An Empirical Analysis of Semantic Network in Online Crowdfunding: Evidence from Kickstarter

Jongho Kim
KAIST College of Business
85 Hoegiro Dongdae moon-gu Seoul, Korea
+82-10-2941-1151
jonghkim@kaist.ac.kr

Daegen Cho
KAIST College of Business
85 Hoegiro Dongdaemoon-gu Seoul, Korea
+82-10-3129-6442
dgcho@business.kaist.ac.kr

Minhyung Lee
KAIST College of Business
85 Hoegiro Dongdaemoon-gu Seoul, Korea
+82-10-3377-9531
white_wishes@kaist.ac.kr

Byungtae Lee
KAIST College of Business
85 Hoegiro Dongdaemoon-gu Seoul, Korea
+82-10-2983-6000
btlee@business.kaist.ac.kr

ABSTRACT
Crowdfunding, which helps getting financial sources for niche market entrepreneurs, lowers the entry barrier to start a social and for-profit project. However, it is widely believed that overwhelmingly successful projects, called “blockbuster” projects, would have a significant impact on the overall crowdfunding projects. In theoretical perspectives, there have been two countervailing effects of blockbuster, cannibalization effects and spill-over effects. Therefore, this motivates our research to investigate the competitions among projects within same categories. We expect to fill in the gaps of prior literatures which concluded that the blockbuster project has the same effects on all the other projects within same categories. As a major contribution of this paper, we obtain market structure insights from the creator generated contents based on a text-mining approach and combine it with semantic network analysis to assess the degree to which the latent competition causes cannibalize or spill-over effects inside the same category. Our study uses unique data set, compiled by Python based self-developed crawler. The dataset includes 148,398 projects and 2,931,821 records of daily pledged amount. Our analysis of the concurrent impact of blockbuster project shows the much larger spillover effects to the inside cluster relative to the outside clusters. However, this spillover effect to the outside cluster significantly increase as the magnitude to the inside cluster in the long run perspective. The results of this paper suggest practical marketing implications to entrepreneurs and platform.

CCS Concepts
• Social and professional topics → Professional topics →

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for components of this work owned by others than the author(s) must be honored. Abstracting with credit is permitted. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee. Request permissions from Permissions@acm.org.

ICEC’16, August 17-19, 2016, Suwon, Republic of Korea
Copyright is held by the owner/author(s). Publication rights licensed to ACM.
ACM 978-1-4503-4222-3/16/08...$15.00
DOI: http://dx.doi.org/10.1145/2971603.2971647

Management of computing and information systems → Information system economics

Keywords
Crowdfunding; Blockbuster Effects; Market Structure; Text-Mining; Semantic Network

1. INTRODUCTION
The winner takes it all. The loser standing small beside the victory → ABBA →

Crowdfunding has recently emerged with the development of information technology which reduces the search and matching costs for entrepreneurs. The basic idea of crowdfunding is simple. Instead of using a small group of sophisticated backers to raise funds, entrepreneurs try to obtain them through the Internet from a large crowd, where each individual provides a small amount. (Burtch et al, 2013)

Crowdfunding is an umbrella term used to describe the request of funding through an online platform and there exist four different types of crowdfunding which are reward-based, loan-based, equity based and donation-based (Zvilichovsky et al. 2013). Especially, in this research, we focus on the reward-based crowdfunding, the most prominent and prevalent model, which gives backers a certain reward as return for investing money to the projects.

Crowdfunding has made it possible for individual founders to bypass the financial intermediaries like bank and venture capital, which means that it would lower the entry barrier to start a social and for-profit project (Beaulieu and Sarker 2013). Therefore, crowdfunding fosters early stage of entrepreneurial firm development by providing a possible alternative for seed capital of angels or venture capitals (Tomczak, and Alexander, 2013). However, as many markets have been considered as “Winner-take-all”, IT technology has taken a role for the change in supply and demand of blockbuster and niche products. This has driven profound effects on market structure and market competition (Brynjolfsson et al. 2010; Fleder and Hosanang 2009). Although, crowdfunding has gotten a lot of attentions as alternatives for niche market projects, it is widely believed that overwhelmingly successful projects, called as “blockbuster” projects, would have a significant impact on the overall Crowdfunding platform (Schwienbacher and Larralde 2010; Tomczak and Alexander,
2013; Liu et al., 2015). However, there is very few research that investigates the crowdfunding platforms in the context of competition between projects.

