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Influence of number of backers, goal amount, and project duration on meeting funding goals of crowdfunding projects

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Abstract

Evaluating potential of crowdfunding projects is challenging, and this challenge has multiplied with increasing number of projects in recent years. Using a sample of 74,618 Kickstarter crowdfunding projects and based on linear growth time-trend mixed-effects logit model, with increasing number of crowdfunding projects over time, fewer projects received funding, furthermore, number of backers reduced, higher goal amount increased and shorter duration to meet the funding goal increased the likelihood of achieving the funding goal. The results suggest that over time crowdfunding platforms increase reliance on costlier signals (higher goal amount and shorter duration) and reduce reliance on noisier signals (number of backers).

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1. Introduction

The market for crowdfunding increased from $880 million in 2010 to $16.2 billion in 2014 (Mass Solution Industry Report 2015) and is expected to surpass the size of venture capital market in 2016 (Mass Solution Industry Report 2015). On a crowdfunding platform, project initiators propose a project, choose the funding goal amount and the duration for meeting the funding goal and backers fund small to large sums for a variety of reasons (ranging from supporting an aspiring entrepreneur to realizing higher returns).

Due to lower cost of entry for project initiators and limited ability to ex-ante verify technological, market, or financial feasibility of a crowdfunding project, there is a possibility of 'market for lemons' (Tomboc 2013, Skoglund and Stiernblad 2013). With the flow of projects increasing exponentially in recent years and the limited ability in evaluating project feasibility could result in "dumb money [that] floods the market and skews valuations" (Ibrahim 2014, page 137). Because ascertaining project quality under increasing project flow is difficult, funders would prefer to lower adverse selection on a crowdfunding platform, an emerging and unregulated investment environment. This results in the need for project creators to ex-ante invest in costly signals.

Based on signaling theory, funders could discount noisier ex-post signals (number of backers) that evolve after a campaign is launched and rely on costlier ex-ante signals (higher goal amount or shorter duration to meet the goal amount) that must be invested into at the start of the project (Riley 1975, Spence 2002). Related to the noisier signal – number of backers – backers have divergent motives for investing and invest varying amounts toward the target goal amount. Backers may be less serious investors who may fund the project because they like the idea or could also be more serious investors seeking a higher return. Adding further 'noise,' to increase interest in the project, project initiators start with a low minimum amount for backing – average pledge on Kickstarter is $25 and ranges from $1 to $100 – that further muddies the value of having more backers as a signal of project potential.

With increasing number of projects over time, investors may rely on costlier signals – a higher goal amount and a shorter funding duration – that must be invested into before launching the crowdfunding project. A higher goal amount or shorter duration to raise funds signals an entrepreneur's confidence in the value of the project and the willingness to take risk of not meeting the funding target.

The analysis shows that over time: (i) number of backers, a noisier signal, lowers the odds of meeting the funding target; and (ii) costlier signals of higher goal amount or shorter duration to meet funding target increase the odds of meeting the funding target. The findings provide guidance to project initiators and funders on crowdfunding platforms.

2. Methods

For a project on Kickstarter platform, the hierarchical data structure is as follows. Projects from a geographic location are distributed across project categories. The two-level hierarchy of a project – random-effects of the geographic location and random-effects of project category – require mixed-effects modeling (West, Welch, and Galecki 2014, Wu 2009).

It is possible that project creators launching multiple projects learn to propose more viable projects over time. However, it could also be argued that project creators may also be uncertain about technological, market and financial feasibilities of their novel projects, and therefore, cumulative learning across successive projects may be less effective. Nevertheless, learning by project creators cannot be discounted. Although Kickstarter uses government issued identifying information and Amazon Payments when registering the participants, the unique identifying information is not publicly available – users can use full name and names alone cannot be used to uniquely identify individuals. Due to incomplete information on unique identities of project creators from publicly available information on Kickstarter, we use the latitude and longitude of the creator location to create unique identity of a project creator. The latitude and longitude information is available at the precision of four decimals that allows identification of location with 11.11 meter (or, 36.45 feet) accuracy. We then sort the projects of each geographic id by date of the project. This measure of unique identity may not be ideal as different creators from the same geographic coordinates (e.g. creators sharing a common university IP address) could launch a project, nevertheless, it allows us to roughly control for random-effects related to project creator.

