Designing successful Kickstarter Crowdfunding campaigns: A causal inference approach

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Abstract

Over the recent years, crowdfunding has become a straightforward and efficient method to raise money while keeping ownership of your project. It enables project creators to expose their ideas to a vast audience of potential funders, hoping to convince them to support their idea. However, although traditional ways of raising funding, such as pitching to venture capital funds, are well-documented processes ensuring entrepreneurs are well prepared, how to structure a successful crowdfunding campaign is yet to be determined. Focusing on 13,029 projects from the reward-based crowdfunding platform, Kickstarter, this papers aims to study the causal effect on the likelihood of success of a campaign of the following: 1) having prior experience of creating campaigns on Kickstarter, 2) receiving the Kickstarter label "Project We Love" and 3) having the $1 reward option activated for your campaign. Our findings suggest strong evidence toward a likelihood of campaign success positively impacted be all of the treatments previously cited. We find strong evidence of an effect for all three hypotheses. However, after covariate matching, the effect of the third hypothesis disappears. Furthermore, our sensitivity analysis demonstrates a lack of robustness to unmeasured covariates in our approach, suggesting confounding that our approach does not capture. For instance, social network effects on crowdfunding campaigns, which has been proved in related work to be crucial on the success of campaigns.

Introduction

Innovation and economic progress strongly rely upon the capability of companies and individuals to raise money to support research and development on new concepts and to turn their ideas into reality. Traditional ways of raising funding generally consist of convincing banks, angel investors or venture capital funds of the future profitability of your project in order to motivate them into investing in it. Nowadays, innovative entrepreneurs use alternative ways to bring momentum around their projects and eventually raise funding.

Crowdfunding is one of the main alternatives to traditional sources of funding. By allowing businesses and individuals to raise capital from a large audience through an online platform, crowdfunding offers a new paradigm for entrepreneurs to initiate, develop, or advertise their business ideas. Such an alternative has become all the more important because traditional sources, deeply rooted in the financial institutions, are running low as a result of the global financial crises that still holds a firm grip on some banks [8]. In addition to support businesses, crowdfunding has proved itself to be a valuable alternative to support scientific research [15][16] and some universities actively encourage their researchers to start crowdfunding campaigns for their work [13].

One of the key differences between crowdfunding and traditional fund raising processes is that while raising funding with the latter is mainly done in a context seeking mutual profitability for the entrepreneur and the funding institution, the relationship between an entrepreneur and its crowdfunders are fourfold depending on the context [14]. The first type of relationship follows a patronage model in which funders are placed in the position of philanthropists, who expect no direct return for their donations. It is mostly to be found in art or humanitarian projects. The second model is the lending model and consists in offering funds as a loan, with the expectation of some rate of return on capital invested. This entrepreneur-funder relationship is closer to traditional funding processes. The third approach, called reward-based crowdfunding, is by far the most prevalent. In this approach, funders receive a reward of diverse nature for backing a project ranging from kudos to opportunities to meet the creators of the project. Alternately, reward-based crowdfunding treats funders as early customers, allowing them early access to the products produced by funded projects at a better price, or with some other special benefit. The fourth type of relationship has been legalized in the United States of America on May, 16 2016 by the Title III of the Jumpstart Our Business Startups Act (JOBS) which authorizes equity crowdfunding i.e. trading shares of the future company with crowdfunding [17].

Launched on April 28, 2009 by Perry Chen, Kickstarter is one of the largest and most popular reward-based crowdfunding platforms in the United States of America. It allows a broad diversity of projects, ranging from creating a giant inflatable sculpture of Lionel Richie's Head for the 2013 Bestival [2] to designing the next generation of smart robots [3]. As of December 2019, 469,863 projects were launched on Kickstarter for which $4,6 Billion were pledge on the platform by nearly 17 Million funders, also called backers. Among these projects 174,728 were successful projects, that is they reached at least the amount of money that they predetermined as their goal at the launch of the campaign. On Kickstarter, only projects which reach their goal get the money pledged by the funders. At the completion of the campaign, if the goal is achieved, Kickstarter will charge a 5% fee on the total money raised. In case the funding campaign ends before the goal is reached the money is returned to the funders.