To the best of our knowledge, only Liu et al. (2015) has recently found the impact of blockbuster project to the existing projects within categories or across categories. As summarized in table 1, they found positive concurrent spillover effect and positive lasting network externalities on within category projects.

<table>
<thead>
<tr>
<th>Table 1 Prior Research by Liu et al. (2015)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Within Category</td>
</tr>
<tr>
<td>Cross Category</td>
</tr>
<tr>
<td></td>
</tr>
</tbody>
</table>

Even though Liu et al. (2015) provided interesting preliminary results, the unit of analysis is limited to categorical competitions which is explicitly provided by platforms. Since it is empirically challenging to see the latent relationship between projects, there has been no visible relationship map between projects within the same category. Only visible classification criteria offered by Kickstarter website are considered in the previous research. Therefore, the motivation of this study is to reveal the latent market structure of crowdfunding projects and analysis of the blockbuster effects according to this market structure. As a major contribution of this paper, we adapt semantic network analysis to find latent competition between projects inside the same category according to the semantic description of each projects. To estimates blockbuster effects, we operationalize competitive relationship into within cluster and outside clusters by counting whether a focal project is included in the cluster containing blockbuster projects. To summarize, it can be divided into these four: (1) Concurrent effect at focal cluster, (2) Lasting effect at focal cluster, (3) Concurrent effect at external cluster, and (4) Lasting effect at external cluster.

According to Liu et al. (2015), the summation of (1), (3) and (2), (4) should be positive. However, our results of concurrent impact of blockbuster project shows the much larger spillover effects to the inside cluster relative to the outside clusters. This spillover effect to the outside cluster significantly increase as the magnitude to the inside cluster in the long run perspective. Our result is based on the daily level data instead of aggregation level of monthly data as Liu et al. (2015) did. We attribute our results from prior literatures to the fact that our data set is more concrete and larger than that of previous literature. Unique data set is compiled in 4 different sites through the self-developed crawler based in Python in order to get richer information, which also makes our result more robust. Our result gives practical marketing implications to entrepreneurs and platform. For instance, if entrepreneur decides to open a similar project with the blockbuster projects then she/he don’t need to hesitate in order to get an advantage from the spillover effect of blockbuster projects.

<table>
<thead>
<tr>
<th>Table 2. Four goals of this research</th>
</tr>
</thead>
<tbody>
<tr>
<td>Focal Cluster</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>External Cluster</td>
</tr>
</tbody>
</table>

2.1 LITERATURE REVIEW

2.1 CrowdFunding

Liu et al. (2015) examined the “blockbuster effect” on the crowdfunding platform by category-level analysis. “Blockbuster” refers to the dominantly successful projects compared to other existing projects Shakan and Bayus (2003). It is shown that there is a positive network effect within category and negative effects across categories (Liu et al. 2015). The projects here are aggregated by summing the pledged amount of projects within same categories. However, it is difficult to say that blockbuster project has same effect with all the other projects within same categories. There will be some projects that are deeply related to each other and the other projects that are almost independent from others.

As a result, the impact of blockbuster project could be different even within categories according to the cluster of projects inside the same category. Yet, there has been no research about the competition between individual projects within the same categories. Our study took on the position of each projects within same categories by analyzing each projects’ semantic description shown in Kickstarter.com via text mining technique. The result tells that there are differences in concurrent and lasting effect between projects within same categories, which is different from the result of Liu et al. (2015).