The analysis is based on multilevel mixed-effects logit regression.[1] Covariates in the model are assumed as fixed-effects and intercept is allowed to vary across project categories to accommodate cross-category differences nested across locations to predict the likelihood of achieving the funding goal. The specification of the mixed model is as follows:

$$\begin{aligned} achieved_{imy} = {} & \alpha + \eta\ timetrend_{my} + \pi\left(timetrend_{my} \times lnbackers_i\right) \\ & +\theta\left(timetrend_{my} \times lngoal_i\right) + \mu\left(timetrend_{my} \times duration_i\right) \\ & +\beta\ lnbackers_i + \chi\ lngoal_i + \delta\ duration_i + project\_category_i \\ & +geographic\_id_i + \varepsilon_{imy} \end{aligned} \tag{1}$$

Where *i* is the *project id* variable from Kickstarter.com, *m* is month, and *y* is year
achieved is a dummy variable (=1) if the project had successfully obtained funding at or above the target, else it is coded as zero.
timetrend is the linear time-trend by month-year
lnbackers is the natural log of number of backers for the project
lngoal is the natural log of desired goal amount, at launch, for the project
duration is the duration of project funding requested (in days)
project_category is the category of the project on Kickstarter
$geographic\_id$ is the unique geographic location that proxies for project creator random-effects.

Due to systematic variation in number of projects (proxied by time-trend), type of projects, and variations in funding decisions across project categories we control from project category random-effects. We also include random-effects associated with geographic locations as systematic variations across project initiators and local resources could influence crowdfunding outcomes.

With increasing number of projects over time, if the crowdfunding platform decreasingly relies on noisier signals related to number of backers, the association of *timetrend* × *lnbackers* on *achieved* should be negative as the investors would perceive decreased value from a higher number of backers who may have pledged small amounts, or are 'hobby' backers who may like the idea. Thus, number of backers could increasingly be a noisier signal due to divergent investment motives among backers.

[1] We use *melogit* routine in Stata 14 (Rabe-Hesketh and Skrondal 2008)

As the feasibility of the project is unknown ex-ante, with increasing number of projects over time, it is expected that investors would fund projects with a higher goal amount, that is, the coefficient of *timetrend* × *lngoal* on *achieved* should be positive.

Finally, with increasing number of projects over time, crowdfunding platforms would prefer projects with shorter duration, a signal that project initiators would increasingly choose if they are confident in their project's potential. Thus, the *timetrend* × *duration* coefficient on *achieved* would be negative, as longer duration would indicate lower confidence in meeting the funding goal.

3. Data

The sample is a public archive data from www.kickstarter.com. Kickstarter does not allow charity or social benefit projects. The project initiators choose a fundraising amount and duration for raising funds. Kickstarter requires projects to have accountability in terms of completion of the project and requires project initiators to outline deliverables (e.g. products, gifts, or even a 'thank you' note). If the fundraising goal is not met, the project initiator does not receive any funding.

Table 1: Descriptive Statistics (n=74,618 observations)

