B.Comp. Dissertation

“Blockbuster Effects” in crowdfunding marketplace:

An Empirical Analysis of Network Externality

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Project No: H175090

Advisor: Assoc Prof Junpil Hahn

Deliverables:

Report: 1 Volume

Program: 1 Diskette

Database: 1 Diskette

Abstract

As a novel mean of fund-raising, crowdfunding platforms have witnessed a number of extraordinary success stories. These ‘blockbuster’ projects create mass media sensation, raise the awareness of the crowdfunding platform, and are observed to have a significant impact on the fund raising performance of the concurrent projects. We used data collected from Kickstarter, the largest crowdfunding platform in the world, to study this type of network dynamics. We found that such blockbuster success is a significant positive network eternality within its own category, and the dynamics is present not only during the fundraising period of the blockbuster projects but contributes to the long-term growth of the platform. However, the existence of blockbuster projects does not change the success distribution within a category, and it has no significant impact on projects in different categories. Evidence of peer effect was found in the underlying mechanism of backing decision marking. Management implications were formulated from the results to help the project creators and platform administration to better leverage on the network effect.

Subject Descriptors:

H.5.3 [Information Interfaces and Presentation]: Group and Organization Interfaces - Web-based interaction.

Keywords:

Crowdfunding, Crowdsourcing, Network Effect, Group Behaviour, Peer Effect

Acknowledgement

Here I would like to express my great gratitude to my supervisor Prof Jungpil Hahn for his insightful guidance and valuable critiques of the research work.

I would like to thank Mr. Wang Zhiyi and Ms Yang Lusi for their great advice and assistance to my work.

I also want to give special thanks to my friend Ms Kang Yueying for her encouragement and company throughout the year.

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1. Introduction

Crowdfunding offers a new paradigm for entrepreneurs to source capital from a larger audience. A typical reward-based crowdfunding platform allows entrepreneurs, who are referred as project creators, to initiate the project and advertise their business. Interested supporters, who are referred as backers, can participate in financing the project by pledging an advance payment for rewards promised by the project creator.

The crowdfunding phenomenon is considered to have passed the embryonic stage and is now rapidly moving towards the growth stage (Giudici et al. 2012). As up to 8 April, 2015, Kickstarter, the world's largest online crowdfunding platform, has helped 82,110 projects to successfully raised fund since it was founded in 2009. Among them there are some immensely successful project campaigns that have exceeded its original funding goals by hundreds of times and raised millions of dollars. For instance, the *COOLEST COOLER* project that started on July 8th 2014 attracted 62,642 backers and received more than US$ 13 million out of its US$ 50,000 goal. These 'blockbuster' projects often manage to create a sensation in the media and bring in a lot of first-time backers to the platform.

It is natural to expect the success of blockbuster projects would have an impact on the ecosystem on the crowdfunding platform, and affect the performance of other concurrent projects. However, the direction and extend of influence is not immediately clear. On one hand, since projects are competing with each other for the attention of supporters, ordinary projects may found themselves overshadowed by the blockbusters, and struggling to obtain expected level of financing, since a large amount of cashflow has been drained by the blockbuster projects. On the other hand, these ordinary projects could also benefit from an increased exposure to potential backers attracted to the platform by the propaganda of blockbuster project.

The objective of this research is to explore the phenomenon and examine how and to what extent blockbuster projects affect the performance of other projects on the same crowdfunding platform. It is found that in general the blockbusters help projects in the same category to attract more funding, but have no significant impact on the performance of projects in other categories. It is also observed that despite the increased capital injected into the category, the likelihood of success for an individual project is not improved as it is still largely associated with own project quality. The findings of the research would provide important practical manageable guidance for project creators as well as the crowdfunding platform. Since the net effect of blockbuster project on others is found to be positive, the owner of a good-quality candidate project could take advantage of the 'piggyback opportunity' by purposely launching his fund-raising campaign immediately after a blockbuster project. There is also an economical interest for the platform to pursue a higher volume of total backing actions for the platform earns 5% revenue of all the funds raised. Therefore the platform administration should use the findings to adjust their promotion strategy to order to focus on the star projects and appeal to new visitors to the website.

2. Related Literatures

2.1 Crowdfunding

Despite the fact that crowdfunding is a relatively novel invention, extensive researches around crowdfunding topic are already available. Existing literatures cover a wide range of topics such as psychological motivation of project backers, entrepreneur learning of project creators and development of crowdfunding platforms. One rapid growing stream of research focuses on the success factors of crowdfunding projects. Many project innate characteristics are found to contribute to the outcome of a crowdfunding project, including whether the project is featured by Kickstarter, personal network of the creator, level of preparedness and geography distribution (Mollick 2013), creator's backing history (Zvilichovsky et al. 2013) and project updates (Xu et al. 2014). These studies provide invaluable insight into the success mechanism for crowdfunding projects. Factors that have been proven to be associated with crowdfunding project's success should be controlled in analytical models.