Projects engaging in crowdfunding on Kickstarter can pursue a vast variety of goals [11]. First, a relatively large number of crowdfunded projects seek to raise small amounts of capital, often under $1000, to initiate a particular one-time project such as organizing a birthday party. In these cases, capital is often provided by friends, family, geographically-close people or more generally people that can easily relate to the creator of the project. Second, as discussed earlier in the introduction, other crowdfunded projects use this alternative as a way to raise the initial capital required to start their new business. One of the benefits of crowdfunding on Kickstarter is the flexibility that it offers in the way entrepreneur can manage their rewards to attract backers and therefore funding as opposed to receiving investment from venture capitals, the traditional source of seed capital, which would then require shares and a key role in the decision-making of the future company. Although venture capital also offer additional services such as guidance or networking opportunities, the concept of independence while receiving funding is a key factor in the attractiveness of Kickstarter. Third, some projects may not directly seek money on Kickstarter, but are instead trying to use the platform to create awareness around their project, or to demonstrate the existence of demand for their proposed products based on the number of backers that they have, regardless of the money raised. They can later on use the results of their campaign to convince other investors.

Thus, crowdfunding financing can now be used to raise funding from a wide range of traditional and non-traditional funders. As a result, a new generation of entrepreneurs took the leap forwards into Kickstarter instead of traditional source of funding. However, on one hand those traditional routes benefit from a lot of high quality information and mentorship. How to make a convincing pitch to investors and what are their expectations are well-known questions among the entrepreneur community and entrepreneurs are awash with resources to best prepare for their face to face with investors. For crowdfunding on the other hand, little is known about how to design a successful campaign. Although an increasing amount of research has been devoted to the economic value of crowdfunding marketplaces, the causal effects of crowdfunding campaign strategies on the campaign success - i.e. its capability of raising the desired amount of money - have yet to be fully studied.

This paper aims to identify casual relationships between some of the design choices faced by entrepreneurs when they create their Kickstarter campaign so that better guidance can be given. This presents an opportunity for statistical analysis of past Kickstarter projects, and of which features can ensure a project to be successfully funded. By establishing causal connections to various potential design aspects of a campaign, this study aims to give statistically backed guidance to help a wide range of entrepreneurs and projects to reach their funding goals on Kickstarter and hopefully further reducing barriers to starting a business via this exciting new channel.

Related Work

A growing number of studies have empirically investigated crowdfunding dynamics in order to better understand patterns in investment strategies and, more precisely, to have a better sense about how to ensure a crowdfunding campaign to be successful.

The factors that lead to successful fundraising have indeed been of great interest to researchers. Several papers have pointed out the importance of the project representation, that is the Kickstarter page, and have found that many attributes related to the crowdfunding website that can strongly influence the success of a campaign.

In their paper of 2013, Greenberg et al. [5] worked on a sample of 13,000 web pages of Kickstarter projects and build a model to predict the success of a campaign based on the key characteristics of the page. In particular, they evidenced how the presence of a video presenting the project was strongly correlated to the success of a campaign. Today, almost all Kickstarter campaigns contain at least one video. Their findings also suggest that the project page content, more precisely the textual descriptions of the project and the videos presenting the project, is the key to a successfully funded campaign and therefore should be of great interest for the project creators.

In the same vein, Mitra et al. [10] collected data from 45,815 Kickstarter projects from 2012, scraped the textual contents from their Kickstarter homepages and build a natural language processing (NLP) based approach to predict whether or not a project was likely to be fully funded based on the wording of its Kickstarter homepage. Their model detected expressions that were the most correlated to the likelihood of a project to be funded. However, their results don't rely on casual inference frameworks and their list of top 100 expression to use or to not use to increase chances of success seemed difficult to turn into an actual guideline for entrepreneur writing their Kickstarter homepage.

Addionally, the choice of reward might have a strong impact on the success of a project. Sahm, Marco and Belleflamme et al. [14] compared two ways of raising money during a crowdfunding campaign: in exchange for their contribution, individuals can either pre-order the product or receive a share of future profits of the company. They showed that the potential funders prefer pre-ordering if the initial capital requirement of the project is relatively small compared with market size, and prefers profit sharing otherwise.

