Winner Takes All? The "Blockbuster Effect" in Crowdfunding Platforms

Research-in-Progress

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Abstract

Crowdfunding has gained momentum in recent years. Even though an increasing amount of research has been devoted to the economic value of crowdfunding marketplaces, the interactions and effects among crowdfunding projects have yet to be fully studied. The current study strives to bridge this gap by examining the impacts of "blockbuster projects" — i.e., overwhelmingly successful projects – on the crowdfunding platform. Hypotheses are formulated based on the theory of network effects. Our preliminary results suggest the blockbuster projects exhibit positive spill-over effects within project category but cannibalization effects across categories. We also find evidence of lasting positive/negative network externality within/across category/categories. Further analysis suggests that fresh backers who are attracted to the platform by the blockbuster projects tend to be more engaged and more active. Our research aims to extend the emergent crowdfunding literature by examining network externalities among projects. We also provide practical implications for project creators and platform administrators.

Keywords: Crowdfunding, Blockbuster Effects, Network Externality, Network Effects, Economic Value, Innovation

Introduction

Crowdfunding has emerged as a viable alternative for sourcing financial capital for innovation (Belleflamme et al. 2013; Burtch et al. 2013; Burtch et al. 2015; Jung et al. 2014; Xiao et al. 2014). Crowdfunding platforms allow individual founders of for-profit, cultural, or social projects to solicit funding from a great number of backers, often in return for future products, equity, or some form of recognition (Bretschneider et al. 2014; Hahn and Lee 2013; Mollick 2013). Since its inception, crowdfunding has helped new ventures to raise billions of dollars (Massolution 2012) and the volume and amount of transactions continue to increase.

Recently, the emergence of several overwhelmingly successful crowdfunded projects has attracted considerable media attention. For instance, the "Exploding Kittens" project which was launched in January 2015 has attracted 219,382 backers who pledged over USD$8 million above and beyond the $10,000 fundraising goal, which makes it one of the most funded crowdfunding projects.[1] These notable projects not only appeal to a great number of new backers to join the platform, but also draw attention from existing ones.

It is widely believed that these overwhelmingly successful projects, which we henceforth refer to as "blockbuster" projects, would have a significant impact on the overall crowdfunding platform. However, their influence remains enigmatic. In general, there may be two plausible predictions. On the one hand, an in-process blockbuster projects may exacerbate platform competition such that other projects' performance would be undermined. On the other hand, other projects may also benefit from the blockbuster projects by "free-riding" on the increased popularity of the platform. The objective of our research is *to examine "blockbuster effect" on the crowdfunding platform, especially the impact of blockbuster projects on the funding performance of other projects*. Our study aspires to contribute to the crowdfunding literature by exploring the influences of blockbuster projects and how network effects operate on this online platform. We formulate hypotheses based on existing theory of network externality and conduct a project category-level analysis. The preliminary results provide the first empirical evidence of both positive and negative network effects in crowdfunding platforms. Our study also offers practical implications for project creators as well as design implications for crowdfunding platforms.

Related Literature

Crowdfunding

Crowdfunding supports the financing of an initiative, usually in the form of a project or a venture, by a large group of mostly unprofessional individuals instead of professional parties (e.g., banks, venture capitalists or business angles) (Schwienbacher and Larralde 2010). Crowdfunding bypasses these traditional intermediaries to raise money by directly "tapping the crowd" on Internet-based platforms (Beaulieu and Sarker 2013). To date, there are broadly four types of crowdfunding business models (Zvilichovsky et al. 2013): reward-based, loan-based, equity-based and donation-based. In reward-based crowdfunding, which is the most prevalent model currently in practice and also the focus of this study, project creators appreciate funders by offering rewards as returns for financially backing the project.