To date, few studies have attempted to explore the reciprocity among projects, i.e., how performance of one crowdfunding project could possibly pose an impact on other projects. Therefore we seek theoretical support from more general context, such as market competition, network dynamics and organisational ecology.

2.2 Network Effect

Network effect describes a type of product whose utility is (at least partially) based on the combination with others (Katz and Shapiro, 1994). Two classic situations where network effect arises are: 1) direct network effect, when the the utility of a product is directly linked to the consumption of the others. For instance, in a telecommunication network, a telephone is more valuable when the line is connected to more users; 2) indirect network effect, when increased usage in one product spawns the value of complementary products or the platform, thus in turn affects the usage of products of own type, as what is observed in software/hardware paradigm. Our study is more likely to fit into the latter scenario because the projects on Kickstarter.com interact indirectly via the shared ecosystem they are in. The projects could benefit from the increased awareness and popularity of the platform.

Many empirical tests have been conducted on information technologies to examine the existence and measure the magnitude of network effect. Examples include computer hardware (Chen and Forman 2006), operating systems (Bresnahan 2001), application software (Brynjolfsson and Kemerer 1996; Gallaugher and Wang 2002; Gandal 1994), popular instant messaging and social networks (Sundararajan 2007) and Peer-To-Peer Music Sharing Network (Asvanund et al. 2004). These researches not only provide guidance on how to conduct an empirical evaluation of network effect, but also reaffirm the idea that online platforms are common demonstration of network effects as modern technologies increase the 'connectedness' of individual actions.

2.3 Peer Effect

Another possible explanation of the blockbuster effect lies in the realm of group behaviour. Peer effect refers to the phenomenon in a social network context that incentive for an individual to act increases in other's actions (Bramoullé et al. 2009). A notable theoretical study was performed by Ghiglino and Goyal (2010) to discuss the social comparison in the context of market economy, where individual's well-being is not only related to our own consumption but also depends on the perceived consumption of 'neighbours' with whom he interacts and compares. Ward and Ramachandran (2010) applied the group behaviour theory to crowdfunding context by analysing data from a music crowdfunding platform Sellaband.com. The researchers adopted a basic peer effect model by using project characteristics (both intrinsic and network-based attributes) together with peer effect indicators to predict project popularity. Variables including number of investor comments and project updates, whether a project is listed on a top-5 popularity list and number of sample tracks played, are selected to represent the observed popularity of a project that could potentially impact a user's investment decision. The statistical result ascertained that peer effect influences consumption of crowdfunding projects.

It is noteworthy that peer effect is commonly found in risky or unhealthy behaviour, e.g., alcohol and drug consumption, suggesting that peer effect is often irrational. Another research attempt was conducted by Burtch (2011) to examine the presence of herding effect on crowdfunding platform. Burtch found that herding behavior increases with the network size, and is harmful for optimality of investor decision-making as the a greater number of inexperience deciders leads to the selection of worse performing projects. This study inspired us to study the selection decision making process of the backers, which is the underlying driving force for inter-project correlation. In our problem we need to understand that due to the selective nature of backing, any change of overall backing traffic on the platform is necessarily evenly distributed to all projects.

3. Hypotheses

3.1 Preliminary Data Exploration

In order to separate and evaluate the two significant compositions of ‘blockbuster effect’, the positive spill-over effect and the negative cannibalisation pressure, we divide the impact of blockbusters projects based on the category attribute.

Backers have relatively stable field of interest but limited financial power. For the additional inflow of backer traffic brought in by blockbuster project, it is likely for them to find projects in related fields of interest more appealing. Hence the projects from categories other than that of the blockbuster project will benefit less from the spill-over effect. The impact of blockbusters on projects in other categories are likely to be negative only, for these smaller-scaled projects face great difficulty in the competition for backer’s attention and wallet.

On the other hand, it is harder to make a conjecture on what would happen within the same category as the blockbuster project. Data about a blockbuster project, video game *Double Fine Adventure*, is presented to help form an intuition about the direction and magnitude of this blockbuster impact. *Double Fine Adventure* was successfully funded on March 14th 2012, and is currently ranked as the 16th most funded project in Kickstarter’s history.

