What factors are responsible for success or failure of crowdfunding campaigns?

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Table of Content

Introduction

According to Investopedia, crowdfunding refers to the “use of small amounts of capital from a large number of individuals to finance a business venture”. One advantage of using crowdfunding is that entrepreneurs can get funding and thus realize their project without having to go through different financial intermediaries. The problem with it is that not all campaigns listed on the crowdfunding platform will be successful in securing the full funding. Here, various factors play role, and accordingly in our work, we aim to answer the following research question: What factors are responsible for success or failure of crowdfunding campaigns? For this, we used the Kickstarter data from the report “Predicting Kickstarter campaign Success” by Rachel Downs and Muhammad Ghuari. Here, we considered the success or failure of the campaigns as our dependent variable. As for independent variables we considered the amount required for the project, choice made by crowdfunding platform’s staff, number of words in the title of the campaign, number of words in the description of the campaign, number of days between the creation to the launching of the campaign and number of days between the launching to the deadline of the campaign as our main independent variables. We used the probit model for our regression, and we also considered other variables present in the dataset as our control variables. We found that the amount required for the project and the number of days from the launch to the deadline of the campaign was negatively correlated, whereas choosing of certain campaign by crowdfunding platform’s staff and the number of words in the title of the campaign was positively correlated to the success of crowdfunding campaigns.

Literature Review

Determining factors responsible for success or failure of crowdfunding campaigns, however, is not new as various research has already been done in this area. So, for our literature review, we at first aim to understand the basic economics and then looked at supply and demand side of crowdfunding platforms. Finally, we looked at literature that identified some factors that led to successful crowdfunding campaigns both in developed and developing countries.

Before delving into factors that might make certain crowdfunding campaign successful, we first would like to know the overall economics of the crowdfunding platform, and as such we reviewed the article “Some Simple Economics of Crowdfunding”. Here, authors Ajay Agrawal, Christian Catalini, and Avi Goldfarb looked at different economic theory that might have explained the growth and then offered framework for the further development of crowdfunding platforms. First, they explained that one of the reasons for rise in crowdfunding was due to low transaction cost because of the internet. For instance, they explained how funders and creators can be matched more easily as the cost for searching one another have gone low. Second, they explained that another reason for the rise in crowdfunding might be because of their good reputation. They indicated this by mentioning the passage of the JOBS Act by bipartisan support, where one of the key provisions was to legalize equity in crowdfunding. Finally, the article went to explain how the information asymmetry and collective action problem in the present market have led to market failure. Authors then provided solution by recommending platforms to establish norms using four market design mechanisms, which were reputation signaling, rules and regulation, crowd due diligence, and provision point mechanism.

The main issue with this paper is that authors only went through the theoretical framework to explain the success and effectiveness of crowdfunding campaigns. That is, they did not conduct any experiment to determine the correctness of their theory. So, although the economic theory they presented looks appealing, it should be only be taken lightly.

Our work will differ from this paper in that we will be conducting experiment to determine factors leading to the success of crowdfunding campaigns instead of explaining the theoretical reasoning behind it.

In the paper, “Demand and supply sides of the crowdfunding ecosystem: The case of Kickstarter campaigns and potential Hungarian investors” authors Roland Zs Szabo, Reka Szasz, and Borbala Szedmak tried to analyze both “the demand and supply sides of the crowdfunding ecosystem.” To analyze the demand side, they conducted a survey to determine how much the public was aware of crowdfunding sites. The survey was conducted among 132 participants, where 84% were from Hungary, and 16% were from elsewhere. To analyze the supply side, they analyzed a database consisting of 259,114 Kickstarter campaigns, which were from 2012 to 2016. From this research, they were able to determine several factors that may have led to success of crowdfunding campaigns. They thus recommended the following to make the campaign successful: the project presentation should be appealing, pool of awards should be diverse, funding goals should have realistic expectation, categories and pledge amounts should be appropriate, and communication about the campaigns should be frequent and satisfactory.

One issue that this paper had was on the inconsistency on the scope of data that they analyzed. While analyzing the supply side, they examined campaigns from around the globe, however while analyzing the demand side, most of their sample data consisted of people from the Hungary only.

