	2164.23***	1060.47***	1582.69***	5276.14***
Observations	30,657	17,196	17,196	17,196	17,196

Note: Model 5 estimates the selection equation; Model 5 and 6 use Probit model; Model 7 and 8 use OLS; Model 9 uses Proportional Hazard model using Weibull distribution (coefficients are presented); Category month and year dummies are included in both stages; Robust standard errors in parentheses.
Significance Levels: *** p<0.01, ** p<0.05, * p<0.1

[7] The model specification with quadratic terms provides better model fit than simple liner specification, supporting our empirical design.

[8] As a robustness check, we also considered the aspect of backers instead of reward tiers. Using the original and quadratic terms of total quota for backers specified in limited rewards gave us consistent results.

Campaign-day Level Analysis

Model Specification

To investigate the dynamics of reward limit during the fundraising process, we construct campaign-day level model to estimate the influence of the current status of limited rewards on daily subsequent funding performance. We adopt a two-way fixed effects model setting on project and day level to account for both project level heterogeneity and time trends (Burtch et al. 2013; Hong et al. 2015). Our econometric models are specified as below:

$$\begin{aligned}\{ln(Pledged_{it+1}), ln(Backers_{it+1})\} = {} & NumLimitReward_{it} + NumLimitRewardGone_{it} \\ & +\{ln(Pledged_{it}), ln(Backers_{it})\} + ln(CumRatio_{it}) \\ & +ImageCount_{it} + VideoHas_{it} + ln(DescriptionLength)_{it} + \varepsilon_i + \eta_t\end{aligned}$$

In the panel model, we consider both amount of contributions ($Pledged_{it+1}$, pledged amount in USD) and number of contributors ($Backers_{it+1}$) to project *i* on day *t+1* as the dependent variables to measure the speed of fundraising. In terms of independent variables, to capture the dynamics of limited rewards, we use total number of limited reward tiers ($NumLimitReward_{it}$) and number of limited reward tiers sold out ($NumLimitRewardGone_{it}$, for limited reward tiers that are marked with "all gone") for project *i* at the end of day *t*. This specification allows us to examine the impact of reward limits status on subsequent contributions and avoid simultaneity issues. In addition, we incorporate first-order lagged dependent variables ($Pledged_{it}$ and $Backer_{it}$) to account for serial correlation, and the cumulative funding percentage ($CumRatio_{it}$) to control the current funding performance by day t. We also include a set of control variables that are variant across time, such as number of images ($ImageCount_{it}$), whether there is a video ($HasVideo_{it}$) and length of description ($DescriptionLength_{it}$). Other factors that are invariant across time (e.g., project goal and duration) will be accounted by the project level fixed effects (ε_i). Time trends of contributions are controlled by η_t.

Results

The results of the campaign-day level analysis are summarized in Table 7. The results show that having more reward limits is associated with more contributions on the following day, implying greater funding speed (see Model 10 and 13). However, the estimates of *NumLimitRewardGone* suggest that funding speed is negatively affected by number of depleted limited rewards. Coefficients of other variables suggest that adding images or video, and being featured by Kickstarter could attract subsequent contributions. We also test the lasting influence of reward limit dynamics. We use contributions at day *t+2* and *t+3* as the dependent variables. The results show that more limited rewards will increase contributions on day *t+2* (see Models 11-12) and *t+3* (see Model 14-15). In addition, limited rewards sold out would exclude new backers and consequently decrease subsequent contributions, suggesting a lasting effect of reward limit status.[9]

[9] We alternatively considered the total number of backer quota and existing backers in limited reward tiers at the end of day t as alternative measures. This specification gave us similar results.

Table 7. Dynamics of Reward Limit on Daily Funding Performance

VARIABLES	Model 10 $ln(Pledge_{t+1})$	Model 11 $ln(Pledge_{t+2})$	Model 12 $ln(Pledge_{t+3})$	Model 13 $ln(Backers_{t+1})$	Model 14 $ln(Backers_{t+2})$	Model 15 $ln(Backers_{t+3})$
NumLimitReward	**0.039*****	**0.030*****	**0.024*****	**0.014*****	**0.010*****	**0.010*****
	(0.006)	(0.006)	(0.006)	(0.002)	(0.002)	(0.002)
NumLimitRewardGone	**-0.046*****	**-0.053*****	**-0.050*****	**-0.021*****	**-0.022*****	**-0.020*****
	(0.009)	(0.009)	(0.009)	(0.004)	(0.004)	(0.004)
CumRatio	-0.189***	-0.151***	-0.130***	-0.038***	-0.018***	-0.012***
	(0.008)	(0.007)	(0.006)	(0.002)	(0.002)	(0.002)
ImageCount	0.007***	0.003	0.002	0.002***	0.001	0.001
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
HasVideo	0.185***	0.113***	0.112***	0.037***	0.015	0.021**
	(0.043)	(0.038)	(0.038)	(0.011)	(0.010)	(0.010)
ln(DescriptionLength)	-0.039**	-0.051***	-0.045**	-0.011*	-0.013**	-0.011*
	(0.018)	(0.017)	(0.018)	(0.006)	(0.006)	(0.006)
Constant	1.233***	1.511***	1.399***	0.299***	0.412***	0.388***
	(0.134)	(0.130)	(0.132)	(0.045)	(0.043)	(0.044)
R^2	0.045	0.044	0.033	0.134	0.133	0.111
Number of Projects	31,907	31,907	31,884	31,907	31,907	31,884
Observations	1,012,635	1,012,635	980,728	1,012,635	1,012,635	980,728