- **Dollars Pledged:** $3,336,371
- **Total Backers:** 87,142
- **First-Time Backers at the time**: 61,692 (71%)

The graph below shows that the average number of pledges per week to projects in the Video Games category before and after the launch of *Double Fine Adventure* (pledges to *Double Fine Adventure* itself are excluded). It suggests that the flood of 60,000 new backers whom *Double Fine Adventure* had brought in extended their activity to other Video Games projects.

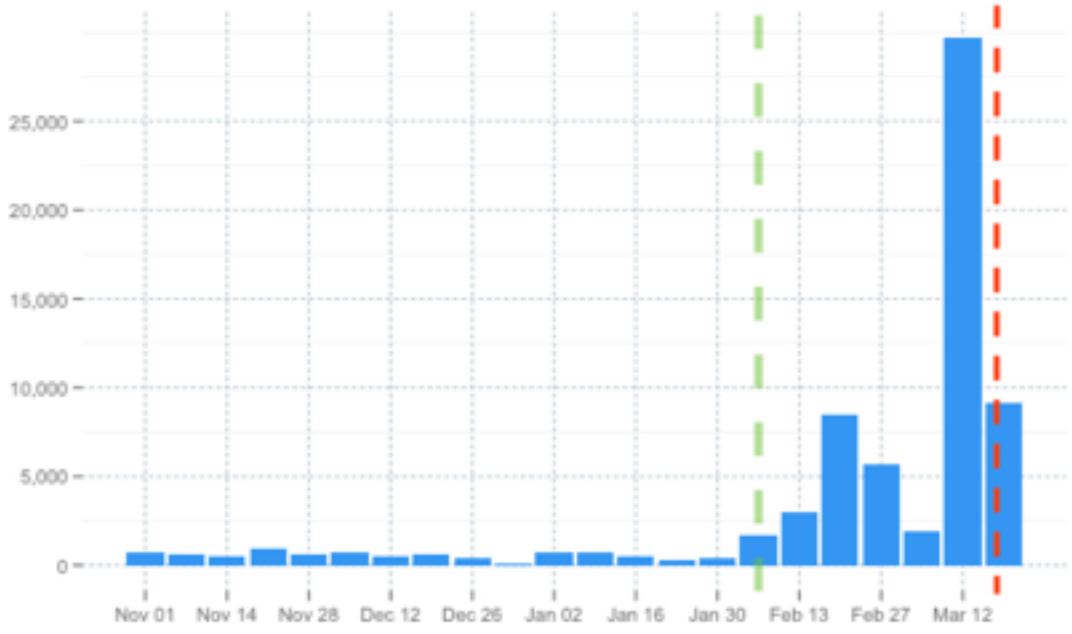

Figure 3.1.1 Pledges per week to Video Games category (the green dotted line marks *Double Fine Adventure*'s launch and the red dotted line marks *Double Fine Adventure*'s completion)

Here are additional indicators of the effect:

- Before *Double Fine Adventure*, one video game project had exceeded $100,000. Nine projects reached that threshold one week after the completion of *Double Fine Adventure*.
- *Wasteland 2*, another million-dollar game project that launched a month after Double Fine, received nearly $400,000 in pledges from Double Fine's first-time backers.

With this data, we would like to make a conjecture that, within same category the spill-over effect of a blockbuster outweighs the competitive pressure it places on the rest of projects. Blockbuster project is a positive network externality to its peer projects.

3.2 Empirical Hypotheses

To order to place our analysis in a formal context, we form the hypotheses to test if there is a correlation between the funding performance and the existence of the concurrent blockbuster projects.

H1(a): The pledge received for a project increases with the number of concurrent blockbuster projects in the same category

H1(b): The pledge received for a project decreases with the number of concurrent blockbuster projects in other categories.

We define success as reaching or exceeding original funding goal, so we also have:

H2(a): The likelihood of success of a project increases with the number of concurrent blockbuster projects in the same category.

H2(b): The likelihood of success of a project decreases with the number of concurrent blockbuster projects in other categories.

H2 is an extension to H1. Whether the test for H2 would render same result of H1 depends on the evenness of the impact in H1 over all projects. If all projects share the same extend of blockbuster impact, then their chance of success will rise (fall) with increased (decreased) money pledge. However if the impact of blockbusters concentrates on a small pool of prominent projects, the financing results of the majority are expected to be of minimal change.

We also wish to examine the change of blockbuster effect with regard to time. Due to purchasing power limit, we conjecture that majority of the backers will only resume backing a while after their investment in blockbuster projects, which implies that the spill-over effect could manifest later than the immediate cannibalisation effect. In other words, there is a lagging of positive blockbuster effect (H1a and H2a). We formulate the hypothesis as:

H3: Within the same category, the funding performance of a project is correlated to the number of blockbuster projects in the past months.