A key feature of crowdfunding platforms is that publicly observable information is recorded and is made available for open consumption (Burtch et al. 2013). Facilitated by this feature, some attention has been focused on the influence of observable project properties on backers' behaviors and decisions, which in turn affect the performance of crowdfunding campaigns. For instance, the effect of prior contributions (e.g., Burtch et al. 2013; Zhang and Liu 2012), geographic and cultural differences (e.g., Burtch et al. 2014; Kim and Hann 2014), and crowdfunding platform/campaign designs (e.g., Burtch et al. 2015; Liu et al. 2014) have thus far been investigated. In particular, Zhang and Liu (2012) found evidence of rational herding among lenders, such that projects exhibiting higher funding levels tend to attract more subsequent funding; Burtch (2011) evaluated the influence of network scale on prevalence of herding behavior in crowdfunding and found that herding was deemed as a negative network externality because it was detrimental to the optimality of backers' decisions. Yet, whereas most recent work has focused on the influences among backers' decisions, whether the performance of one project may affect that of another has yet to receive much attention. In crowdfunding platform, which serves as a two-sided

[1] See https://www.kickstarter.com/projects/elanlee/exploding-kittens

marketplace (Zvilichovsky et al. 2013), both the backer (demand) and project creator (supply) sides are equally crucial for sustainable development of the platform. We therefore intend to bridge this gap in crowdfunding literature by exploring the influences among project performance.

Network Effects

Network effects (or network externalities)[2] exhibit in many online markets (Kauffman et al. 2000; Liu et al. 2012) where the utility of a product (or service) is (at least partially) based on its combination with others (Katz and Shapiro 1994). It depends on the marginal effect that an additional party brings to existing parties in the network, whereas this effect is not necessarily attributed to the additional newcomer (Asvanund et al. 2004). A large body of research explores network effects in technology-related contexts including the computer hardware industry (Chen and Forman 2006), operating systems (Bresnahan 2001), application software (Gallaugher and Wang 2002), instant messaging and social networks (Sundararajan 2007), and peer-to-peer music sharing networks (Asvanund et al. 2004).

By and large, much of the existing discussion of network effects has centered on *positive network effects*, where larger networks create more value for participants compared to smaller networks (Brynjolfsson and Kemerer 1996; Saloner and Shepard 1992; Strahilevitz 2003). For instance, Gallaugher and Wang (2002) found a positive relationship between companies' market shares and product prices in the software industry. That said, some studies have investigated *negative network effects* as well (Belleflamme and Toulemonde 2009). For example, Asvanund et al. (2004) opined that negative effects occur when incoming parties tend to merely consume existing resources instead of contributing new resources.

The literature also distinguishes between 1) *direct* network effects, when the utility of a product is directly linked to its consumption by users such as in a telecommunication network, a phone service affords greater utility when more users are connected to the service (Katz and Shapiro 1985); and 2) *indirect* network effects, when increased usage of one product spawns the demand of complementary products, which generate increasing returns to the utility of products in its own type (Clements and Ohashi 2005; Forrell and Solaner 1986; Gandal 1995; Katz and Shapiro 1986). A classic example of indirect network effects is software/hardware products where the demand of software/hardware depends on the supply of the other interactively (Clements and Ohashi 2005). Recently, network effects are also prevalent in online marketplaces and communities, given that technological advancements facilitate more intensive interactions among geographically separated individuals. Particularly in crowdfunding platforms, both direct and indirect network effects exist. Direct network effect occurs when backer utility depends on the participation of other backers in the same project (Burtch 2011). Indirect network effect is fomented when the performance of a project is influenced by that of other projects, insomuch as certain projects may impact the overall crowdfunding platform by attracting new backers or increasing platform popularity.

In summary, our study aims to uncover the influences among projects in the crowdfunding context. Specifically, motivated by the "blockbuster project" phenomenon, and drawing insights upon network effects theory, we focus on how the performance of these exceptionally successful crowdfunding projects impact other projects. In next section, we develop hypotheses about the "blockbuster effect" based on this theory. Particularly, the effects within category (i.e., in the same project category) and across categories (i.e., in different project categories) will be discussed.