Note: All the models perform OLS with two-way fixed effects; The first-order lagged dependent variable is included in each model to account for serial correlation; Project fixed effects are implemented by within transformation and day fixed effects (dummies) are controlled for time trends; Robust standard errors in parentheses.
Significance Levels: *** p<0.01, ** p<0.05, * p<0.1

Discussions

Our previous econometric analyses investigate the effectiveness and dynamics of reward limit in crowdfunding. Three major findings are revealed from our results: (1) It is beneficial to include reward limits in crowdfunding campaigns; (2) The number of limited reward tiers exhibits an inverted U-shaped relationship with fundraising performance; (3) Introducing new limited rewards is helpful but limited rewards that are sold out decrease subsequent contributions. These findings provide further insights into project design and contribution behaviors in crowdfunding.

Although there are tensions on the effectiveness of scarcity strategy (i.e., reward limit), we find the empirical evidence on the positive effect of reward limit. The inclusion of reward limits at the beginning of campaign significantly increases campaign performance in terms of all the four measures. This practice on reward design is able to increase the exclusivity of backing the project and induce the "reference group" effect in backer community. However, our second set of analysis using selection models suggest that although it is beneficial to include reward limits, only moderate level of limited reward tiers should be offered at the beginning of fundraising. Too few reward tiers with limits is easy to reach a "sold out" status, which excludes backers in the subsequent stage since they cannot obtain additional utility (e.g., uniqueness) by supporting the project. But if there are too many limited rewards provided, the exclusivity may also be reduced since some backers (leader group consumers) cannot distinguish themselves with others in the project. The uniqueness of limited rewards will also be undermined when there are a large number of limited reward tiers. Thus, our findings suggest that there exists an optimal point to set reward limits in crowdfunding campaigns and it is not always beneficial to incorporate more limited rewards. The results of our campaign-day level analyses provide richer insights into the positive and negative effects of limited reward's status – including more limited rewards in the fundraising process is helpful to enhance funding speed (at the same time, removing reward limits can harm the trends), suggesting the importance of creating exclusivity and uniqueness in crowdfunding rewards. However, limited rewards that are depleted would let backers feel loss of uniqueness and weaken the reference group effect so that they may no longer contribute to the project. This implies that reward limits not only create distinctiveness or exclusivity for early backers but may also demotivate subsequent backers.

Conclusion

This study investigates the scarcity strategy in crowdfunding. Drawing on the marketing literature on limited edition products, product scarcity and reference group effects, we examine the effectiveness and dynamics of reward limit, which is a common practice used by crowdfunding project creators. Using data from Kickstarter, our econometric analyses suggest a positive effect of including reward limits and an inverted U-shaped effect of reward limit setting on campaign performance. Furthermore, our campaign-day panel data analyses identified both the positive and negative effects of reward limits during the fundraising process.

Our study contributes to the current literature and practice in several aspects. First, we contribute to the emerging literature on crowdfunding by investigating an important strategy in project design – the use of reward limits. We test the effectiveness of reward limit while addressing the potential endogeneity concerns, and provide initial empirical evidence of the dynamics of reward limit. Second, we provide additional insights to the marketing literature about limited edition products and product scarcity. We not only examine an online market with several characteristics that may enhance or counteract the effectiveness of scarcity strategy, but also extend the existing works by empirically identifying both the positive and negative effects of scarcity strategy. We find that although it is beneficial to include limited rewards, there exists an optimal level to make them effective. In addition, our findings suggest that limited edition products that reach their purchase limits can create “barriers” for potential consumers. Lastly, our study offers practical insights for project creators for designing their rewards by setting the limits. Creators should carefully set the number of limited reward tiers for backers and keep track of the status of limited reward tiers. By moderately introducing new limited rewards or additional quota, they could obtain stronger momentum in their fundraising process.

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