Any mass media sensation cannot last for long. At the same time the current promotion strategy of Kickstarter focuses on diversity so that each project on the 'staff-pick' list would only be featured and advertised for a short window of time. Therefore we speculate that blockbuster effect would eventually subside over time, as attention of the backers switches to new targets. Thus we hypothesise:

H4: After a certain period, all types of blockbuster effect start to decrease in magnitude and become less significant over time.

4. Data Collection

4.1 Kickstarter Dataset

The data was extracted from Kickstarter (www.kickstarter.com) the largest crowdfunding platform. The data set contains all past and live projects on Kickstarter since the launch of the platform up to 6 December, 2014. The following metadata was collected by the web-page crawler:

- **Project data:** project id, project page url, category, the use of videos and images in the description, location and currency, project creator profile, reward levels, financing goal, financing duration, project updates, project state at completion, amount of money pledged.

- **Backing data:** the project-backer pair associated by project id and backer profile url.

Individual Project	Average pledge (USD$[1])	7,387
	Standard deviation of pledge (USD$)	68,828
Category	Average number of live projects in a month	373
	Standard deviation of number of live projects	470
	Average monthly total pledge (USD$)	2,689,377
	Standard deviation of monthly pledge (USD$)	4,745,985
Platform	Total number of projects	192,274
	Average success rate	39.02%

Table 4.1.1 Descriptive Statistics - General

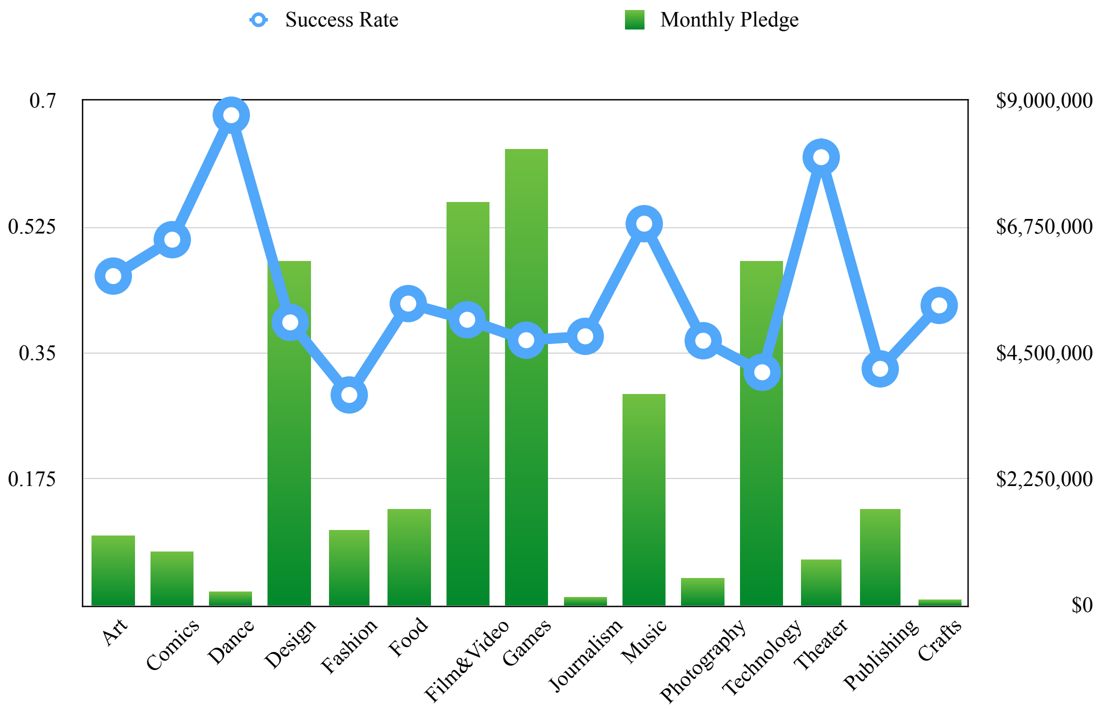

Figure 4.1.2 Descriptive Statistics - Project Category

1. For projects outside US their pledge amount is converted to US dollar.

4.2 Blockbuster Projects

We would like to define the threshold of a ‘blockbuster project’ to be US$ 1,000,000. The reason for this arbitrary choice of number is not only due to its linguistics root (one-million is a commonly used criteria for ‘grand’ in English, e.g., ‘millionaire’), but also with practical importance: using this criteria we will be able to identify 84 most funded blockbuster projects (0.044% of the total), which is a feasible size of sample for statistical analysis.