Finally, keeping the page content active may have an impact on the how successful the campaign is. For instance, Xu, Anbang and Yang et al. [18] focused on the impact of updates during the campaign and showed that updates are critical to the success of a campaign. They sampled 8,529 campaigns from Kickstarter and showed that campaigns with updates would be more likely to be successful than campaigns without updates. Then, focusing on campaigns with updates, they analysed the impact on the how successful a campaign is based on the type of updates: Social Promotion, Promotion, Progress Report, New Content, Reminder, Answer Question, New Reward and Appreciation. They trained a hierarchical logistic regression and then interpreted the weights to have their results. They found that the type of updates and the time of the campaign during which the update was made (beginning, middle or end) would have different impact. For instance Progress Report made at the middle of the campaign will have positive effects on the likelihood to succeed while if made at the beginning or at the end of the campaign, it will have a negative effect.

Moreover, in addition to the project page, which encapsulates intrinsic characteristics of the projects, other papers highlighted how external phenomenon can also have an impact on the capacity of a crowdfunding campaign to fulfill its goal.

In their work, Gerber et al. [4] reported findings on what motivates individuals to invest in crowdfunding campaigns by relying on a qualitative exploratory study of funders from three popular crowdfunding platforms: RocketHub, Kickstarter, and IndieGoGo. They evidenced that aside from obvious motivators such as the early access to exiting products, people are also motivated to participate in crowdfunding campaigns because of social interactions and feelings of connectedness to a community with similar interests and ideals. Their research suggests that a growing community of funders could attract more even more funders seeking to join the community around a project.

Interestingly however, Kuppuswamy et al. [7] shows in their paper that potential backers choose not to contribute to a project that has already received a lot of support because they assume that others will provide the necessary funding. Which could suggest that a project with a growing number of funders exited to bring the project to life could at some reach see a slow down in its new number of backers given they would feel less "important" for the project success. More broadly, in their paper, using two years of publicly available information on successfully and unsuccessfully funded Kickstarter projects, they empirically studied the role of social information in the dynamic behavior of project backers, and presented a couple of additional findings. First, their findings illustrated the deadline effect, which states that the a project which has momentum behind it has a much better chance of being funded, especially late on in the process. Second, they found that project updates asking for a last help near the deadline tended to increase the revenue pledged.

Still on the topic on the influence of social networks on campaign success, Agrawal et al. [1] studied funding patterns on Sellaband, a crowdfunding platform launched in 2006 and dedicated to new musical artists that have not yet signed to a record label . In their paper, they followed over weeks 18,827 artist-funder pairs split by rather or not the artist and the funder are within 100 km. They evidenced that local funders are more likely to invest in the early stage of the fundraising campaign - before the artist raises $20,000 suggesting that a proximity with the artists could contribute to create the interest needed to motivate the investment.

Finally Mollick E. [11] studied 48,500 projects with combined funding over $237 M and suggested that personal networks and underlying project quality are associated with the success of crowdfunding efforts, and that geography is related to successful fundraising.

Thus, previous research work conducted on Kickstarter projects but more broadly on crowdfunding dynamics evidenced that several characteristics intrinsic to the campaign such as project page content or updates, and/or extrinsic to the campaign such as the social network of the campaign creator may have an impact on the likelihood for a project to succeed. However, only a few of them rely on a rigorous causal inference methodology to support their findings. Moreover, the causal effect of some specific features from Kickstarter are yet to be studied.

Motivation

Kickstarter has managed to create momentum around its platform and has a loyal community of people looking for the next exciting project that they will help funding. In addition, Kickstarter offers some unique features that are designed to help creators to make their project a reality. For instance, the platform offers a service of A/B Testing enabling each creator to try several versions of their homepage to potential funders. As such, they can measure which version is more likely to create the conversion of a potential funder to an actual one. However, the success rate on Kickstarter is only at 37.45% and only a few creators are comfortable with using the Kickstarter A/B testing tool. There is no knowledge sharing at scale about the results of these specific experiments to establish statistically-backed guidance.