Hypotheses Development

Effects within Category

The emergence of blockbuster projects in certain crowdfunding project category may exert both positive and negative externalities to the performance of projects within the same category. On the positive side, these exceptionally successful projects increase the size of the project network (Shankar and Bayus 2003), insomuch as they are likely to attract new backers into the platform and increase the activeness of existing backers, which will concurrently benefit the funding performance of other projects in the same category. Simply put, the additional resources (i.e., new backers and more active existing backers) would be shared by other related projects (Strahilevitz 2003) (i.e., projects within the same category). Therefore, a positive "spillover effect" may occur such that other projects in the same category reap benefits from blockbuster

[2] In this paper, the terms "network effects" and "network externalities" are used interchangeably.

projects (Boudreau 2012) resulting in higher overall fundraising performance of the focal category.

On the other hand, a blockbuster project may also intensify market competition by funneling attention and financial resources from prospective backers who might otherwise potentially back other projects in the absence of a concurrent blockbuster project. If this effect were to occur, it would be more arduous for other concurrent projects to achieve expected funding, since a large amount of cash flow will be absorbed by the blockbuster projects (Noe and Parker 2005; Schilling 2002). As a result, a "cannibalization effect" may arise, resulting in a negative impact on the performance of other projects (Ghose et al. 2006). Within the same project category, both positive and negative network externalities are expected to be strong. Due to the limited relevant research in crowdfunding and the dual potential impacts, the overall direction and extent of influence is enigmatic. Thus, we formulate two competing hypotheses:

> ***Hypothesis 1a:*** *The emergence of blockbuster projects within the category is positively associated with the funding performance of same category.*
>
> ***Hypothesis 1b:*** *The emergence of blockbuster projects within the category is negatively associated with the funding performance of same category.*

Effects across Categories

When a blockbuster project emerges, we argue that its effect on projects in other categories will predominantly be negative. Backers who are new to the platform will be inclined to be impressed with the overwhelming success of the blockbuster project. Such positive feedback will likely induce them to selectively invest in similar projects in the near future with the expectation of backing successful projects (Greve 2003), rather than exploring other unfamiliar projects in other categories. They may develop the impression that similar projects are more likely to have the same favorable quality compared to others (Boudreau 2012). This positive feedback mechanism also happens to existing backers who are attracted by blockbuster projects. In this way, the benefits from blockbuster projects are less likely to "spill over" other categories. However, similar to the aforementioned reasons, cannibalization effects are likely to persist to other project categories. Blockbuster projects may reduce the network size of other categories by draining existing backers' financial resources (Shankar and Bayus 2003), which otherwise could have been directed to support those categories. Based on these arguments, we hypothesize:

> ***Hypothesis 2****: The emergence of blockbuster projects is negatively associated with the funding performance of other categories.*

Lasting Effects

Further, network effects are expected to not only occur concurrently, but persist over time (Ghose et al. 2006). Network effects, especially indirect effects, are characterized by the subsequent influences brought by new comers (Katz and Shapiro 1994). On crowdfunding platforms, blockbuster projects not only increase network size by drawing new backers into the category, but also attracting existing backers from other categories. The overwhelming success of blockbuster projects may signal high perceived backing utility (Katz and Shapiro 1985), which will subsequently further increase backers' engagement to the community. Thus, both new and existing backers will likely continue to back other related projects (i.e., projects within the same category) subsequently as new projects are introduced into the platform. This implies that the positive "spillover effect" within category could manifest as well in the following months in the focal category after the completion of blockbuster projects. Besides, the cannibalization effect would gradually fade away after the completion of blockbuster projects (Dranove and Gandal 2003). Hence, lasting effects of positive network externality will show up.

