# Emotional Crowdfunding Blurbs Lead to Success (of the campaign, at least)

Dr Preet Deep Singh

09/09/2021

**Abstract**

Using a dataset of 150,011 projects from Kickstarter, we analyse factors that influence the success of a campaign. Results show that goal amount, day of launch, category of project, and duration of the project are statistically significant. We find the use of certain words is correlated ($p<0.1$) with the success and overachievement of the project. Invoking positive words such as 'please','thanks', 'father', 'together', 'ease','new' etc has a positive effect.

## 1 Introduction

While traditional finance theories such as pecking order theory, predict that firms would raise debt before equity , the new era of companies based on new market segments and product offerings that cannot be compared to those existing, has led to a new paradigm of looking at risk and its distribution. While over 80% of startups fail [1], crowd-funding is changing the way risky enterprises are being financed. Through this study we set out to examine a few basic questions:

- Summary: how many successful, how many over, how many rising
- Impact of readability on Total funds raised
- Impact of certain words on the total funds raised

We use success, overfunding, and take taken to fulfill the objective of the campaign to measure the impact of our variables of interest. We follow @singh2021perception1, @singh2021perception3 and @singh2021perception2 to see how perception of certain traits about the founders matters. Similar to that we look at the perception of the audience to the project based on the use of certain words.

[1] CITE

## 1.1 About Crowdfunding

### 1.1.1 Previously

4 types of crowd funding - Reward, Debt, Equity, Donation. In India SEBI has not allowed investors to go the equity route to invest in startups. This is because of the inherent problems in inviting public to subscribe to the shares of the company . Donations, if made to registered entities under section 80 (Whatever subsection) of the Income Tax Act, 1961, are exempt from income tax. Therefore if the organisation raising funds is an entity covered under the relevant sections of the Act, then the investor (donor in this case) can get a tax exemption on the money so donated. Under the reward base, the investor is promised the product. Thus this method works as a pre-order facility. While the company is assured of a minimum sale and gets cash to keep it going, the investor gets a right to get his/her hands on a product before it hits the market. <. Debt based model is difficult to execute on a platform only mode and therefore requires more interaction between the organisation and the the creditor. However debt is an important part of funding and risk disbursement.

## 1.2 About Kickstarter

What it is, when it was founded, how much money has it already disbursed. This will come from the Data stats that it itself shows.

## 1.3 About the study

In this paper we look at 150011 projects on Kickstarter from April, 2009 to November, 2015. Our sample includes failed, cancelled, suspended and successful projects. . While efficient market hypothesis and familiarity bias would predict that people prefer to invest in projects that are in the same category as that of existing Unicorns [2]; crowd-funding does not have any equity component and follows a donation or a customer based model. Under a donation model, the people who fund projects get nothing in return. Under the customer based model the people who contribute get the product or another gift depending upon the amount they have contributed. The gift is of much less worth than the contribution. Therefore, there is an emotional and altruistic angle to the whole process. We hypothesize that projects that appeal to emotion would receive more funding than those which do not. We check this by looking at the use of words that evoke emotion. Because of the presence of multiple people we cannot rule out herding. This could be owing to better information or conformation to the norms . However, herding would have to be explained differently because it is in a donation/gift setting. Crowd-funding is a social network and previous record

[2] <Say Something>

of entrepreneurs is a key determinant in the success of their projects. There is also a strong element of reciprocity. If one entrepreneur contributes to another persons project, his/her own project is more likely to get funded. Reciprocity alone cannot explain all results as it is less likely that every contributor is an entrepreneur looking to raise funds. Our results indicate that certain words such as mother, son, love, dream, student have an effect on the success, plausibly because they appeal to an emotion or to pity.

## 2 Literature

Mollick (2014) look at the dynamics underlying the success of crowdfunding projects. They show that personal effects, project quality and geography are related to the success of the project. They also find that most projects (75%) deliver projects later than the promised date.

Inbar and Basrzilay (2014) find evidence of reciprocity. They use data from Kickstarter to show that entrepreneurs who have backed projects earlier are more likely to get funded. Using network theory they advise that backing projects is a good strategy that contributes to success of your own project. It is possible that they find this relation due to learning. If someone backs multiple projects, he/she is likely to have learnt what works and what not. If those learnings are incorporated in his/her own projects then the success of that project would reflect confounding effects of network theory and learning by being in the system.

Bellaframme, Lambert and Schewienbacher (2014) find that crowdfunding initiatives that are presented as non-profit organisations tend to be more successful at raising funds after controlling for other factors. They say that this is in line with contract failure literature that purports that due to reduced focused on projects, NPOs can raise money easily for initiatives in which the general public is interested. We extend this literature by looking at the level to which a project can connect with the people.