In this paper, we are interested in conducting experiments across Kickstarter projects to evidence causal effects of some campaign characterises to the likelihood of success. As seen in the "Related Work" section, many factors can have an impact on the success of a campaign and detecting some of these signals will be difficult. For the sake of feasibility, we are making a strong assumption by focusing our approach on the characteristics that are defined at the very beginning of the campaign and which remained fixed during the whole duration of the campaign.

A campaign creation on Kickstarter mainly consists of the creation of the campaign page and all its content, which is by far the most crucial part of the process. The design of the campaign includes:

1. Find a name for its project.
2. Write down a quick description of the project called a blurb which will be shown under the name of the project homepage.
3. Write an inspiring story of the project to attract potential funders.
4. Write the full description of the project specificity by putting yourself in the shoes of a potential funding to anticipate his or her questions.
5. Create a Campaign Video.
6. Set a Campaign Goal and Duration.
7. Choose the rewards that the funders will receive upon the completion of the campaign if it reaches its goal.
8. Choose Launch Date and Time.

Although, there are no clear methods on how to successfully fulfill each of the previous points, there is some general advise shared by people with some previous experience such as "Never launch your campaign on a weekend or on Black Friday". Looking at the steps to follow, it is also possible to just use intuition to estimate which choices have a positive or negative impact on the success of a campaign. In order to support our intuition and to come up with some hypotheses to test, we collected data from previous Kickstarter projects.

Data

In order to investigate the factors that have an impact on the success of a campaign, we constructed a list all the projects that had been launched on Kickstarter, made available by the scraper robot from the website Web Robots [12]. For each project, Web Robot added some information such as the id of the creator, the date at which the campaign was launched, the Kickstarter project URL. From that list we collected a sample of 17,652 Kickstarter projects by randomly sampling among the 287,430 Kickstarter projects launched between 2016 and 2019 which reached the end of their campaign. Projects that were still live and projects that were canceled by their creators or by Kickstarter, for instance for intellectual property dispute, were not considered. We aimed at collecting around 5% of all the projects available in order to match the sample size used in past studies of Kickstarter projects. Then, using the URLs of the sampled projects, we created a script to scrape each Kickstarter homepage project, in order to collect all the campaign information that we needed from the HTML project homepage. Only projects that were still publicly available at the time of this study were considered. Our goal was to collect enough covariates to characterize the specificity of each of the Kickstarter projects, and also to collect the information needed to flag our treatment groups. The selection of the collected covariates and of the characteristics to use as a treatment are discussed in the Hypotheses and in the Method sections. After additional filtering, the final number of projects considered is 13,029. The Table 1 shows the distribution of our data across the 15 Kickstarter project categories and the Table 3 and Table 2 respectively shows the description of the covariates used and the distribution of our control and treatment groups.

Category	**Successful**	**Failed**	**Total**
Art	406	512	918 (44.2%)
Comics	223	105	328 (68%)
Crafts	60	156	216 (27.8%)
Dance	117	32	149 (78.5%)
Design	617	103	720 (85.7%)
Fashion	328	571	899 (36.5%)
Film/Video	1,109	852	1,961 (56.6%)
Food	331	613	944 (35.1%)
Games	677	496	1,173 (57.7%)
Journalism	47	181	228 (20.6%)
Music	1,063	808	1,871 (56.8%)
Photography	145	170	315 (46%)
Publishing	587	968	1,555 (37.7%)
Technology	329	1,084	1,413 (23.3%)
Theater	266	73	339 (78.5%)
Total	6,305	6,724	13,029 (753%)

Table 1: Distribution of the sampled projects across the 15 Kickstarter project categories

Hypotheses

Based on more reading and research, we found 3 main phenomenon, measurable from our data and which may be suggested to have an effect on the likelihood of having a successful campaign.

Having prior experience on Kickstarter

Building on the previous section, most of the resources which gives concrete and actionable advice to future crowdfunding campaign creators are not based on rigorous causal experiments but mostly based on anecdotal evidence and personal experience. In fairness, it should be said that some online resources were found based on A/B Testing experiments, but the framework used in their experiments were specific to one creator campaign using the Kickstarter A/B testing tool, and the generalisability of the results is yet to be proved.