2.2 Semantic Network

In the online market, the product brand can be described through the consumer-posted text description and this text co-occurrence can reflect the associative and semantic network between product brands (Netzer et al. 2012). Many things inside the consumer’s comment can reflect the invisible product characteristics which can be noticed only by using the product personally. In fact, the validity of using the frequency of term occurrence on the website is proved to reflect the likelihood of corresponding phenomenon (Saiz and Simonsohn 2007). It is also found that direct comparison of products in the semantic network of consumer comments is one of the main motives to seek information for content generators (Schindler and Bickart 2005). Mostafa (2013) also finds that there is a positive consumer sentiment in consumer tweets towards famous cosmopolitan brands. Yet, there is few research that focuses on the semantic network between product description rather than consumer comments. Especially, the description of crowdfunding project includes more contents than common product description. It includes the background, purpose, risk, current situation and developing product itself more in detail. Even though projects are separated according to the characteristics of the main project, there can be latent relationship between projects in respect to project description. Our research tried to investigate the latent market structure of crowdfunding projects within the same category via analyzing the text description of each projects to shown the different semantic network.

2.3 Network Effect

Our study also connected to the network effect between projects. Network effect, which is also referred to network externality, has been appeared in many online markets and society where product utility is affected by the combination with other products (Katz and Shapiro 1994). Mostly network effects can be distinguished into two effects, which are direct network effect and indirect network effect. The classical example of direct network effect could be the telecommunication network where the utility of a product is directly connected to the consumption by users. The more users are linked to the service, the more utility of the phone
service will be (Katz and Shappiro 1985). Indirect network effect could be achieved when the increase of complementary product usage impacts on the usage of certain product with similar type (Clements and Ohashi 2005, Gandal 1995).

In crowdfunding, both direct and indirect network effects could exist. Burtsch(2011) investigated that the participation of other backers in the same project affects to the utility of certain backer and this is referred to be direct network effect in crowdfunding platform. Additionally, Liu et al. (2015) suggested that there is indirect network effect when the performance of certain project influences to the other projects’ performance by attracting new backers and making the platform more popular. Our study focuses on the indirect network effect of crowdfunding projects within same categories. Especially, we investigate the indirect network effect by blockbuster project to existing projects according to their cluster separated by semantic analysis.

3. THEORETICAL PERSPECTIVES

3.1 Two Countervailing Effects: Cannibalization Effect vs. Spillover Effects

Shakan and Bayus (2003) suggested that the blockbuster project, will increase the size of the network of projects as many backers are attracted by the blockbuster project. Strahilevitz (2003) found that the additional input resources like new backers could be shared with other related projects within same category. In this respect, Liu et al. (2015) also found positive spillover effect to the projects in the same category as the blockbuster project raise the fundraising performance in the focal category.

However, there also could be the negative spillover effects, which is called “cannibalization effect” (Ghose et al. 2006), because of the blockbuster project, as it absorbs the attraction and cash flow overwhelmingly (Shilling 2002; Noe and Parker 2005). In the product sales, consumers tend to choose blockbuster products since they consider product sales as a signal of product quality, and to minimize the searching cost and cognitive cost (Brynjolfsson et al. 2010).

Both of positive and negative spillover effect of blockbuster could be existed in crowdfunding, even though projects are in the same category. Therefore, the degree to which latent competition causes cannibalization or spill-over effects inside the same category according to the cluster of projects becomes our empirical question. Our research focuses on within category competitions to gives the answer on this. We also analyze lasting effect to find the duration of blockbuster effects with various time windows.

4. EMPIRICAL METHOD

4.1 Data

4.1.1 Source

Here, we briefly outline the procedure adopted for data collection and preprocessing. In this study, we compiled data into a project-daily level dataset from Kickstarter.com and various tracking sites. Our dataset covers the two years of period from March 1th 2014 to February 29th 2016, and contains a total of 148,398 Kickstarter campaigns that ended within this timeframe. These projects received USD $1.221B in total from 13M of contributions from backers. The procedures to collect our data is described in Figure 4. Firstly, we identify URLs of Kickstarter campaign from www.kicktraq.com because Kickstarter.com only shows currently active projects and provides a limited search engine. Based on this URL information, we retrieve project information from Kickstarter.com and historical daily level pledged amounts from Crowdlogs.com. After then, we merge this with the data from Alexa.com which records daily traffic of Kickstarter.com to control platform level popularities.