Ahlers et al(2012) examine signals that induce providers of finance to commit to crowdfunding projects. They find that financial roadmaps, risk factors and internal governance are key factors that determine the success of a crowdfunding project.

Similar but not same is an analysis of Lui (2013) on microloans where he finds that on Prosper.com [3] there is herding but it is not irrational herding. Lender make informed decisions after looking at the past record of borrowers and borrowers traits-favourable or not- are amplified.

[3] a microloan website

# 3 Method

## 3.1 Data

Our sample includes 171,436 observations.After removing projects for which we do not have complete data, we are left with 150,011 observations.

Table **??** and **??** gives a summary of the data.

% Error: Argument 'font.size' must be NULL (default), or one of the available font sizes. See documentation.

Our data spans 80 months ranging from April, 2009 to November, 2015. We have data from 16 categories viz. Theatre, Design, Fashion, Technology, Film and Video Games, Publishing, Crafts, Arts, Music, Comics, Food, Photography, Others, Journalism and Dance. The projects have one of four states: cancelled, suspended, failed or successful. Successful and failed are the two dominant categories. The projects on Kickstarter can be from any nation and therefore can pertain to different currencies. Projects in our sample span 10 currencies GBP, USD, CAD, AUD, NZD, NOK, EUR, CHF, DKK and SEK.

## 3.2 Various Steps

### 3.2.1 Timing

We look at the month in which the project is launched and the relevant impact it has on the probability of success of the project.

Figure 1 might be slightly misleading as our data is not evenly spread. We would be better off looking at the proportion of success to failure. In Figure 2 we see the proportion of success to failure for each month. Month 2 to Month 6 are in the top 5. While the ratio of successful to unsuccessful projects is more than 97 percent for projects launched in march are successful, it is 59 percent projects are successful in September.

Similar to months, we do this exercise for days. [4].

In Figure 3we plot the proportion of successful to unsuccessful projects. We see that the propotion of success is higher on Sunday as compared to other days of the week, especially Monday. We do not see any 'Friday Effect' in this.

Something[5]

[4] Friday Effect

[5] See if you want to do overachievement etc.