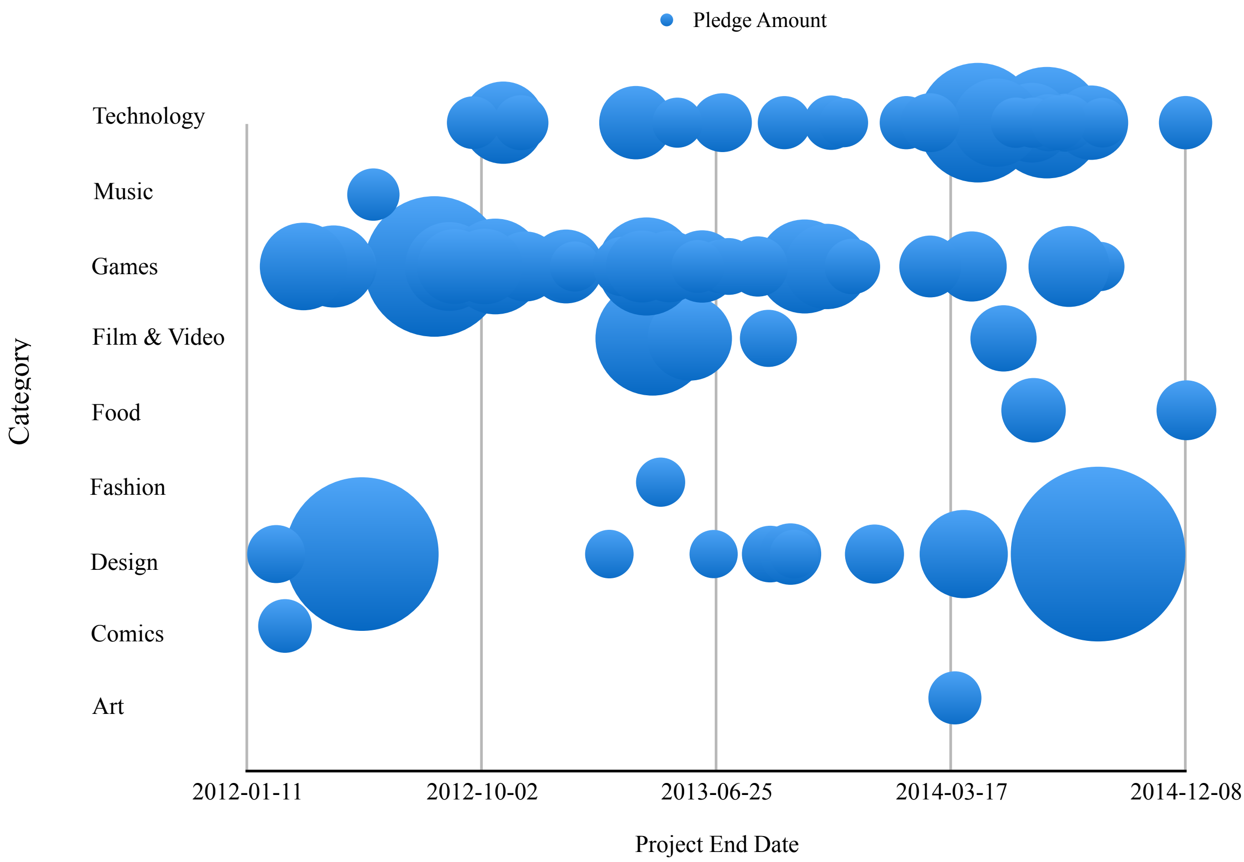

Figure 4.1.3 Descriptive Statistics - Blockbuster Projects

5. Methodology and Result

5.1 Project Model

We build our investigation on top of the prior work by Ward and Ramachandran (2010). They adopted a model that the performance of a crowdfunding project is a linear function of three components: project own characteristics (X), time indicators (T) and global network effects (N). We attempt to study the impact of blockbuster projects by adding a new group of independent variables: blockbuster effect (B). The prediction model is shown below:

$$Y = \alpha + \sum \beta_n X_n + \sum \gamma_n T_n + \sum \delta_n N_n + \sum \eta_n B_n$$

In order to test Hypotheses 1 & 2, two dependent variables are used to measure the funding performance of a project. Different to our original hypothesis H1, we use the funding ratio instead of absolute pledge level as dependent variable Y_1, because the monetary value of all kinds of projects varies significantly even within same category. For instance, a smart watch is much more expensive then an emoji keyboard despite that they are both technology gadgets.