4.1.2 Identification Strategies

A natural way to identify the effects of blockbusters is to examine changes of clusters when blockbusters come in or pass away, relative to when blockbusters do not exist. Based on this basic idea, we borrow the difference-in-difference specification by constructing the sub samples for each of concurrent effects and lasting effects. We first look at how blockbusters concurrently affect the projects in the inside cluster and outside clusters using 120 days of data prior to the start of the blockbusters to its end date. Secondly, we construct the sub samples to see lasting effects of blockbusters using 120 days of prior to the start of the blockbusters and 120 days after its deadline. Also for each sample, we drop the blockbuster projects because our research focuses on the effects of blockbusters to non-blockbuster projects.

4.2 Identifying “Blockbuster” Projects within category

In this study, we firstly define categorical blockbusters with percentile of pledged amounts within the same category. Figure 2 shows examples of blockbuster identification based on a percentile based approach with the 0.05% threshold. We call this as “Categorical blockbuster”. As a result, we identify 61 categorical blockbusters from 15 different categories including Art, Comic, Crafts, Dance, Design, Fashion, Film & Video, Food, Games, Journalism, Music, Photography, Publishing, Technology and Theater. Descriptive statistics for these 61 blockbusters are summarized in Table 3. Blockbuster received a mean of $2,107,902 pledges from a mean of 18,028 backers. These blockbusters account for 12.35% of total pledged amount across every category during two years of our timeframe.

4.3 Semantic Network Construction Using Text-mining Technique

Step1. Preprocessing: We tokenize documents into words using NLTK 3.0 which is the statistical Natural Language Processing (NLP) libraries for the Python programming language including WordNet. WordNet is a lexical database of English to find conceptual relationship between words such as hypernyms, hyponyms, synonyms, antonyms etc.

Step2. Extracting important words using Tf-idf (Term frequency inverse document frequency): If a word appears frequently in a document, then we count it as the important word. However, if a word appears in many documents, then it's not a unique identifier. Therefore, we give a low score for that word. For instance, ‘a’ or ‘the’ appear many times in a focal document and many other
documents, so we need to reduce the spurious relationship caused by such words.

Step 3: Measuring distance: We measure distance between documents which are the text description of each project by converting vector of correlation of words. Firstly, correlation is defined as: $\rho_{ij} = \frac{<Y_i^j>-<Y_i><Y_j^j>-<Y_j>}{\sqrt{(Y_i^j>-<Y_i>)(Y_j^j>-<Y_j>)}}$ and $i$ and $j$ indicates each words in documents. Then correlation distance can be derived by converting correlation which satisfy metric space property. The definition of correlation distance: $d(i,j) = \sqrt{2(1-\rho_{ij})}$ Where $-1 \leq \rho_{ij} \leq 1$ and $0 \leq d(i,j) \leq 2$. If correlation closes to 1 then correlation distance also closes to 0. Conversely, if correlation distance closes to -1 then distance is closes to 2.

Step 4: Construct semantic network: Using the correlation distance, we can build complete network, every node is connected each other with some weights. However, this complete network has certain limitations because of their high dimensionality and complexity which make it for us impossible to derive meaningful relationship. Therefore, we filter out unimportant edges of the network using a hierarchical clustering method called a minimal spanning tree (MST). The MST is widely used in various research areas including biology, physics and mathematics, and it shows salient advantages by revealing underlying structures of the complete graph. (Dusser et al. 1987; Mantegna 1999; Onnela et al. 2002; Tumminello et al. 2007) The key idea of MST is that it keeps only the important edges which satisfy the tree structure.