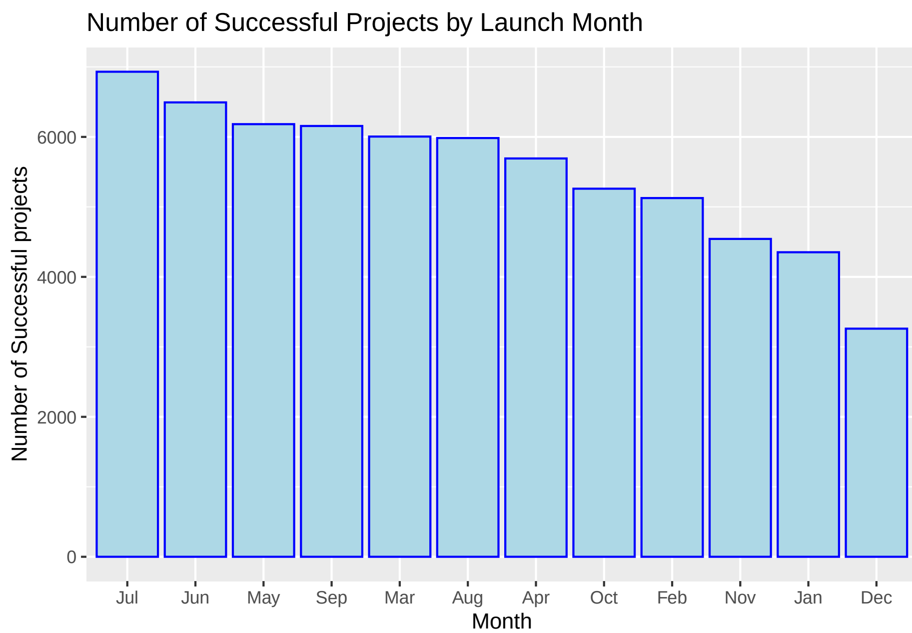


Figure 1: Proportion of Successful to Unsuccessful Projects by Month

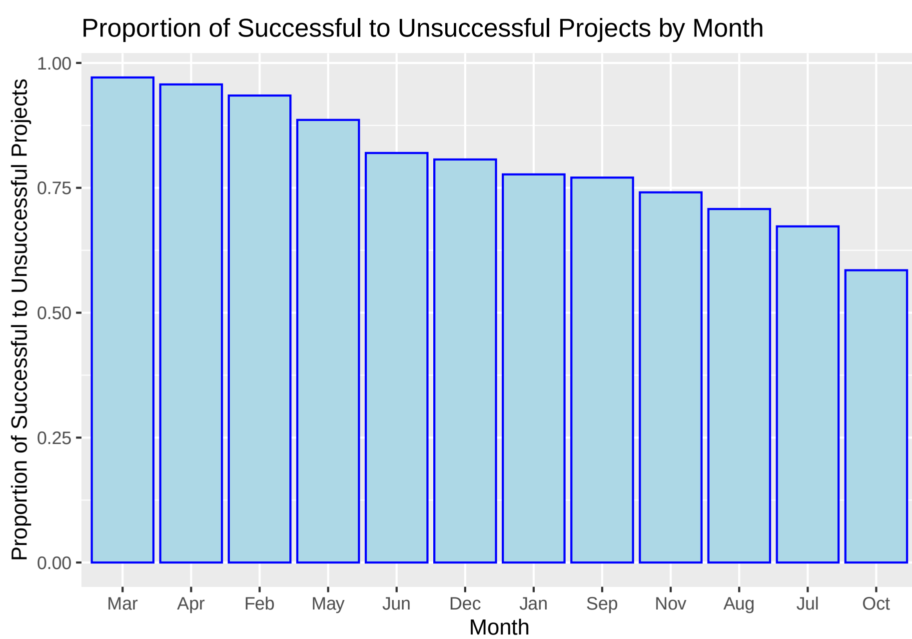


Figure 2: Proportion of Successful to Unsuccessful Projects by Month

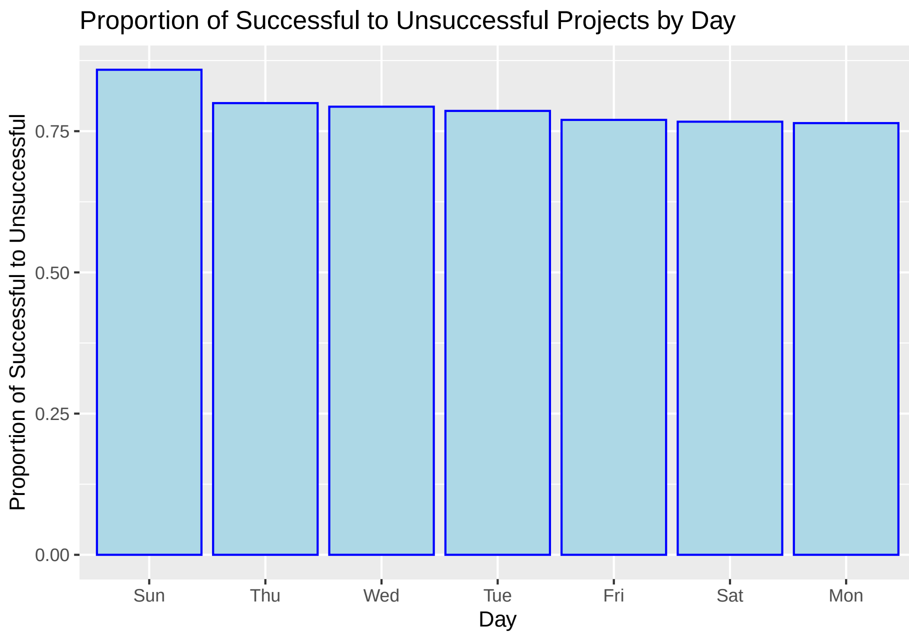


Figure 3: Proportion of Successful to Unsuccessful Projects by Day

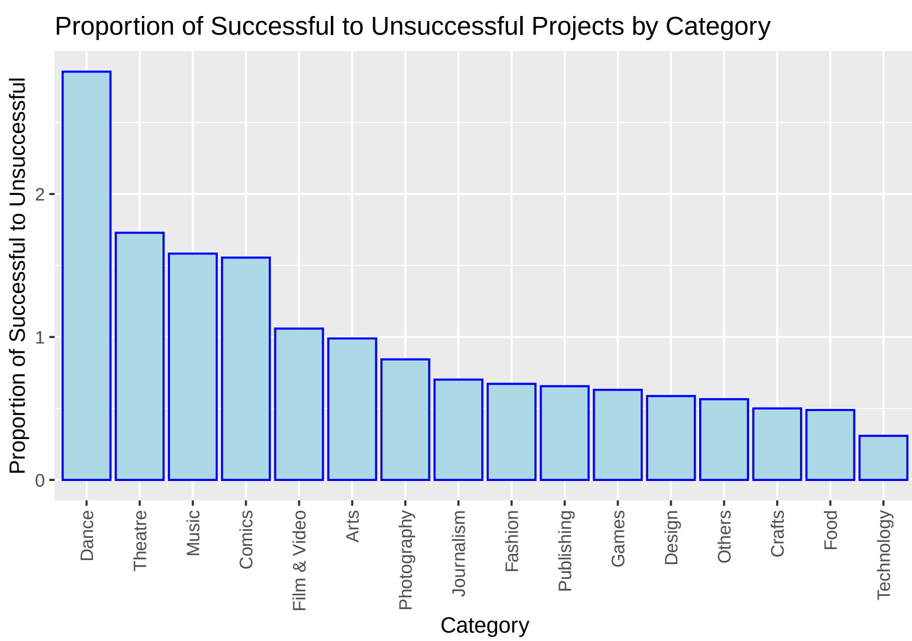


Figure 4: Proportion of Successful to Unsuccessful Projects by Category

### 3.2.2 Words

findFreqTerms(course_dtm,10000) [1] "game" "help" "make" "new" "will" findFreqTerms(course_dtm,5000) [1] "album" "art" "book" "bring" "can" "creat" "design" "film" "first" "game" "get" "help" "life" "love" "make" "music" "need" "new"
[19] "one" "project" "record" "stori" "time" "use" "want" "will" "world" "year"

findFreqTerms(course_dtm,2000) [1] "adventur" "album" "app" "around" "art" "artist" "back" "band" "base" "beauti" "best" "book"
[13] "bring" "build" "can" "card" "chang" "children" "citi" "collect" "come" "comic" "communiti" "creat"
[25] "custom" "day" "design" "documentari" "dream" "experi" "explor" "famili" "featur" "film" "find" "first"
[37] "food" "free" "friend" "full" "fun" "fund" "game" "get" "give" "great" "hand" "help"
[49] "high" "home" "inspir" "journey" "just" "kid" "learn" "let" "life" "like" "live" "local"
[61] "look" "love" "made" "make" "man" "music" "need" "new" "now" "old" "one" "open"
[73] "origin" "part" "peopl" "perform" "play" "power" "print" "produc" "product" "project" "qualiti" "rais"
[85] "record" "releas" "seri" "set" "share" "short" "show" "song" "space" "start" "stori" "studio"
[97] "style" "support" "take" "time" "togeth" "travel" "tri" "two" "uniqu" "use" "video" "want"
[109] "way" "will" "work" "world" "year" "young"