Given how experience seems to be a factor of improvement for the design of Kickstarter campaigns, we decided to explore that road by studying the likelihood of campaign success based on the experience of the creator on Kickstarter. Essentially we are interested in knowing the impact on the success of the campaign of whether or not it is the first Kickstarter campaign from the creator .

From our dataset this means that we used the whole Web Robots dataset with all projects from 2016 to 2019, and for each project we counted how many prior Kickstarter campaigns its creator had launched at the time of the project's launch. We did not take into account projects created before 2016.

The Kickstarter ”Project We Love” label

Kickstarter always keep on eye on the projects that are launched on its platform. When a project stands out, the project is awarded with the label ”Project We Love”. The label will appear on the project homepage and shows to the Kickstarter community that Kickstarter support the project. It also allows the project to appear on a different search category among the others ”Project We Love” campaigns.

Although Kickstarter does not disclose the exact criteria used to determine if a project will receive this label, common characteristics of ”Projects We Love” include a very crisp project page with a clear description, captivating images or video, a thorough plan for completion, an excited community and strong creativity. The effect of the presence of this label on the likelihood of success for a campaign has not yet been studied, however, it seems reasonable to think that this label reinforces the image of the project ensuring it to gain momentum and eventually to raise money.

The power of $1 dollar

One of the key features of Kickstarter is the reward-based system ensures that campaign creators clearly decide how the potential funders can contribute to their campaign, and what they can expect in return of their financial support. The campaign creators set a number of rewards, called levels, and for each level they can set a the minimum price that the backers would be expected to pay, and what they can expect in return. Potential funders who are interested in a particular reward can then decide which amount of money they want to pay, as long as it is above the minimum amount set by the campaign creators. In short, rewards are the hook to motivate potential backers to support a project.

However, Kickstarter also allows its creators to activate the option of a ”$1 dollar” reward. This option ensures potential funders to give a minimum of $1 dollar to the campaign, with nothing in return except the joy of knowing that they contributed to making a project become a reality. Although, this option may surprise at first, Kickstarter itself described in its blog the power of $1 [6] by explaining that this reward is a way to capture backers' attention and to influence them into growing interest around your project. Giving $1 is a simple gesture but one which contributes to support the project, to keep engaged with the project and to join its community. The idea behind this reward is to increase the community around the project even though the amount of money pledged does not increase much. This new community can then be the key to create the momentum needed to attract other backers which are willing to invest more money into the project, and that is why we are interested in studying the effect of the presence of $1 reward in the campaign.

Hypotheses formulation

The three previous intuitive phenomenon are the three hypotheses that we shall study in this paper. We designed our 3 treatments to be mutually exclusive to focus on the ”pure” treatment effect of each the 3 treatments versus the control. As such for each unit / project i the assignment vector was three dimensional and our analysis considered four potential outcomes: $Y_i(0,0,0)$, the control, and $Y_i(1,0,0)$, $Y_i(0,1,0)$, $Y_i(0,0,1)$, pertaining to pure treatment assignment of prior experience, being a ”Project We Love”, and having a $1 reward respectively. Assignments involving multiple treatments were not analysed. In order to further motivate our choice of hypotheses, the table 2 and Fig 2 shows the success rate across this 3 treatment groups and in the control group. We can indeed see that a possible treatment effect may be observed.

Therefore, we would like to test the three following hypotheses:

Hypothesis 1:
A project campaign created by an experienced entrepreneurs - founders who have previously launched a project on Kickstarter - has a higher chance of reaching its funding goal than one created by someone new to the platform.

Hypothesis 2:
Being marked on the list of ”Projects We Love” by Kickstarter give projects a better chance of being funded.

Hypothesis 3:
Allowing $1 reward positively impact the likelihood of a project to get funded.