Step 5: Clustering Method: We adapt widely used fast non parametric heuristic method that is based on modularity optimization (Vincent et al. 2008). It has outperformed all the other known community detection algorithms in terms of computation time. Moreover, the quality of the communities detected is turned out to be good, as measured by modularity (Vincent et al. 2008)

4.4 Panel Regression Model

Our empirical evaluations address the effects of blockbusters to the subsequent capital pledged of other projects. Firstly, we estimate the concurrent effects of blockbusters based on the following general model:

$$E(Y_{it}|X_{it}) = \beta_0 + \beta_1 \text{InsideBB}_{it} + \beta_2 \text{OutsideBB}_{it} + X_{it} + \theta_i + \gamma_t$$

where $i$ indicates a project and $t$ indexes time in days. The dependent variable, $Y_{it}$, is the daily level pledged amount. InsideBB$_{it}$ is one when the cluster is the same as the blockbusters, otherwise 0. OutsideBB$_{it}$ becomes one for days when the outside of the cluster has the blockbusters, otherwise 0. These two, InsideBB$_{it}$ and OutsideBB$_{it}$, are not mutually exclusive since we define the inside or outside cluster in the category level. For example, if one blockbuster exists, then the projects in the same category with the same cluster have one as the value for InsideBB$_{it}$ and other projects in the same category has one as the value for OutsideBB$_{it}$. The remaining projects in the other categories have all zero values for InsideBB$_{it}$ and OutsideBB$_{it}$. To control both unobserved campaign level heterogeneity and any unobserved time trends, our empirical model incorporates with two-way fixed effects. The term $\theta_i$ reflects project level fixed effects and $\gamma_t$ are year and monthly fixed effects. We control time-varying measure using $X_{it}$ for the platform, the cluster and the project. More specifically, $X_{it}$ control the platform level popularity using the time trends of website ranking, page view per million, page view per user and reach per million based on alexa.com dataset. For the cluster level control, we include number of projects inside the same cluster and the outside of the cluster. Also, we add a project level control variable which is the goal achieved as a percentage for the prior to the day (t-1) in $X_{it}$. The coefficient of interest is $\beta_1$ and $\beta_2$. The term $\beta_1$ shows the differential impact on the inside of the cluster that has the blockbusters as compared to the outside of the clusters. Conversely, the term $\beta_2$ represents the impact of the blockbusters on the outside of the cluster where the blockbusters are located at the same category.

Table 4. Variables which relevant to panel regression model.

<table>
<thead>
<tr>
<th>Dependent Variable</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pledged$_{it}$</td>
<td>Total pledged amount uptake for Project$_i$ on day t.</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Independent Variable</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>InsideBB$_{it}$</td>
<td>Number of blockbusters for inside clustering of Project$_i$ on day t.</td>
</tr>
<tr>
<td>OutsideBB$_{it}$</td>
<td>Number of blockbusters for outside clustering of Project$_i$ on day t.</td>
</tr>
<tr>
<td>Lasting_InsideBB$_{it}$</td>
<td>Number of blockbusters ended before the 120 days ago in inside clustering of Project$_i$ on day t.</td>
</tr>
<tr>
<td>Lasting_OutsideBB$_{it}$</td>
<td>Number of blockbusters ended before the 120 days ago in outside clustering of Project$_i$ on day t.</td>
</tr>
<tr>
<td>Num_Project_Inside$_{it}$</td>
<td>Number of all projects for inside clustering of Project$_i$ on day t.</td>
</tr>
<tr>
<td>Num_Project_Outside$_{it}$</td>
<td>Number of all projects for outside clustering of Project$_i$ on day t.</td>
</tr>
</tbody>
</table>

Secondly, we test the lasting impact of the blockbusters with the following model:

$$E(Y_{it}|X_{it}) = \beta_0 + \beta_1 \text{Lasting_InsideBB}_{it} + \beta_2 \text{Lasting_OutsideBB}_{it} + X_{it} + \theta_i + \gamma_t$$

In this model specification, Lasting_InsideBB$_{it}$ or Lasting_OutsideBB$_{it}$ have the value of one if the blockbusters are finished within 1 to 120 days at the inside of the cluster or the outside of the cluster accordingly.

5. RESULTS

To estimate our empirical model, we use negative binomial regression as our dependent variable is a significantly over-dispersed and skewed (Cameron and Trivedi 2005). We firstly analyze our concurrent effects with equation (1) by progressively adding control variables to a base model. In the base model, we just put blockbuster variables and the number of projects both inside and outside the cluster to confirm the concurrent impact of number of blockbuster projects inside or outside cluster. Then we add time-varying control variables, year fixed-effect variables and month fixed variables in a row. The result is described in the table 5.
The result in table 5 showed that there is spillover effect of blockbuster projects inside the cluster, having positive coefficients. Meanwhile, there are cannibalization effect of blockbuster projects inside the cluster, having positive coefficients. The result in table 5 considered, the spillover effect of blockbuster inside the cluster was significant. As more control variables are included, the effect is also enlarged.