We look at words that are most likely to appeal to emotion or pity. In case a particular word is present we assign a dummy of 1 to that particular project. In case more than one such word is present in the project blurb, we add the two. Thus the coefficient on the SumOfWords variable is indicative of the effect of using both the words over and above the effect of any one of those words. We use words such as mother, baby, kids, environment, dream, amputee, accident, death, friend, love etc.[6]. The dependent variable is coded as 1, in case the project is successful and 0 in case the project is not successful. Because of the binary nature of the variable, we use the following logit model:

We use a definition of 125% for overachievement.

$Success = \alpha + \beta_1 Word1 + \beta_2 Word2 + \beta_3 SumOfWords + Control + \epsilon$

[6]For a complete list of words that we ran, please refer Annexure <Refer>

Table 1: This tables shows the coefficient of correlation and p value, between projects that used the particular word and their success.

| | Coefficient of Correlation | pValue of Correlation |
|---|---|---|
| success | 1 | |
| baby | -0.010 | 0 |
| mother | 0 | 0.770 |
| poor | -0.010 | 0.050 |
| love | 0.010 | 0 |
| enviro | -0.010 | 0 |
| student | 0.010 | 0 |
| amputee | 0 | 0.420 |
| dream | -0.010 | 0 |
| lost | 0.010 | 0.010 |
| child | -0.020 | 0 |
| kids | -0.020 | 0 |
| disease | 0 | 0.210 |
| together | 0.010 | 0.010 |
| every | -0.030 | 0 |
| story | 0.020 | 0 |
| mom | 0 | 0.110 |
| ma | 0.010 | 0 |
| save | -0.010 | 0 |
| sum1 | 0.020 | 0 |
| sum2 | -0.020 | 0 |
| sum3 | -0.030 | 0 |
| lngoal | -0.250 | 0 |
| more | 0.950 | 0 |
| cancer | -0.010 | 0.030 |
| fear | 0.010 | 0 |
| overcome | 0 | 0.610 |
| support | 0.020 | 0 |
| shit | 0 | 0.230 |
| therapy | 0 | 0.080 |
| over | 0.490 | 0 |
| always | -0.010 | 0 |
| never | -0.010 | 0 |
| forgive | 0 | 0.490 |
| please | 0.010 | 0.020 |
| thank | 0.010 | 0 |
| father | 0.010 | 0 |
| dad | 0 | 0.270 |
| papa | 0 | 0.320 |
| children | -0.020 | 0 |
| dear | 0 | 0.590 |
| est | 0.010 | 0 |
| worst | 0 | 0.120 |
| best | -0.010 | 0.010 |
| prevent | -0.010 | 0 |
| technology | -0.020 | 0 |
| comfort | -0.010 | 0 |
| new | 0.060 | 0 |
| smart | -0.030 | 0 |
| ease | 0.030 | 0 |
| simple | -0.020 | 0 |