Our work will differ from this paper in two ways. First, we will not be examining the demand side but will only focus on the supply side of the crowdfunding ecosystem. Next, instead of using a simple statistical analysis of the data, we will utilize regression model to get meaningful results from the data.

There has also been an attempt to look at the role of gender characteristics in determining the success of crowdfunding projects. In the paper, “Gender role congruity and crowdfunding success”, authors Birton J. Cowden, Steven A. Creek and Joshua D. Maurer attempted to explore whether an entrepreneur aligning with feminine or masculine characteristics based on his/her gender can affect the success of crowdfunding projects. Here, ratings were given to 2071 entrepreneurs from Kickstarter based on agreeableness and humility, which authors determine as feminine characteristics, and assertiveness and emotional stability, which authors determine as masculine characteristics. These ratings were then used in the regression model to determine the success of the project. They found that gender role congruity did play a role in determining the success of crowdfunding projects. In other words, they found that when female entrepreneurs were more feminine and when male entrepreneurs were more masculine, it increased the success of their Kickstarter project.

The issue with this paper is two folds. First, is that the sample size was of limited nature. Even though they mentioned that they used random sample of videos, they only used 234 videos for this research. Second, is that they only considered male and female characteristics for their regression model. Other factors must also have affected the success of crowdfunding project, but they did not consider it.

Although we will be using similar regression methods, our work will be different in that we will not be including gender characteristics in our regression model.

The success of crowdfunding campaigns so far we discussed looked at developed countries. But, the question may arise whether those factors still remain same if we analyze it in developing nations such as in Africa. The paper "Crowdfunding in Kenya: Factors for Successful Campaign" attempts to do just that. Here, the authors, Esther Wanjiru Wachira and Virginia Kirigo Wachira, attempted to analyze and identify factors for a successful crowdfunding campaign in Kenya. For the data, they used Kickstarter data, and for the techniques they used multiple regression and Pearson correlation methods. From their study, they found that the number of successful campaigns were strongly and positively correlated with the updates about the project, the number of backers, i.e number of people funding the project, and the amount pledged by backers. Next, the number of successful campaigns were moderately but positively correlated with comments i.e. communication between founder and backers, number of new backers, and number of returning backers. Finally, the number of successful campaigns were negatively but insignificantly correlated with the goal i.e. the amount that needed to be raised and the funding period i.e. the duration of the campaign. From this, they concluded that factors for successful crowdfunding campaigns in developing countries like Kenya were no different as seen in other countries.

On issue with this paper is that they failed to mention the details of the data. They did not provide details on how it was acquired, and which year of Kickstarter data was used. The next issue was their sample size. They mentioned that only 173 crowdfunded projects of Kenya were used for the analysis, which might be too small to draw appropriate conclusion.

Although we will also be implementing similar regression analysis in our work, the main way our project will differ is that we will not limit our data to Kenya but look at crowdfunding campaigns globally.

Till now, we looked at different factors that led to the success of crowdfunding campaigns. But what if there was some way where we can predict the success of campaigns beforehand. The two papers that we are going to discuss have looked at this aspect.

In the project report, “Predicting Kickstarter Campaign Success” by Rachel Downs and Muhammad Ghauri, authors were trying to build a model, which can predict the success of the campaign so that the Kickstarter can provide timely advice and material to campaign, which were predicted to be not successful. For this, they looked at 20,632 campaigns taken from the Kickstarter website on February 1st, 2017. Then, they built the model by comparing five different modeling techniques and choosing the best one from them. The main outcome was they were able to build a model, which was able to predict the outcome of a Kickstarter campaign. One implication of this work was that the Kickstarter can use this model to aid campaigns that were below the prediction threshold of success by assigning “staff pick” tag to increase the number of campaigns succeeding in their platform. Here “staff pick” refers to the tag that Kickstarter staffs give to certain campaigns that they liked.

The potential issue with this project might be overusing of the “staff pick” tag. As they mentioned in their report, when this tag is assigned to many campaigns that are predicted to fail, it might lose its value, and may not increase the platform’s success rate as desired.