Model	Name	Meaning
Y_1	Funding Ratio	fraction of funding goal reached
Y_2	Success	if project is completed with funding goal reached

Table 5.1.1 Dependent variables

A key issue of the operationalisation of the data is to deal with time, since a project usually spans over a period of time (the average fundraising duration of a project is 32.6 days). To avoid ambiguity, in this research when we compute for time-related attributes (T_1, T_2) for a project, we use its launch year and month. But when we need to determine the concurrency of two projects we judge by whether there is any actual overlapping of their financing period. As long as the start date of one project is earlier than the end of the other, and the end date of the formal is later than the start of the latter, we call them 'concurrent' projects.

Simple linear regression analysis for Y_1 and logistic regression for Y_2 are applied for the estimation. The omitted dummy variables are Crafts, U.S., January and 2014, so the base data entry is the funding performance of a craft project in U.S. that started in January 2014. Since we are evaluating the funding results we focus on the projects that have ended. Thus the 6,100 project that were in 'live' funding state at the time of data collection are removed from the dataset. The 84 blockbuster projects are also removed from the population. The regression results are as followed:

Variable	Name	Description	Model 1	Model 2
X_1	Description	word count of the description		-0.000003814 *** (<2E-16)
X_2	Video	if there is a video in the description		0.0908 *** (<2E-16)
X_3	Image	number of images in project description		-0.000986 *** (1.88E-9)
X_4	Reward	number of reward choices for backers	0.116 · (0.0998)	0.003991 *** (<2E-16)
X_5	Update	number of project updates	0.2227 *** (3.49E-8)	0.02618*** (<2E-16)
X_6	Category Dummies	the fourteen categories excluding Crafts		
X_7	Location Dummies	the nine countries excluding U.S.A		
T_1	Year Dummies	year 2009 to 2013 (based on project completion time)		
T_2	Month Dummies	eleven months excluding January (based on project completion time)		
N_1	Local Competition	number of live projects within category		-0.00002481 *** (5.66E-14)
N_2	Global Competition	number of live projects in other categories		-0.000005789 *** (<2E-16)
B_1	Local Blockbuster	number of concurrent blockbuster projects within category	0.8117 · (0.0653)	-0.01653 *** (<2E-16)
B_2	Foreign Blockbuster	number of concurrent blockbuster projects in other categories		-0.003449 *** (8.38E-15)
Adjusted R-square / Log likelihood		coefficient of multiple determination for multiple regression	0.0003602	-100681.3 (df =50)
Fit Statistics		the fitness of the model	F(186038) = 2.397 ***	X-square (8) = 8714.767 ***

· - Significant at the 0.05 level **-Significant at the 0.01 level *** - Significant at the 0.001 level

Table 5.1.2 Summary of project-level regression result

The result that we are interested in would be that for Variable B_1 and B_2.

The estimation for B_1 are significant in both models (in Model 1 it is one of the only three significant variables that generated causality to the pledge amount). However interestingly the signs of the coefficients are opposite: Model 1 indicates that an addition of one concurrent blockbuster in own category would increase the funding ratio by 0.8117, which is a big gain of more than 80% of the original funding goal. In model 2 the negative estimation means the odds of success will be discounted by 0.9836 with an additional blockbuster. Our Hypothesis 1(a) is supported but H2(a) is rejected. The net impact of a blockbuster on other projects in the same category seems to be complex: it helps them to raise a significant amount of additional money, but at the same time slightly reduce their likelihood of success. We need more analysis to explain this paradox.

The estimated coefficient for blockbusters in different category are too insignificant statistically in Model 1 to draw any conclusion for Hypotheses H1(b). It is slightly negative and significant in Model 2, meaning that an additional blockbuster project in other category will give an discounted odds of success funding at 99.66% of the original likelihood — an almost negligible decrease. Therefore, blockbuster projects have minimal impact on projects of different categories from its own.

It is worth noticing that the R-square statistics of Model 1 is so small that the reliability of the result is doubtful. This is much expected given the difficulty of predicting funding performance of a project with only limited number of variables. In order to minimise the uncertainty of project-level success and provide a stronger support to our claim of the causality between the existence of blockbuster projects and the performance of other projects, we construct a second group of models.