Also we estimated the lasting effect of blockbuster with the sub samples which includes 120 days before and after the lifetime of blockbusters. The variables of interest are Lasting_InsideBB and Lasting_OutsideBB. Other control variables are applied in the same way with concurrent model. The result is described in table 6. From table 6, it is found that there is spillover effect of blockbuster projects both inside and outside the cluster. The results were statistically significant. The lasting effect of blockbuster projects outside the cluster showed more spillover effect compared to the concurrent model. As more control variables are included, the effect is also enlarged. The blockbuster projects attract backers’ attention and the whole category will receive spillover effect as the blockbuster project finished. It can be summarized that blockbuster projects showed the concurrent spillover effect only to the projects inside the cluster, but its effect expanded to projects outside the cluster within the same category as blockbuster projects end. The number of projects inside the cluster doesn’t show the consistent result in three models, but those of outside cluster showed the consistent negative result. The less the number of projects outside the cluster is, the more the pledged amount is received. This may imply that the competitiveness of projects increases than the pledged amounts are decreasing. Also, the interest and attention of backers will be distributed widely if there’re many projects outside the cluster.

### Table 5. Results of concurrent effects with two way fixed effect non negative binomial estimation

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>(1) Pledged</th>
<th>(2) Pledged</th>
<th>(3) Pledged</th>
</tr>
</thead>
<tbody>
<tr>
<td>InsideBB</td>
<td>0.158***</td>
<td>0.139***</td>
<td>0.142***</td>
</tr>
<tr>
<td></td>
<td>(9.15)</td>
<td>(10.46)</td>
<td>(10.58)</td>
</tr>
<tr>
<td>OutsideBB</td>
<td>-0.000596</td>
<td>0.00741*</td>
<td>0.014***</td>
</tr>
<tr>
<td></td>
<td>(-2.02)</td>
<td>(4.24)</td>
<td>(4.68)</td>
</tr>
<tr>
<td>Num_Project_Inside</td>
<td>0.000539***</td>
<td>0.000398***</td>
<td>0.000286**</td>
</tr>
<tr>
<td></td>
<td>(6.04)</td>
<td>(4.32)</td>
<td>(3.1)</td>
</tr>
<tr>
<td>Num_Project_Outside</td>
<td>-0.000952***</td>
<td>-0.00292***</td>
<td>-0.000797***</td>
</tr>
<tr>
<td></td>
<td>(-33.57)</td>
<td>(-31.96)</td>
<td>(-33.81)</td>
</tr>
<tr>
<td>Time-varying Controls</td>
<td>No Yes Yes</td>
<td>No Yes Yes</td>
<td>No Yes Yes</td>
</tr>
<tr>
<td>Year FE</td>
<td>No Yes Yes</td>
<td>No Yes Yes</td>
<td>No Yes Yes</td>
</tr>
<tr>
<td>Month FE</td>
<td>No Yes Yes</td>
<td>No Yes Yes</td>
<td>No Yes Yes</td>
</tr>
<tr>
<td>Project level FE</td>
<td>Yes Yes Yes</td>
<td>Yes Yes Yes</td>
<td>Yes Yes Yes</td>
</tr>
<tr>
<td>Observations 121154</td>
<td>114659</td>
<td>114659</td>
<td></td>
</tr>
<tr>
<td>Wald Chi  1286.9</td>
<td>3385.8</td>
<td>5265.2</td>
<td></td>
</tr>
</tbody>
</table>