Our work will differ with this project in two ways. First, we will not work to build predictive model that determine the success of different Kickstarter campaigns. Second, the project only did some statistical analysis to the given dataset, however, we will be using the regression model to obtain insights from the dataset.

The above paper looked at how a predictive model can be built which benefitted crowdfunding platforms. But the question may arise whether similar kind of predictive model can be built to instead help creators of crowdfunding campaigns. This was looked at the paper, “Do Machine Learning and Business Analytics Approaches the Question of ‘Will Your Kickstarter Project be Successful?”. Here, the main research question that authors, Murat Kilinc, Can Aydin, and Cigdem Tarhan, looked at was whether business analytics and machine learning methods together can be used to aid in the decision process that entrepreneurs make? The main outcome was that they were able to devise a web application system which provided success prediction for different Kickstarter projects. The methodology that they used is described as follows. First, an analysis and evaluation of data consisting of different project features were conducted using business analytics. Then, using machine learning methods, data was trained and prepared for classification. Finally, business analytics and machine learning were implemented together to determine the success of projects. In this step, features of the project that an entrepreneur entered were considered as input, business analytics was then utilized to make comparison with other projects, and finally machine learning methods was implemented to estimate the success of the project.

One issue with this paper, which they have mentioned, is that they have excluded certain factors present in the dataset such as past experiences of the project owner, audio materials and project visual. As a result, the system they have built might not provide accurate estimate to a higher degree.

The way our work will be different is that we will not be working on building predictive model using machine learning. Instead, we will only be focusing on regression techniques to determine factors leading to success of crowdfunding campaigns.

After going through the literature, we firmly believe that using regression model to determine factors that lead to success or failure of crowdfunding campaigns can fill up the existing hole in the literature. For our analysis, we determined to use the same data present in one report mentioned in the literature. However, the report had used simple analysis to extract features from the dataset. But, in our work, instead of simple analysis, we will use regression model to do the same. We also came across papers that were using similar regression model that we intend to use in our analysis. However, in our work, we will be implementing similar regression model but in different dataset.

Methodology

The purpose of our work is to determine various factors that result in the success or failure of crowdfunding campaigns. Since Kickstarter is one of such crowdfunding platforms, and since data was readily available, we chose to answer our research question by looking at factors that led to success or failure of Kickstarter campaigns. In fact, the data for our research will be same as that utilized in “Predicting Kickstarter campaign Success” by Rachel Downs and Muhammad Ghuari, and the required data was obtained from the Kaggle. According to the report, the dataset contained data on “20,632 Kickstarter campaigns on the site as of February 1st 2017” (Downs and Ghuari).

<u>Variable description:</u>

A) Dependent Variable:

State will be our dependent variable, and its description is given below.

a)state:

This represents the state of the campaign at the time the data was gathered. There were four states of the campaign: successful, failed, canceled, live or suspended. Here, we considered the campaign to be successful when the state was “successful”, but failed when its state was “failed”, “canceled” or “suspended”. However, we did not considered “live” data, and thus removed it because it would not provide much meaning when considering it either on the success or failure of the campaign.

B)Independent Variables:

a) goal:

It refers to the amount of money needed for the successful completion of the project. We consider it to be an important variable which can affect negatively the success of the campaign. Here, the amount was in different currencies, so we changed all of them to USD from the conversion rate provided in the data. To verify that these conversion rates were accurate, we compared them with the conversion rate from Organisation for Economic Co-operation and Development(OECD), and found that these rates were pretty close to each other. For the analysis, however, we used the natural logarithm of this variable as it was strongly skewed to the right.

b) country:

It refers to the country from where the campaign was launched. Some of the countries are the United States, Great Britain, Canada and so on. Here, we have taken the US as our base category.

c)staff_pick:

It refers to the campaign that the staff from Kickstarter themselves liked. Its state was TRUE when they liked certain campaign. We consider this to be another important variable as we assume that the campaign which get liked more will have higher probability of success.

d)category:

It refers to the type that the campaign fell into. Here, we considered Academic to be our base category so that we can look how successful non-academic categories are in comparison to the academic category.

e) name_len_clean:

It refers to the number of words in the title of the Kickstarter campaign after removal of stop words. Stop words refers to common words such as articles, conjunctions, and so on.