5.2 Category Model

The dataset used in this model is the category-month pair. For each calendar month, the data of projects is aggregated by category to compute the category parameters, such as the total money pledged and the success rate. The operationalisation process creates 1011 data pairs with the 68 months in 5 years starting from April 2009 to December 2014 over 15 categories (some categories do not to have any projects at the first few months since platform launch so we are short of 9 pairs). Since many projects span over multiple months, a linear growth model is adopted to estimate the average daily pledge of each project. The category total pledge is the sum of the amount raised during the 'live' period of the projects within this specific calendar month — if project A starts on 15 March and ends on 14 April, then half of its final fund raised would be included in March's pledge total and other other half in April's pledge total for that category. As for the success rate, it is determined by the ratio of projects completing 'successfully' out of all the project that end within the month. To illustrate with the example mentioned above, project A would only be taken into consideration in April for the calculation of success rate.

Since we are now looking at an aggregate level, all the project-specific attributes (X) such as funding goal, location description and video, are not relevant anymore. The only exception is the fifteen categories which will be controlled to isolate the category variation. Time indicators (T) and global network effects variables (N) remain unchanged.

$$Y = \alpha + \beta_6 X_6 + \sum \gamma_n T_n + \sum \delta_n N_n + \sum \eta_n B_n$$

Since we expect the aggregation to reduce the randomness and render more significant result, we would also use this model to test H3 to see if there is any lagging/ decay of the blockbuster effect. Base on our findings from 5.1 we decide to study the blockbuster effect within same category only, as it is much stronger compared to cross-category impact.

In order to test H1 and H2, we use total category monthly pledge and overall category success rate as dependent variables. Furthermore, we add another dependent variable, the total category monthly pledge excluding the blockbuster projects' contribution. This will decouple the spill-over effect and the cannibalisation effect, allowing a better understanding of how the rest of the category are influenced by the blockbuster projects.

Model	Name	Meaning
Y_3	Total Monthly Pledge	the sum of the money pledged to all the live projects of the category within this month
Y_4	Non-blockbuster Pledge	Y3 minus the money raised by blockbuster project itself
Y_5	Category Success Rate	proportion of the successful projects among all projects completed within the month

Table 5.2.1 Dependent Variables

All three models are conducted with simple linear regression, and the results are presented in Table 5.2.2 (non-dummy variables only).

Variable	Variable	Model 3	Model 4	Model 5
N_1	number of live projects within category	0.0401E+05 *** (<2E-16)	0.03977E+05 *** (<2E-16)	
N_2	number of live projects in other categories	-0.001516E+05 ** (0.001122)	-0.002384E+05 ** (4.68E-10)	-1.895E-05 *** (3.81E-6)
B_1	number of concurrent blockbuster projects within category	28.58E+05 *** (<2E-16)	7.069E+05 *** (<2E-16)	
B_2	number of concurrent blockbuster projects in other categories			
B_{3-1}	number of blockbusters within category ended last month (~30 days)	9.297E+05 *** (8.83E-7)	9.674E+05 *** (4.37E-10)	
B_{3-2}	number of blockbusters within category ended in second last month (30~60 days)		4.405E+05 ** (0.004256)	
B_{3-3}	number of blockbusters within category ended three months ago (60~90 days)	5.558E+05 ** (0.003355)	4.108E+05 ** (0.007909)	
B_{3-4}	number of blockbusters within category ended four months ago (90~120 days)	8.232E+05 *** (1.45E-05)	8.753E+05 *** (1.83E-08)	
B_{3-5}	number of blockbusters within category ended five months ago (120~150 days)	14.62E+05 *** (1.55E-11)	11.71E+05 *** (3.67E-11)	
B_{3-6}	number of blockbusters within category ended six months ago (150~180 days)	9.787E+05 *** (9.28E-06)	11.87E+05 *** (6.06E-11)	
	Adjusted R-square	0.8878	0.8738	0.3877

· - Significant at the 0.05 level ** - Significant at the 0.01 level *** - Significant at the 0.001 level

Table 5.2.2 Summary of second regression result

The results conform to our previous findings. Firstly, there is no significant impact of blockbuster projects cross category, hence H1(b) and H2(b) do not stand. Secondly, the blockbusters significantly increase the pledge amount to own category. The $706,900 increase of category total pledge (blockbuster pledge exclusive) with the addition of one blockbuster project is substantial, given the category average is around $2,689,000 (a 26.3% increase).

Nevertheless, the blockbusters has no significant impact on the overall success rate, and even decreases the success likelihood for an individual project. Evidence of peer effect is found here, as the backers are observed to follow the trend and invest their money into a smaller subset of projects. The selective backing results in a more concentrated distribution of success: those projects started with a hopeful prospect will receive far beyond expectation, while those that were not competitive will be further over-shadowed and more likely to fail the competition.