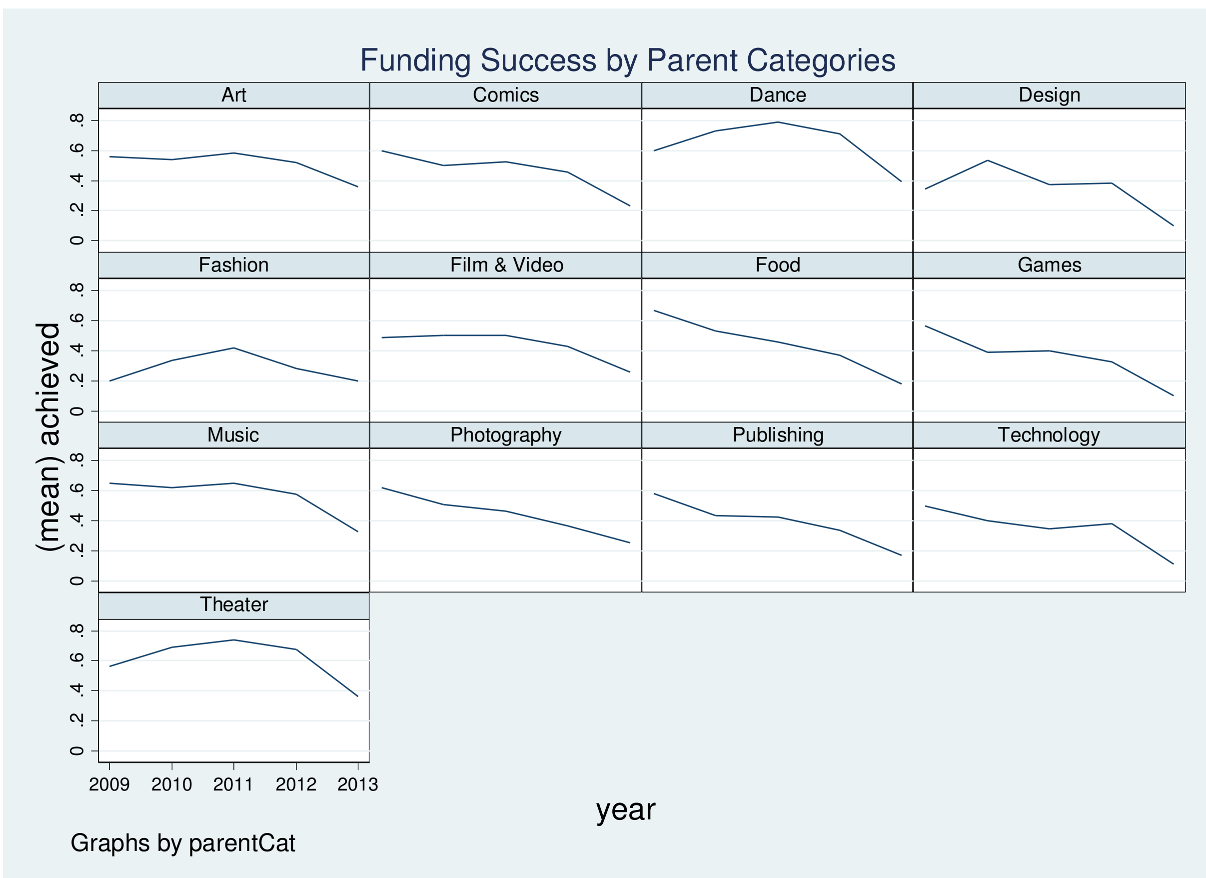
Variable	**Variable Definition**	**Mean**	**Std. Dev**	**Min**	**Max**
achieved	Achieved the funding goal (=1, else = 0)	0.4702	0.4991	0	1
backers	Count of number of backers associated with the project	75.5663	718.1069	1	87,142
lnbackers	Natural log of number of backers associated with the project	2.9673	1.5531	0	11.3753
goal	The target amount to be raised at the launch of the project	$14,295.46	$187,172.6	$0.01[2]	$21,474,836
lngoal	Natural log of the goal amount	8.3586	1.3800	-4.6052	16.8824
duration	Duration of project (in days) as requested by the project initiator	37.4653	15.8680	1	91.9583
timetrend	Linear time-trend variable in month-year	33.5169	9.9202	1	50

[2] Although the lowest value for goal amount is 1 cent, only 1 observation had 1 cent as the goal amount. A total of 469 projects set $100 or less as the goal amount, and dropping these observations did not influence the direction or significance of effects. Alternatively, to ensure that the results are not driven by projects with low goal amount, a subsample of projects with goal amount below the median goal amount ($4,500) in the sample led to inferences consistent with the main results. Dropping projects with the goal amount at the 90th percentile ($25,000) or above, also led to results consistent with the main results.

All projects launched from the founding of Kickstarter in March 2009 until May 2013 are included in the analysis and those that were open for funding in May 2013 were dropped, as the funding outcome of these projects is censored. If the ratio of received funding to goal amount is greater than or equal to '1,' the funding goal achieved is coded as '1'. Any ratio less than 1 was coded as '0,' or failure to meet the desired funding goal within the selected duration. Projects with missing values on ratio or number of backers were dropped as such projects could be withdrawn or removed from the site for violation of user guidelines. Our final sample had 74,618 projects. The descriptive statistics of the variables in the model are presented in Table 1. Around 47% of projects achieved their funding goal in the sample.