Group	Success Rate	# Projects
Control	40.11%	8,332
Treatment 1	70.22%	1,209
Treatment 2	85.44%	1,168
Treatment 3	48.1%	2,320
Total	100%	13,029

Table 2: Description of the data across the 4 groups.
Treatment 1: Having prior experience of Kickstarter
Treatment 2: Having the Kickstarter ”Project We Love” label
Treatment 3: Allowing a $1 reward

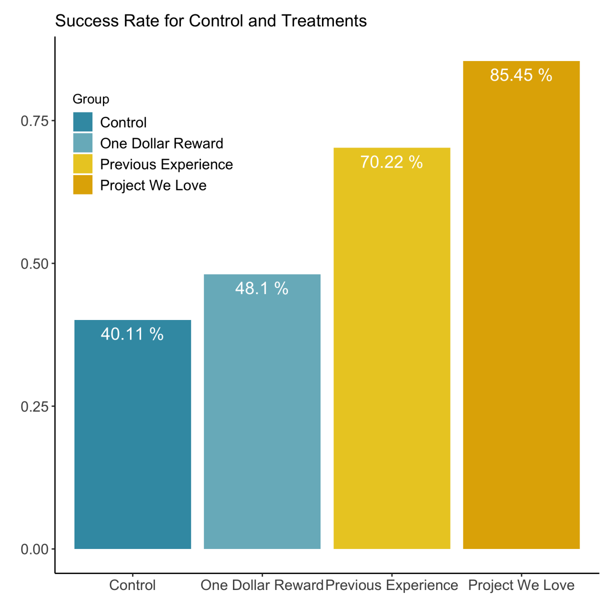

Figure 1: Success rates for each of the different treatments

Method

Sample

As explained in the data section, the Kickstarter projects were randomly selected among those publicly available and launched between 2016 2019, and which reached the end of their campaign deadline.

Unit of Analysis

The unit of analysis in this paper are all projects which have reached their last date for collecting money. This ensures that our dataset contains only those projects which have reached their end date and thus have a clear outcome: funded or not funded.

Pre-processing Protocol

The goal of our project is to capture the effect of choices made by the campaign creator when designing the campaign on the final outcome i.e. if the project reached its funding goal. As explained in the introduction, some projects, such as those with a goal of less than \$1000, tend to attract funding more from people associated in some way to the creator of the campaign. This could result in complex network effects which interfere with some of our assumptions, so we decided to remove these projects.

Moreover, given the vast diversity of the projects on Kickstarter, especially regarding the amount of money raised, we decided to remove the outliers by removing outside the 1.5 times the Inter Quartile Range of the total amount of money pledged. This served to improve the integrity of the underlying data. We did not identify any other sources of outliers.

Assumptions

To conduct this study, we would like to rely on the Stable Unit Treatment Value Assumptions (SUTVA). We therefore assume that our treatment does not affect the outcome of other projects and that each of treatment is unique at least at first approximation. We also assume strong ignorability, that the assignment mechanism is probabilistic, individualistic, and unconfounded. We discuss the implications of these assumptions later in the paper, in particular SUTVA and the unconfounded part of ignorability.

Outcome

The outcome studied here is whether or not the project reaches its goal regarding the funding. Projects who just reached their goal and projects which exceed their goal will be considered equally successful in this approach.

Estimands

The estimand that we are trying to estimate in this study is the average treatment effect of one of our three treatments versus our control group that we define as projects that are the first Kickstarter projects from their creators, does not have the "Projects We Love" label, and does not have \$1 dollar reward. For these three treatments then, the estimands are:

$$\tau_1^{ATE} = \frac{1}{N}\sum_{i=1}^{N}(Y_i(1,0,0) - Y_i(0,0,0))$$

$$\tau_2^{ATE} = \frac{1}{N}\sum_{i=1}^{N}(Y_i(0,1,0) - Y_i(0,0,0))$$

$$\tau_3^{ATE} = \frac{1}{N}\sum_{i=1}^{N}(Y_i(0,0,1) - Y_i(0,0,0))$$

Estimator

We use the appropriate difference in means estimator which is unbiased for τ^{ATE}:

$$\frac{1}{N_k}\sum_i Z_{(k)i}Y_i - \frac{1}{N_0}\sum_i (1 - Z_{(k)i})Y_i$$

Where $k \in \{1,2,3\}$ and Z_k is an indicator variable taking value 1 if treatment k is applied, and 0 if the unit is assigned a control.

Experimental Design

For each hypothesis, we calculated the p-value both under Fisher's null that there is no treatment effect at the level each unit, and under Neyman's Null that the average treatment effect is zero. The value for our estimand, the variance, and confidence intervals under Neyman's null were reported. For the latter we used the normal approximation given that our dataset was large.