Similarly, in the situation of cross categories, those who attracted by the blockbuster project may switch their backing focus to the category where blockbuster arises. Then similar backing behaviors in the same category will follow (Jordan and Audia 2012). This leads to a negative lasting blockbuster effect on other categories. Taken together, we hypothesize:

> ***Hypothesis 3a:*** *The impact of blockbuster projects has a lasting effect within category, such that the funding performance of the same category is positively associated with the number of blockbuster projects in past months.*
>
> ***Hypothesis 3b:*** *The impact of blockbuster projects has a lasting effect across categories, such that the funding performance of the focal category is negatively associated with the number of blockbuster projects in other categories in past months.*

Data and Empirical Context

Our data was retrieved from *Kickstarter.com*, one of the largest reward-based crowdfunding platforms currently in operations. *Kickstarter.com* categorizes projects within 15 broad domain categories: art, comics, journalism, photography, publishing, crafts, dance, film & video, music, theater, fashion, food, games, technology and design. Using a software crawler, we collected relevant information on all crowdfunding projects that were launched before 11/30/2014. Our data covers all projects since the inception of *Kickstarter.com* – 190,845 projects created by 162,797 unique creators. These projects collectively received a total amount of USD$ 1.422B from over 7M unique backers.[3] The time span of our data is from 04/22/2009 to 11/30/2014.

Identifying "Blockbuster" Projects

Following the definition of "blockbuster projects", we need to select a group of projects that are "true" blockbuster projects (significantly outperformed than others). Otherwise, the accuracy of estimations would be undermined by including projects that are actually not blockbuster projects or excluding projects that are indeed extremely successful and influential. Additionally, it should be a small set of projects that capture a significant amount of money pledged in the platform, meeting the "overwhelmingly successful" trait.

Table 1. Descriptive Statistics of Blockbuster Projects

Category	Num. Blockbusters (Non-Blockbusters)	Ave. Goal	Ave. Pledge	Ave. Duration (days)	Ave. Backers
Games	39	517,668.1	2,203,202.0	32.5	24,574.3
	13,578	37,122.5	14,816.1	30.5	278.7
		(12.67***)	(150.0***)	(0.97)	(96.86***)
Technology	27	223,171.0	1,879,469.0	37.1	12,126.3
	9,259	91,431.5	18,380.5	31.6	170.1
		(0.42)	(100.0***)	(2.11**)	(49.76***)
Design	13	104,769.2	3,027,878.0	40.9	17,906.9
	11,247	29,157.0	16,136.1	32.0	212.0
		(1.41)	(77.47***)	(2.59***)	(62.06***)
Film	4	1,687,500.0	3,034,590.0	30.3	42,131.3
	41281	44,946.7	5,764.8	34.2	63.7
		(4.22***)	(240.0***)	(-0.48)	(200.0***)
Food	2	87,500.0	1,685,425.0	48.5	10,400.5
	11,088	39,792.9	5,232.2	31.6	60.9
		(0.042)	(120.0***)	(1.84*)	(72.49***)
Art	1	38,000.0	1,226,810.0	30.0	5,030.0
	15,004	15,895.2	2,907.9	31.8	40.3
		-	-	-	-
Comics	1	57,750.0	1,254,120.0	30.0	14,952.0
	4,968	32,932.6	6,049.6	34.4	130.8
		-	-	-	-
Music	1	100,000.0	1,192,790.0	32.0	24,883.0
	34,258	10,568.5	3,796.5	34.4	55.0
		-	-	-	-
Fashion	1	50,000.0	1,053,830.0	45.0	9,226.0
	8,914	15,083.8	5,195.9	30.5	65.4
		-	-	-	-
All	89	390,420.5	2,205,270.0	35.5	19797.9
	190,756	29088.7	6,427.3	32.8	87.4
		(4.55***)	(410.0***)	(1.71*)	(290.0***)

Note: *t*-values of comparisons between blockbuster and non-blockbuster projects are reported in parentheses.
Significance Levels: $^{***}p<0.01$, $^{**}p<0.05$, $^{*}p<0.1$.