f) blurb_len_clean:

It refers to the number of words in the description of the Kickstarter campaign after the removal of stop words.

g) deadline_weekday:

It refers to the day of the week that the campaign deadline fell.

h) created_at_weekday:

It refers to the day of the week that the campaign was created.

i)launched_at_weekday:

It refers to the day of the week the campaign was launched.

j)deadline_month:

It refers to the month that the campaign deadline fell.

i)deadline_year:

It refers to the year that the campaign deadline was set.

j)created_at_month:

It refers to the month the campaign was created. Here, 1 refers to January, and 12 refers to December.

k)created_at_yr:

It refers to the year the campaign was created.

j)launched_at_month:

It refers to the month the campaign was launched.

k)launched_at_yr:

It refers to the year the campaign was launched, where 1 refers to January, and 12 refers to December.

l)create_to_launch:

It refers to the number of days passed from the creation to the launching of the campaign.

m)launch_to_deadline:

It refers to the number of days passed from the launch to the deadline of the campaign.

Summary Statistics:

Here is the summary statistics for all our variables.

Table 1: Numerical variables

	goal	name_len_clean	blurb_len_clean	create_to_launch	launch_to_deadline
Minimum	1	1	1	0	1
1st Quartile	3539	3	11	3	30
Median	13028	5	13	14	30
Mean	166527	5.293	13.08	49.58	34.72
Standard Deviation	3094760	2.418168	3.283547	111.1062	11.87352
3rd Quartile	46867	7	15	45	40
Maximum	331278562	14	30	1754	91

Table 2: Categorical variables

a)

state	counts
canceled	2455
failed	11416
live	508
successful	6018
suspended	230

b)

country	counts
US	14138
GB	2497
CA	1098
AU	673
DE	377
NL	322
Other	1522

c)

staff_pick	counts
FALSE	18442
TRUE	2185

d)

category	counts
Web	3324
Hardware	3247
Software	2630
Gadgets	2336
Unclassified	1889
Plays	1184
Other	6017

Here, Other consists of remaining categories

e)

deadline_weekday	counts
Friday	3764
Monday	2221
Saturday	2984
Sunday	3041
Thursday	3444
Tuesday	1976
Wednesday	3202

f)

created_at_weekday	counts
Friday	2699
Monday	3474
Saturday	2090
Sunday	2277
Thursday	3155
Tuesday	3612
Wednesday	3325

g)

launched_at_weekday	counts
Friday	2818
Monday	4200
Saturday	1075
Sunday	1059
Thursday	3094
Tuesday	4645
Wednesday	3741

h)

deadline_month	counts
8	1954
12	1954
7	1906
3	1778
9	1732
10	1713
Other	9595

Here, Other consists of remaining months.

i)

deadline_yr	counts
2015	7366
2016	5237
2014	4819
2013	1110
2017	1081
2012	519
Other	500

Here, Other includes remaining years.

j)

created_at_month	counts
7	2106
10	1847
5	1835
6	1777
8	1756
4	1686
Other	9625

k)

created_at_yr	counts
2015	6953
2014	5732
2016	4850
2013	143
2012	733
2017	358
Other	572

l)

launched_at_month	counts
7	1996
11	1895
6	1871
10	1788
5	1754
8	1737
Other	9591

m)

launched_at_yr	counts
2015	7264
2014	5228
2016	5223
2013	1191
2012	660
2017	523
Other	543

Model:

In our model, we considered the state i.e the success or failure of Kickstarter campaigns to be our dependent variable, and among various variables, we chose goal, country, staff_pick, category, name_len_clean, blurb_len_clean, deadline_weekday, created_at_weekday, launched_at_weekday, deadline_month, deadline_yr, created_at_month, created_at_yr, launched_at_month, launched_at_yr, create_to_launch and launch_to_deadline as our independent variables. Since our dependent variable is a binary variable, we used the probit model instead of the Ordinary Least Square (OLS) measure for our analysis.