To justify the ignorability assumption, we used a number of covariates, summarized in the table below, to perform propensity score matching, and the analyses were run again. The Mahalanobis distance was used as the distance metric, and a propensity caliper of 0.1 was included. The purpose of this was to simulate, as closely as possible, a paired randomized design and so $\eta^* = PRD(1/2)$. Finally, as one of the key potential problems with the setup was the assumption of no unmeasured confounders, and given that our covariate set was potentially still light even

Covariate	Description	Min	Max	Mean	STD
blurb_word_count	Number of words in blurb	1	33	19.03523	4.969301
category_art	Dummy variable for the category	0	1	0.07045821	0.2559275
category_comics	Dummy variable for the category	0	1	0.02517461	0.1566612
category_crafts	Dummy variable for the category	0	1	0.0165784	0.1276903
category_dance	Dummy variable for the category	0	1	0.01143603	0.1063302
category_design	Dummy variable for the category	0	1	0.05526134	0.2284984
category_fashion	Dummy variable for the category	0	1	0.06899992	0.2534637
category_film_video	Dummy variable for the category	0	1	0.1505104	0.3575847
category_food	Dummy variable for the category	0	1	0.07245376	0.2592477
category_games	Dummy variable for the category	0	1	0.09002993	0.2862356
category_journalism	Dummy variable for the category	0	1	0.01749942	0.1311279
category_music	Dummy variable for the category	0	1	0.1436027	0.3506999
category_photography	Dummy variable for the category	0	1	0.02417684	0.1536038
category_publishing	Dummy variable for the category	0	1	0.1193491	0.3242113
category_technology	Dummy variable for the category	0	1	0.1084504	0.3109603
category_theater	Dummy variable for the category	0	1	0.02601888	0.1591975
duration_campaign_launch_to_deadline	Number of days of the campaign	1	92	34.44593	12.18118
has_faq	If the campaign has a FAQ	0	1	0.1820554	0.385905
is_asking_for_help	If the burb says 'Please help'	0	1	0.008519457	0.09191041
rewards_levels	The number of levels	1	102	8.270167	5.533338
rewards_max	The maximum reward	0	10525	1810.812	2712.906
rewards_mean	The average reward	0	10000	391.4246	659.6496
rewards_min	The minimum reward	0	10000	39.86607	412.1359

Table 3: List of covariates and their description

after the data mining and preprocessing steps, we performed sensitivity analysis to determine the largest sensitivity parameter Γ_α for a significance level $\alpha = 0.05$.

Results

For all three Hypotheses, Fisher's p-value was zero after 1,000 permutations. Although this may seem surprising, given that 1) we had a very large dataset, 2) the observed treatment effect is large and 3) Fisher's null is sharp, this actually should not be unexpected, and showed some promised for the analysis. Similarly under the less strong Neymanian model p-values were seen to be very close to zero, at 1.54E-33, 8.96E-40, and 1.75E-05 for Hypotheses 1,2 and 3.

Covariate matching was performed as described above. After matching the effect from Hypothesis 3 was sharply reduced, causing Fisher's p to rise to 0.25. This suggests that indeed the effect we observed before matching was due to confounding from our covariate set, so we conclude that there is not information in the data to support the hypothesis that having a one dollar reward has a causal impact on funding success. For the other two hypotheses, after matching the effects were still extremely statistically significant, and so we performed sensitivity analysis to test whether the matching sufficiently controlled confounding.

The parameter $\Gamma\alpha$ tells us how much we can alter the odds ratios of treatment assignments for the two groups, and specifically how large this can get while still showing significance at the 5% level. For hypothesis 1 we observed $\Gamma\alpha = 2.07$, and for hypothesis 2 we observed $\Gamma\alpha = 2.90$. These tell us that there was considerable unmeasured confounding outside of our covariate set. However, this was something we had foreseen as a potential issue with the analysis, and although we would like to see a far lower sensitivity parameter, there is good evidence to suggest a potential effect and the causality of this can be supported in a follow up study with a richer set of covariates.

Discussion

There are three main points about our assumptions which cause concern, and are grounds for further work on this topic.