Note: t statistics in parentheses

Significance Level: * p<0.05, ** p<0.01, *** p<0.001

### Table 6. Results of lasting effects with two way fixed effect non negative binomial estimation

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>(1) Pledged</th>
<th>(2) Pledged</th>
<th>(3) Pledged</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lasting_InsideBB</td>
<td>0.0912***</td>
<td>0.143***</td>
<td>0.156***</td>
</tr>
<tr>
<td></td>
<td>(10.71)</td>
<td>(16.34)</td>
<td>(17.1)</td>
</tr>
<tr>
<td>Lasting_OutsideBB</td>
<td>0.0957***</td>
<td>0.102***</td>
<td>0.145***</td>
</tr>
<tr>
<td></td>
<td>(23.5)</td>
<td>(23.74)</td>
<td>(31.66)</td>
</tr>
<tr>
<td>Num_Project_Inside</td>
<td>0.000377***</td>
<td>0.000069*</td>
<td>-0.0000012</td>
</tr>
<tr>
<td></td>
<td>(3.31)</td>
<td>(0.34)</td>
<td>(-0.77)</td>
</tr>
<tr>
<td>Num_Project_Outside</td>
<td>-0.000982***</td>
<td>-0.00329***</td>
<td>-0.000418***</td>
</tr>
<tr>
<td></td>
<td>(-30.16)</td>
<td>(-29.96)</td>
<td>(-38.69)</td>
</tr>
<tr>
<td>Time-varying Controls</td>
<td>No Yes Yes</td>
<td>No Yes Yes</td>
<td>No Yes Yes</td>
</tr>
<tr>
<td>Year FE</td>
<td>No Yes Yes</td>
<td>No Yes Yes</td>
<td>No Yes Yes</td>
</tr>
<tr>
<td>Month FE</td>
<td>No No No</td>
<td>No No No</td>
<td>No No No</td>
</tr>
<tr>
<td>Project level FE</td>
<td>Yes Yes Yes</td>
<td>Yes Yes Yes</td>
<td>Yes Yes Yes</td>
</tr>
<tr>
<td>Observations 765716</td>
<td>721452</td>
<td>721452</td>
<td></td>
</tr>
<tr>
<td>Wald Chi  1314.7</td>
<td>2667.6</td>
<td>5138.1</td>
<td></td>
</tr>
</tbody>
</table>

Note: t statistics in parentheses

Significance Level: * p<0.05, ** p<0.01, *** p<0.001

### Table 7. Summary of Results

<table>
<thead>
<tr>
<th>Clustering within Category</th>
<th>Daily Data</th>
<th>Lasting Effects</th>
</tr>
</thead>
<tbody>
<tr>
<td>Inside Cluster</td>
<td>(1) Spill-over Effect</td>
<td>(2) Spill-over Effect</td>
</tr>
<tr>
<td>Outside Cluster</td>
<td>(3) Weak spill-over effect</td>
<td>(4) Spill-over Effect</td>
</tr>
</tbody>
</table>

Our result can be summarized as it is shown in table 7. There is concurrent spillover effect of blockbuster projects both inside the cluster and outside the cluster. Positive lasting effect is observed after 120 days of period. The results of this paper give practical marketing implications to entrepreneurs and platform. Crowdfunding platform needs to properly boost projects through its recommendation systems with the consideration of blockbuster project in order to collect more fees and backers.

Our study presents preliminary findings through the semantic network analysis to discover “blockbuster effects” in crowdfunding. Our future research will be extended to several directions. Firstly, as Granovetter (1973) investigated, we will consider more detailed network topological characteristics such as tie-strengths of blockbusters. Secondly, our project level estimation could be generalized with categorical properties. Some of categories may have different impact from blockbuster projects. To achieve this, we need to extend our theoretical frameworks to build the logical hypothesis according to categorical properties such as experience goods, search goods and credence goods. Thirdly, we will extend definitions of blockbusters into categorical blockbusters and total blockbusters for the robustness
check since there is no universal and concrete definition of blockbuster projects. Fourth, we do not consider heterogeneity among the blockbusters. So we extend our model to consider their intrinsic characteristics like creativity. Lastly, also for the robustness, we will extend our empirical model with difference GMM and system GMM methods to solve the untreated endogeneity issues.

7. REFERENCES
crowdfundingplatforms/14277 , 04. 10. 2012.