In terms of how the blockbuster effect change with time, Model 1 and Model 2 demonstrate a “U-shape” fluctuation. The magnitude of blockbuster impact would subside after two to three months, and rise again afterwards. This contradicts with our original Hypotheses H3 and H4, and suggests that the new backing traffic, no matter whether they are new comers or returning backers, have a tendency to stay on the platform, and contribute for long-term growth of the platform.

In addition, we would like to test for the robustness of our model. The difference of the model in our study with previous research is the addition of dependent variables for blockbuster effect (B_n). By comparing the the regression results between our model and the partial model without blockbuster effect variables, we identify a significant improve of adjusted R-square statistics in Model 3 and Model 4 but not in Model 5. This is in accordance of our findings that the blockbuster effect is an important dynamic force for predicting the pledge amount but not the success distribution.

Adjusted R-square	Model 3	Model 4	Model 5
Partial Model Without Independent Variables B_n	0.6461	0.761	0.3902
Full Model With Independent Variables B_n	0.8878	0.8738	0.3877

Table 5.2.3 Comparison among models with or without blockbuster variables

6. Further Look at Backers' Behaviour

The rather surprising findings of long-lasting blockbuster effect over time encourages us to speculate on the underlying mechanism of the project reciprocity — the backers' behaviour. It is apparent that blockbuster projects successfully bring in more backers and larger cashflow, but it is not clear if the explanation has captured the full story: does the improved funding dynamics is purely due to a increase of backer quantity, or could it be because this group of new backers behave inherently differently from others?

We differentiate the backers community based on their fist backing activity and divide them into two user group: those who were first attracted to Kickstarter by a blockbuster project ("B-attracted" backers) and those who started by backing an ordinary project. Records of backing activities are used to compute backer characteristic statistics in order to profile the two groups. Since Kickstarter does not capture dates for backing actions, the end date of the project backed is used as an estimate. Table 6.1 describes the differences between the two groups of backers.

Type of backers	Average total number of backing	Average backing interval (days)	Proportion of one-time backers	Time before second backing (for multiple-time backers)	Variety of categories of the projects they backed	Average success rate of the projects they backed
B-attracted (9.74%)	3.37	372.66	60.07%	187.65	1.4736	0.967
Normal backer (90.26%)	2.41	469.59	70.77%	252.75	1.4051	0.831

Table 6.1 Backer's behavioural characteristics

The statistics show that the "Blockbuster-attracted' backers are more active participants across all evaluation criteria: they back more times and more frequently; there are less one-time 'tourists'; people commit to next backing more quickly; they have broader interest. It also reveals that the “Blockbuster-attracted’ backers have a preference towards more successful projects. In a word, the “Blockbuster-attracted’ backers are valuable users that any crowdfunding platform should strive to grab and maintain.

7. Conclusion and Limitation

This research has investigated how the funding performance of a project is linked to the blockbuster projects on the crowdfunding platform Kickstarter. We have examined such ‘blockbuster impact’ with the change over category and time. The paper has also attempted to explain the phenomenon at the level of backer decision marking. To summarise we have found that:

1) blockbuster projects significantly raise the pledged amount received by projects of same category;
2) blockbuster projects do not have a impact on the distribution of success within its category due to selective backing;
3) blockbuster effect demonstrates a ‘U-shape’ trend over time: the magnitude of the positive correlation decreases after two to three months due to backers’ limited spending power, but then the magnitude rises again;
4) blockbuster projects do not have significant impact on the performance of projects in different categories; and
5) blockbuster projects not only increase the quantity of backers but also improves the participation level of the backer community by attracting more active users.

The findings of the research could be applied to provide manageable recommendations to potential project creators as well as Kickstarter administration. For individual project creators, the study has shown that the existence of blockbuster projects offers a ‘free-ride’ opportunity that to follow a recent hit in your category could significantly raise the fund-raising potential of the project. However, all projects in the category need to compete for the benefits brought by the blockbuster projects, and to what extent the project could realise the potential depends on its own appeal to the backers. The project creators should ensure the quality of own project to maximise the benefit of the ‘blockbuster effect’.

Since the blockbuster project is net positive network eternality, the Kickstarter platform admin should strive to promote and create more ‘blockbuster’ projects in order to leverage on the positive network effect. In addition, when a blockbuster emerges, the platform should try to retain the group of new backers with recommendation and promotion schemes, because they are high-valued customers.

One limitation of our research is that the only the static project data was collected and used for analysis. The lack of important dynamic project metadata such as being listed as ‘staff pick’ has significantly affected the explanatory power of model for individual project success prediction. Further research directions include sensitivity analysis on different threshold for the definition of blockbuster projects, or to conduct similar analysis on other crowdfunding platforms.

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