To achieve this, we use the threshold of top 0.05% in terms of pledged amount across all the projects. Using this criterion, 93 projects are identified. Further, for each emerged project, we calculate the moving average and standard deviation of pledged amount for all the projects that are launched within a 7 months

[3] For projects using foreign currencies (i.e., non-USD), the pledged amount was converted to USD using the exchange rate for the month when the project was launched.

(3 months before and after) time window. We exclude projects whose pledged amount was within 5 standard deviations from the category-level moving average. [4] Finally, we were left with 89 overwhelmingly successful projects that account for 13.8% of all fund raised on *Kickstarter.com*.[5] This set of blockbuster projects was deemed reasonable in terms of face validity and sample size for statistical analysis. Descriptive statistics comparing the blockbuster and non-blockbuster projects are shown in Table 1. These blockbuster projects come from 9 categories, which suggests that there were no blockbuster projects in the *dance*, *journalism*, *photography*, *publishing* and *theatre* categories. The *games* category has the highest number of blockbuster projects (39; 43.8% of our sample). Overall, *games*, *technology* and *design* categories show higher activeness compared to other categories, since the majority of blockbuster projects emerged in these categories. Compared to non-blockbusters, the blockbuster projects not only have higher pledged amounts but also a larger number of backers.

Empirical Model

We conduct a category-level analysis to estimate the overall blockbuster effect on the crowdfunding platform. We construct our dataset at the category-month level. For each calendar month, data on projects is aggregated by category to operationalize the variables for the econometric estimations.

Category Performance – The measure of category performance is based on the total pledged amount within the category in a certain month ($PledgedAmount_t$). Since data from *Kickstarter.com* does not provide the pledged amount for each day, we took the average across the predetermined funding duration (days) for each project to obtain daily pledged amount. So the total pledged amount for each project in certain month equals to the product between the number of days within the month the project was live and average daily pledged amount. Then the category performance within a certain month is operationalized by summing the pledged amounts (based on live days) across all projects except for the blockbuster project(s) in that calendar month.[6] We take the log form to account for the skewed distribution. Thus, our dependent variable is ln(*PledgedAmount*).

Blockbuster Projects – We operationalize the existence of blockbuster projects using the number of live blockbuster projects in the focal and other categories (*NumBB* and *NumBBOther*). When blockbuster projects span over multiple months, for each month, we use the percentage of live days within that month with respect to the predetermined funding duration (days). For instance, if a blockbuster project with a 40-day funding duration was launched on the 20^{th} of the month (i.e., 10 days remaining in the month), the measure will be 0.25 (10/40) for that month (and 0.75 for the following month).

Lasting Effects Indicators – The variables of first order lasting effect of blockbuster projects are operationalized by the number of blockbuster projects in the same category/other categories that ended in the last month (*NumBBEndLast1*/*NumBBOtherEndLast1*). To find out if the lasting effect persists over several months, additional variables of higher order lasting effects (*NumBBEndLast2*/*NumBBEndLast3*; *NumBBOtherEndLast2*/*NumBBOtherEndLast3*) are generated in a similar manner.

Control Variables – Two variables are included to account for competition within and activeness of the platform: the number of monthly concurrent live projects in the same category and other categories (*NumProjects* and *NumProjectsOther*). Besides, category, year, month dummies are also included to account for category-specific characteristics and platform maturity.

Preliminary Results

Since the earliest blockbuster project we identified was launched in November 2010, we exclude the category-month pairs before November 2010, and use the records since that month. Finally, from Nov 2010 to Nov 2014, we have 735 (49 month × 15 categories) observations in our estimation sample.

[4] The rationale here is to rule out those projects that only have absolute rather than relative (in terms of other projects around the same period within the same category) extremely high pledged amount.