Our probit model is then given as below:

Pr(state = 1|goal,country, staff_pick, category, name_len_clean, blurb_len_clean, deadline_weekday, created_at_weekday, launched_at_weekday, deadline_month, deadline_yr, created_at_month, created_at_yr, launched_at_month, launched_at_yr, create_to_launch, launch_to_deadline) = Φ(w) …………………………………………………………….(1)

where,

w = population regression model given as: β_0 + β_1*goal + β_2* country + β_3* staff_pick+ β_4 * category+ β_5 * name_len_clean+ β_6 * blurb_len_clean+ β_7 *deadline_weekday + β_8 * created_at_weekday+ β_9 * launched_at_weekday + β_{10} * deadline_month+ β_{11} * deadline_yr+ β_{12} * created_at_month+ β_{13} * created_at_yr+ β_{14} * launched_at_month+ β_{15} * launched_at_yr+ β_{16} * create_to_launch+ β_{17} * launch_to_deadline + ε

Φ = cumulative distribution function (CDF) of the standard normal distribution

Using the above model, we then proceeded to compute the coefficient estimates for variables. However, since we think that goal, staff_pick, name_len_clean, blurb_len_clean, create_to_launch and launch_to_deadline are most important factors impacting our dependent variables, thus we only considered coefficient estimate for these variables. But, since we also had other variables, we considered to use the remaining as control variables in order to better isolate the impact of these variables on the success or failure of Kickstarter campaigns.

Accordingly, we looked at two probit models: one without control variables (Model 1), and one with control variables (Model 2). Then, our Model 1 will be given as follows:

Pr(state = 1|goal, staff_pick, name_len_clean, blurb_len_clean, create_to_launch, launch_to_deadline) = Φ(w) ……………………………………………………….(2)

where,

w = population regression model given as: $\beta_0 + \beta_1$*goal + β_2* staff_pick+ β_3 * name_len_clean+ β_4 * blurb_len_clean+ β_5 * create_to_launch+ β_6 * launch_to_deadline + ε

Φ = cumulative distribution function (CDF) of the standard normal distribution

Whereas our Model 2 is given by equation (1). Also, during our regression analysis, we used the natural logarithm of the goal variable as the data was heavily skewed to the right.

Results:

The coefficient estimate was obtained from the RStudio and it is given in Table 3 for both Model 1 and Model 2.

Since we are using the probit model, these estimated coefficients do not provide us with desired marginal effect, and thus we had to look for other options. In our work, we used probitmfx() function in the RStudio. But, we were not able to compute the marginal effect initially, as the memory space was not enough. This made sense since our dataset consisted of around 20,000 rows, and thus our dataset was too large for the memory. So, to get around this problem, we calculated the fixed effect at the mean, and the result is given in Table 4.

Table 3: Probit Regression where “state”(success or failure of campaigns) is a dependent variable

	Model 1	Model 2
(Intercept)	0.7648*** (0.01909)	0.4834359*** (0.1112009)
goal	-0.06625*** (0.001493)	-0.0614482*** (0.0016201)
staff_pick	0.524*** (0.009165)	0.4646815*** (0.009062)
name_len_clean	0.02204*** (0.001196)	0.0169266*** (0.0011665)
blurb_len_clean	0.003229*** (0.0008744)	0.0010697 (0.0008367)
create_to_launch	0.00006276* (0.00002545)	-0.0003487 (0.0002467)
launch_to_deadline	-0.001917*** (0.0002409)	-0.0014813*** (0.0003872)
Adjusted R-squared	0.2168	0.301

Notes: ***: significant at the 0.1% level. **: significant at the 1% level. *: significant at the 5% level. “.”: significant at the 10% level. All coefficients come from Probit regressions. Standard errors are reported parentheses below the coefficient estimates. This regression come from analyzing 20,627 rows of data.

Table 4: Marginal effects for slope coefficients of Probit Regression where “state” (success or failure of campaigns) is a dependent variable

	Model 1	Model 2
goal	-0.080445*** (0.0018947)	-0.0784014*** (0.01540035)
staff_pick	0.57232*** (0.0096976)	0.54126407*** (0.02437745)
name_len_clean	0.027656*** (0.0014123)	0.02190184*** (0.00449095)
blurb_len_clean	0.0038096*** (0.0010341)	0.00143033 (0.00104675)
create_to_launch	0.000097555*** (0.000029051)	-0.0004038 (0.00030141)
launch_to_deadline	-0.00239*** (0.00028975)	-0.0019269** (0.00059667)

Notes: ***: significant at the 0.1% level. **: significant at the 1% level. *: significant at the 5% level. “.”: significant at the 10% level. All marginal effects come from coefficients of Probit regressions. Standard errors are reported in parentheses below the marginal estimates. This observation resulted from analyzing 20,627 rows of data.