Figure 1 shows that random-effects of project category and fixed-effects of time are applicable in the sample. The trends are not the same for all the categories. Incorporating and estimating the variability accounted for by project category over time in the empirical model is necessary and taking into account fixed-effects of time allows for control of omitted variables and the confounding factors that change within category and across projects over time.

Figure 1: Average funding success by project categories over time



4. Results

Table 2 shows the mixed model estimates. Specification 2 includes time-trends and its interactions with number of backers, goal amount, and duration. The Wald test shows that variables in models are jointly significant. Only small variance across projects are explained by the geographic id (variance = 3.94%), whereas the variance explained by project category nested within the geographic id is larger (variance = 51.24%). The likelihood ratio test (LR = 736.97, p-value=0.0000) rejects the null hypothesis that the intercept is same across all the project categories.

Table 2: Estimates from mixed-effects model with covariates

VARIABLES	(1) achieved	(2) achieved
timetrend	-0.0615***	-0.0365***
	(0.00184)	(0.0130)
lnbackers	3.444***	4.819***
	(0.0320)	(0.113)
lngoal	-2.487***	-2.942***
	(0.0255)	(0.0882)
duration	-0.0117***	-0.00786***
	(0.00108)	(0.00298)
timetrend*lnbackers		-0.0406***
		(0.00306)
timetrend*lngoal		0.0138***
		(0.00240)
timetrend*duration		-0.000173*
		(0.0000959)
Constant	11.30***	10.43***
	(0.156)	(0.477)
Random-effects of geographic id		
variance (_cons)	0.0464	0.0394
Random-effects of project category		
variance (_cons)	0.5622	0.5124
Wald (Chi-square) test	11931.05***	12013.42***
Observations	74,618	74,618
Number of groups	6,911	6,911

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

In Model 1 of Table 2, we introduce the time-trend and the direct effects of number of backers, goal amount and duration. As these three characteristics are considered jointly in funding decisions we introduce all three interactions in the full model (Model 2).

Related to noisier signal of number of backers, over time, higher number of backers are negatively associated with likelihood of achieving the funding goal. Supporting the need for ex-ante costly signals, with increasing number of projects over time, projects with higher goal amount and shorter duration are more likely to be funded.

5. Additional tests

We perform additional diagnostic tests on the mixed-effects model (Model 2 of Table 2). We first estimate the deviance residuals for each project category. The horizontal box plot with deviance residuals in x-axis and project category in y-axis is presented in Figure 2. The mean and median residuals for most project categories are close to zero. Next, we test if the residuals are normally distributed and compare the histograms of standardized residuals obtained from best linear unbiased prediction (BLUP) to a theoretical normal distribution. Figure 3 shows that the residuals are normally distributed.