[5] Accounting for 13.8% of all funds raised on the platform attests to the overwhelming success of these projects. These 89 projects raised on average USD$2.2M whereas all other projects had an average of USD$6.4K.

[6] The rationale here is that excluding the pledge to blockbuster projects allows us to explore the effect of blockbuster projects on other projects.

Descriptive statistics for all the variables (excluding the dummies) are shown in Table 2.

Table 2. Summary Statistics for Estimation Sample (N=735)

	Variables	Mean	Std. Dev	Min	Max
Outcome	*PledgedAmount*	1,574,817	1,997,181	4,524	10,931,900
Blockbuster Indicators	*NumBB*	0.116	0.424	0	4.200
	NumBBOther	1.630	1.599	0	5.922
Lasting Effects Indicators	*NumBBEndLast1*	0.117	0.478	0	5
	NumBBOtherEndLast1	1.638	1.785	0	7
	NumBBEndLast2	0.117	0.478	0	5
	NumBBOtherEndLast2	1.638	1.785	0	7
	NumBBEndLast3	0.114	0.476	0	5
	NumBBOtherEndLast3	1.600	1.799	0	7
Controls	*NumProjects*	236.2	245.9	3.918	1,226
	NumProjectsOther	3,306	1,509	751.4	8,791

Ordinary Least Squares (OLS) models are used to estimate the effects of the explanatory variables. For all the variables, Variance Inflation Factors (VIF) were checked for potential multicollinearity problems and were below the recommended thresholds (Belsley et al. 2005; Cohen et al. 2013).

Table 3 shows the regression results. We estimate our parameters progressively by first estimating a model with control variables only (Model 1) and then adding the variables of interest from Models 2 to 5. As shown in Model 1, *NumProjects* is positive and significant (β=0.00183, p<0.01), which suggests that one more live project will increase the category total monthly pledged amount by 0.18%. Due to the large magnitude of pledged amount (Mean: USD$1.57M), the extent of this effect is quite large (more than $2,800 for one project). The negative and significant coefficient for *NumProjectsOther* (β=-0.000151, p<0.01) suggests on average, with one additional project launched in another category, the focal category will suffer 0.015% decrease in the monthly pledged amount. It shows there is competition for limited capital resources across different categories.

In Model 2, we add the blockbuster indicators. The difference in explanatory power between Model 2 and Model 1 indicates that the blockbuster indicators are significant predictors of category-level monthly performance (Model 1 vs. Model 2: ΔR^2=0.005, F=16.03, p<0.01). The positive and significant coefficient of *NumBB* (β=0.284, p<0.01) lends support for H1a (H1b is rejected). The result suggests that positive network externalities exist within category. The emergence of blockbuster projects is beneficial to other projects within the same category. Specifically, one additional blockbuster project gives rise to a 28.4% increase in the category's monthly pledged amount, which is a substantial amount at the category level. Furthermore, consistent to our expectation, the coefficient of *NumBBOther* is negative and significant (β=-0.0363, p<0.05), suggesting that the presence of a blockbuster project in other categories would reduce the current category's monthly performance by 3.6%. This result supports our arguments for cross-categories cannibalization effect. Therefore, H2 is supported. Largely, the blockbuster projects benefit related projects but undermine less-related projects.