Firstly, there are two routes by which assignment of each of the treatments could affect the funding chances

	When	$\hat{\tau}$	p_Fisher	p_Neyman	$\hat{V}$	CI_lower	CI_upper	Γ_α
H1	before matching	30.11%	0	1.54E-33	0.000628	30.06%	30.16%	
	after matching	15.30%	0					2.07
H2	before matching	44.23%	0	8.96E-40	0.001132	44.16%	44.30%	
	after matching	24.35%	0					2.9
H3	before matching	6.55%	0	1.75E-05	0.000250	6.51%	6.58%	
	after matching	0.59%	0.25					NA

Table 4: Results Table

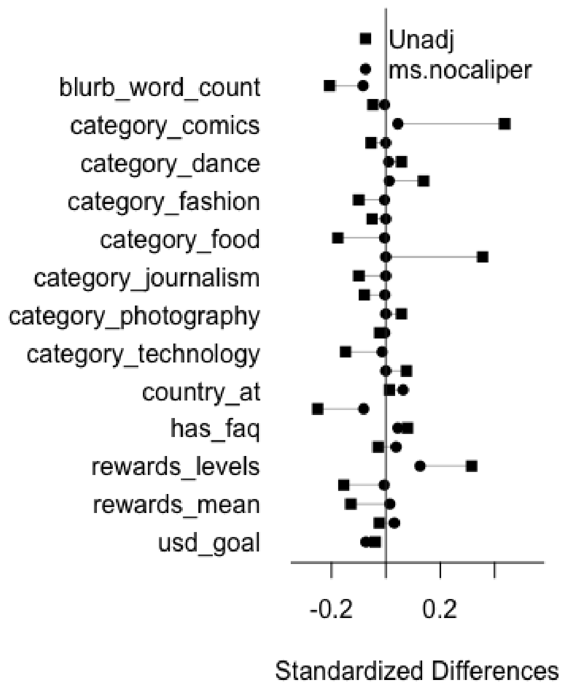

Figure 2: Covariate Balance pre and post matching

of other projects, thus violating SUTVA. Liu et. al. [9] suggest that "blockbuster" projects exhibit positive spill-over effects within project category, but cannibalization effects across categories. Extremely successful projects attract attention and create publicity to the platform, creating an increase in the overall amount of funding, and so increasing the chances of success for individual projects. A contrary but also very valid phenomenon is if these kind of effects do not exist, and so the total amount of funding is fixed, an intervention which increases the chances of one project must, via this zero-sum process, reduce another project's chances.

Our sensitivity analysis demonstrated that there is more work to be done in establishing causality. Although steps were taken to try to do feature engineering with the data, a deeper preprocessing pipeline is required to capture enough of the unmeasured confounding to better support causality.

There are potential sources of bias in the assignment mechanism. One very salient example is that Kickstarter are likely to give its endorsement to projects which already have a high chance of success, which is determined by external factors potentially not in our analysis. Again, this could be addressed by having better covariates.

Conclusion and Future Work

There are a number of potential enhancements which could be made to the covariate set. The most promising of these involve better mining the text elements using NLP techniques. Specifically, if a pipeline could get more information on the specifics of the project itself, and capture a metric for how professionally and well presented the information is, this should create meaningful improvements of the analysis. As an extension, computer vision techniques could be used to get information from the video content.

Given that Kickstarter sees so many projects on the platform, they could carry out a Controlled Randomized Trial on a small subset of the projects with the intention of improving the overall funding experience. The same set of treatments discussed in this paper could be used as a multi treatment, Completely Randomized Design with balanced group sizes.

This could lead to a whole new branch of experimentation on the platform, with far more defensible causal arguments than can be achieved in an observational study without significant work on study design and feature engineering. They would likely be low cost to run. For example, does time, day, or even seasonality affect chance of success? Do traditional A/B testing experiments such as colors on the web page have an effect?

In conclusion, our analysis shows that both having had prior experience on Kickstarter and being featured on their "Projects We Love" have a statistically and practically significant effect on the chances of the project being funded. More work is required for strong support of a causal claim, but the study presents a framework with which study design could become something that crowdfunding platforms continually and quantitatively improve, creating a more fertile funding environment in this exciting, fast growing area.

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