Figure 2: Box-plot of standardized residuals across project categories

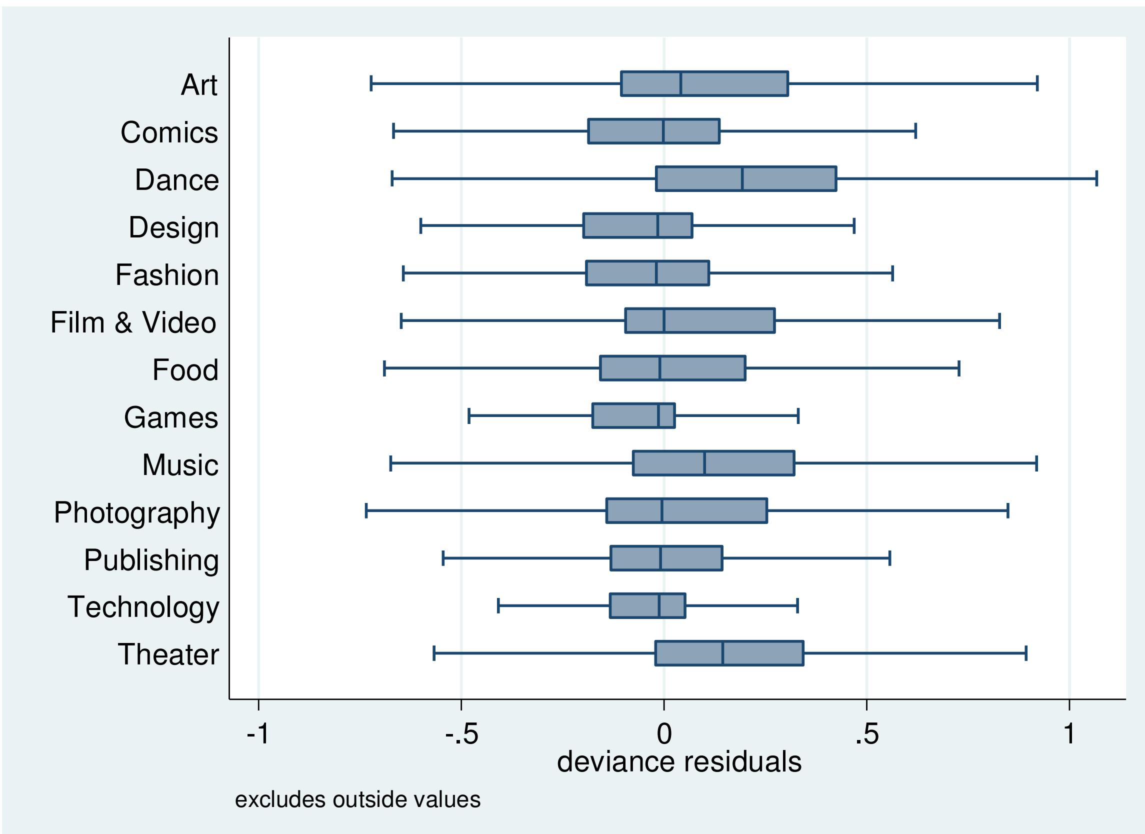
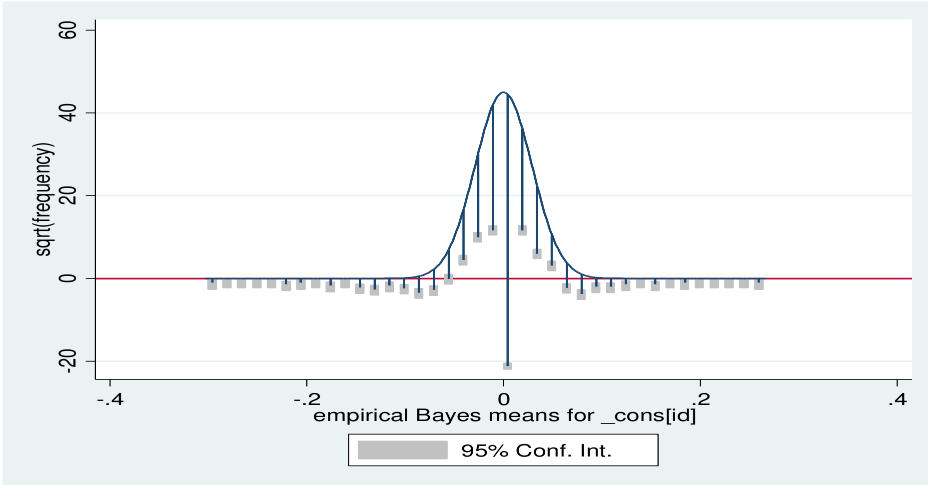


Figure 3: Best Linear Unbiased Predicted (BLUP) residuals to theoretical normal distribution



6. Conclusion

Crowdfunding is an area of increasing academic and practitioner interest (Agrawal, Catalini, and Goldfarb 2011, Kuppuswamy and Bayus 2013, Agrawal, Catalini, and Goldfarb 2013). Number of projects has increased significantly over time on crowdfunding platforms. Due to the limited ability to ascertain project potential under increasing number of projects, funding success decreases over time. The platform decreases reliance on noisier signal – number of backers – and increases reliance on costlier signals – higher goal amount and shorter project duration. The effects are present after controlling for geographic location and project category. The findings have implications for individuals seeking funding through crowdfunding platforms.

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