Models 3 to 5 investigate the lasting effects of blockbuster projects. We add the first, second and third order lasting effect variables respectively in Model 3, 4, and 5. Compared with Model 2, the increased explanatory power shows the lasting effects also significantly predict category's performance (Model 2 vs. Model 3: ΔR^2=0.001, F=4.42, p<0.05; Model 2 vs. Model 4: ΔR^2=0.002, F=5.22, p<0.01; Model 2 vs. Model 5: ΔR^2=0.002, F=6.68, p<0.01). The positively significant within category lasting effect indicators (*NumBBEndLast1:* β=0.0893, p<0.05; *NumBBEndLast2:* β=0.109, p<0.05; *NumBBEndLast3:* β=0.0843, p<0.05) illustrate the evidence that blockbuster projects also have positive lasting impacts for projects in the same category in the following months. It is possibly because the blockbuster projects attract a large number of backers (both new backers and existing backers) who may continue to support other projects in the same category (consistent with our expectation). Therefore, H3a is also supported. However, the lasting effects of blockbuster projects in other categories are all negative (*NumBBOtherEndLast1*: β=-0.0307, p<0.1; *NumBBOtherEndLast2*: β=-0.0297, p<0.05; *NumBBOtherEndLast3*: β=-0.0466, p<0.01). The lasting effects of blockbuster projects in other categories also remain in the subsequent months. Blockbuster projects continuously cannibalize backer resources and pledged money in other categories, consistent with our arguments of a larger network size in blockbuster project category. Therefore, H3b is also supported by the results.

Table 3. Regression Results for Blockbuster Effects

	DV: ln(*PledgedAmount*)				
VARIABLES	Model1	Model2	Model3	Model4	Model5
NumProjects	0.00183***	0.00160***	0.00152***	0.00145***	0.00146***
	(0.000232)	(0.000205)	(0.000202)	(0.000207)	(0.000205)
NumProjectsOther	-0.000151***	-0.000136***	-0.000119***	-0.000124***	-0.000130***
	(2.70e-05)	(2.64e-05)	(2.79e-05)	(2.66e-05)	(2.67e-05)
NumBB		**0.284****	**0.245****	**0.256****	**0.243****
		(0.0557)	(0.0536)	(0.0543)	(0.0546)
NumBBOther		**-0.0363****	**-0.0293***	**-0.0349****	**-0.0516****
		(0.0168)	(0.0173)	(0.0168)	(0.0189)
NumBBEndLast1			**0.0893****		
			(0.0438)		
NumBBOtherEndLast1			**-0.0307***		
			(0.0159)		
NumBBEndLast2				**0.109****	
				(0.0470)	
NumBBOtherEndLast2				**-0.0297****	
				(0.0143)	
NumBBEndLast3					**0.0843****
					(0.0413)
NumBBOtherEndLast3					**-0.0466****
					(0.0177)
Constant	15.24***	15.08***	15.07***	15.07***	15.23***
	(0.149)	(0.162)	(0.169)	(0.168)	(0.190)
R^2	0.911	0.916	0.917	0.918	0.918
Observations	735	735	735	735	735

Note: Category, month and year dummies are included; Robust standard errors are reported in parentheses.
Significance Levels: ***p<0.01, **p<0.05, *p<0.1.

Further Insights into Backers' Behaviors

From the previous results, it is apparent that blockbuster projects successfully bring in more backers and cash flow, but the underlying mechanisms (e.g., backers' behaviors) remain unclear. Whether the increase in the pledged amount merely arises from more backers, or also from the different characteristics of new backers is uncertain. Thus, further analysis was conducted to generate insights into backers' behaviors.

Table 4. Backers' Behavior Characteristics

Type of backers	Average total backing exp.	Average backing interval (days)	Proportion of serial backers	Time before second backing (for serial backers)	Variety of categories of the projects they backed (for serial backers)	Average success rate of the projects they backed
Blockbuster -attracted (10.01%)	3.42	382.10	40.37%	191.75	2.5780	0.965
Normal backer (89.99%)	2.40	471.43	29.25%	250.58	3.0222	0.835

We differentiate the backers' community into two groups based on whether their first backing activity was for a blockbuster project. Several backing characteristics are computed based on the backers' backing history (see Table 4). The statistics reveal that the "Blockbuster-attracted" backers are more active in terms of the characteristics: they exhibit higher number of backing experience and backing frequency (i.e., shorter inter-backing interval). The proportion of serial backers is higher, and they take shorter time to become serial backers. But for serial backers, blockbuster-attracted backers are more focused when backing subsequent projects (lower backing diversity), lending support for our argued mechanisms about new backers in our hypotheses (more likely to back related projects). Furthermore, they are more likely to selectively back projects that are more likely to succeed, showing the tendency of rational herding (Zhang and Liu 2012). Based on this, we propose that blockbuster projects benefit related projects through two mechanisms: 1) they increase the network size of backer community by attracting a multitude of fresh backers, and 2) they stimulate the backer community by instilling highly active backing activities.