Summary:

Now, we will look at how each variable impacted the probability of success of Kickstarter campaigns.

Goal: We found that 1% increase in the money required for the campaign would decrease the probability of success of campaign by about 0.0008 in Model 1 and by 0.0009 in Model 2.

Staff_pick: We found that when a campaign is picked by the Kickstarter staff, the probability of the campaign being successful increases by 57% in Model 1 and by 54% in Model 2.

Name_len_clean: We found that for a unit increment of word in the title of the Kickstarter campaign, the probability of the campaign being successful increases by 2.7% for Model 1 and by 2.2% for Model 2.

Blurb_len_clean: We found that for a unit increment of word in the blurb of the Kickstarter campaign, the probability of the campaign being successful increases by 0.3% in Model 1. However, this variable was found to be not significant in case of Model 2.

Create_to_launch: We found that for a unit increase in the number of days from the creation to the launch of the campaign, the probability of the campaign being successful increases by around 0.01% for Model 1. However, the variable was insignificant in Model 2.

Launch_to_deadline: We found that for a unit increase in the number of days from the launch to the deadline of the campaign, the probability of the campaign being successful decreases by 0.24% for Model 1 and by 0.2% for Model 2.

Conclusion and Discussion

We were interested in knowing factors that were significant in determining the success or failure of crowdfunding campaigns. To determine this, we looked at the data from the Kickstarter, which is one of the crowdfunding platforms. For the dependent variable, we chose the state variable. Here, we considered the campaign to be successful when the state was "successful", and failed when the state was either "failed", "canceled" or "suspended". Among independent variables, we considered the amount required for the project, choice made by crowdfunding platform's staff, number of words in the title of the campaign, number of words in the description of the campaign, number of days between the creation to the launching of the campaign and number of days between the launching to the deadline of the campaign as our main independent variables that affected the success or failure of crowdfunding campaigns. Besides these, we also used some of the remaining variables as control variables. Since our dependent variable was a binary variable, we chose the probit regression model for our analysis. Accordingly, we conducted regression on two models: one without control variables (Model 1), and one with control variables (Model 2). Using RStudio, we then computed coefficients for each probit model. Since coefficients from probit regression do not provide marginal effects, we used the probitmfx() function in RStudio to compute the desired marginal effects. Using this marginal effect, we then conducted our analysis.

Now, we will look at what we learned from our analysis. Our initial assumption for the goal variable was that when the project needed more amount of money, the campaign might have lower chance of succeeding. This negative relationship was found to be true from the regression. Our assumption for staff_pick was that campaign chosen by crowfunding platform's staff will have higher chance of succeeding. From the regression, this positive relationship was found to be true. Our assumption for name_len_clean variable was that more words in the title might lead to more success. From the regression, it was determined to be true. For blurb_len_clean, we assumed that more words in the blurb might lead to more success as users will have more details about the campaign. However, this variable was found to be not significant at all when we controlled our variables. For create_to_launch variable, we thought that a greater number of days between the creation and launching of the campaign will somewhat negatively affect the success of Kickstarter campaigns. From the regression, upon considering control variables, this variable was found to be not significant at all. Finally, for launch_to_deadline, we thought that a greater number of days between the launch and deadline of the campaign will more negatively affect the success of the campaign. Here, our reasoning was that people will have less motivation to donate when they see substantial time available for the campaign to collect funding. From the regression, this negative relationship was found to be true.

Lastly, for our future work, we wish to look at how some of these factors will fair for recent crowdfunding campaigns. We were able to find one resource which provided data on recent Kickstarter campaigns. If factors for these new campaigns were consistent with factors that we had determined in this work, it would provide more support for our current analysis.

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