Future Research

This research-in-progress presents some preliminary findings relating to "blockbuster effects" in crowdfunding. Our future research will extend the current results by pursuing several directions. First, given that our preliminary analysis shows some evidences about how relatedness (more related within category and less related across categories) affects the blockbuster effects, it may be an important extension to examine whether heterogeneous influences exist across different categories because the relatedness between different categories varies. The extent of blockbuster effects would depend on the degree of relatedness among categories. Second, our category-level estimation suggests that blockbuster projects exhibit both positive and negative effects, depending on the relatedness of projects. In future, more nuanced estimation from project level will be conducted to identify the impacts on individual projects as well the contingent impacts on project characteristics. Third, in order to further identify the changes in the network size, additional analysis will be carried on to track the trajectory of two types' backers' activities. For example, we will next attempt to identify how their backing decision/participation activities (e.g., posting comments to projects) are influenced by project properties. Fourth, our current analysis only focuses on the effects *within* a particular platform. The network effects about projects outside platform can also be examined. Finally, our current analysis only focuses on showing the general network effects in a reduced form model; however, the network effects in two-sided markets are quite complex, especially given the plausible mechanism through increased backer activities. In the future, we will extend our analysis using structural analysis or more rigorous identification strategies (e.g., propensity score matching to address the potential endogeneity concerns about blockbuster projects) to provide more accurate estimates for "blockbuster effect".

Conclusions and Expected Contributions

In the present study, we investigate the "blockbuster effect" within a crowdfunding platform. Using network effects as our theoretical lens, we empirically document positive network effects within category and negative effects across categories. The presence of blockbuster projects would boost the performance of related projects but hurt the performance of less-related projects. Within the same category, blockbuster projects also exhibit lasting spillover effects. While across the categories, they exhibit negative lasting effects.

Our study bridges a gap in the current literature on crowdfunding by investigating network effects from projects' perspective. Particularly, our study resolves the uncertainty arising from the effects of blockbuster projects, and presents empirical estimations of these effects. Further, the positive and negative network effects suggest projects on crowdfunding platforms not only compete but also benefit each other. The influence is differential to the relatedness between projects.

Theoretically, our findings also contribute to the growing body of literature that has documented the network effects in online market (e.g., Boudreau and Jeppesen 2015). Specifically, examining network effects in crowdfunding enables us to discover a contingency framework of positive/negative network externality. The direction of network effects is contingent on the relatedness between projects. The positive network effects occur when two projects are highly related (i.e., in the same category). Otherwise, negative cannibalization effects will emerge. Further, the blockbuster effects show that the addition of one unit of some resources (e.g., a blockbuster project) may make a saliently distinctive effect. This is an extension to existing research – i.e., the additional one unit of resource is the same – which are primarily focusing on interchangeable projects/services.

Practically, a few of managerial implications can be distilled from our findings. For project creators, they could take advantage of the "piggyback opportunity" when a blockbuster project appears, by launching their projects in the same category. They can enjoy positive blockbuster effects, and therefore, are more likely to achieve fundraising success. Otherwise, when they have a campaign in other (less related) category, they should try to avoid launching when there is an existing blockbuster project in progress. For platform administrators, they can selectively increase the exposure of some very successful projects to attract backers to the platforms who are more likely to become more active backers. The active backer community will attract more innovative projects, and further generate more profit for the platform.

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