Table 2: Regression results for use of particular words and success.

| | *Dependent variable:* | | |
|---|---|---|---|
| | success | | |
| | (1) | (2) | (3) |
| ease | 0.072** | | |
| | (0.034) | | |
| father | | 0.138* | |
| | | (0.077) | |
| please | | | −0.169*** |
| | | | (0.058) |
| lngoal | −0.299*** | −0.299*** | −0.300*** |
| | (0.004) | (0.004) | (0.004) |
| totalduration | −0.010*** | −0.010*** | −0.010*** |
| | (0.001) | (0.0005) | (0.001) |
| Constant | 2.863*** | 2.865*** | 2.868*** |
| | (0.045) | (0.045) | (0.045) |
| Month | Yes | Yes | Yes |
| Day | Yes | Yes | Yes |
| Super Category | Yes | Yes | Yes |
| Observations | 150,011 | 150,011 | 150,011 |
| Log Likelihood | −93,992.310 | −93,992.890 | −93,990.180 |
| Akaike Inf. Crit. | 188,056.600 | 188,057.800 | 188,052.400 |
| *Note:* | | *p<0.1; **p<0.05; ***p<0.01 | |

Table 3: Regression results for use of particular words and success.

| | *Dependent variable:* | | |
|---|---|---|---|
| | success | | |
| | (1) | (2) | (3) |
| thank | −0.034 | | |
| | (0.077) | | |
| every | | −0.296*** | |
| | | (0.031) | |
| never | | | −0.117** |
| | | | (0.057) |
| lngoal | −0.299*** | −0.300*** | −0.299*** |
| | (0.004) | (0.004) | (0.004) |
| totalduration | −0.010*** | −0.010*** | −0.010*** |
| | (0.0005) | (0.001) | (0.0005) |
| Constant | 2.866*** | 2.877*** | 2.865*** |
| | (0.045) | (0.046) | (0.045) |
| Month | Yes | Yes | Yes |
| Day | Yes | Yes | Yes |
| Super Category | Yes | Yes | Yes |
| Observations | 150,011 | 150,011 | 150,011 |
| Log Likelihood | −93,994.410 | −93,949.410 | −93,992.370 |
| Akaike Inf. Crit. | 188,060.800 | 187,970.800 | 188,056.700 |
| *Note:* | | | *p<0.1; **p<0.05; ***p<0.01 |

Table 4: Regression results for use of particular words and success.

| | *Dependent variable:* | | |
|---|---|---|---|
| | success | | |
| | (1) | (2) | (3) |
| best | $-0.087^{**}$ | | |
| | (0.044) | | |
| est | | $0.082^{***}$ | |
| | | (0.024) | |
| child | | | $-0.178^{***}$ |
| | | | (0.037) |
| lngoal | $-0.299^{***}$ | $-0.300^{***}$ | $-0.299^{***}$ |
| | (0.004) | (0.004) | (0.004) |
| totalduration | $-0.010^{***}$ | $-0.010^{***}$ | $-0.010^{***}$ |
| | (0.0005) | (0.0005) | (0.001) |
| Constant | $2.866^{***}$ | $2.863^{***}$ | $2.865^{***}$ |
| | (0.045) | (0.045) | (0.045) |
| Month | Yes | Yes | Yes |
| Day | Yes | Yes | Yes |
| Super Category | Yes | Yes | Yes |
| Observations | 150,011 | 150,011 | 150,011 |
| Log Likelihood | −93,992.560 | −93,988.780 | −93,982.860 |
| Akaike Inf. Crit. | 188,057.100 | 188,049.600 | 188,037.700 |
| *Note:* | | | $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01 |

Table 5: Regression results for use of particular words and success.

| | *Dependent variable:* | | |
|---|---|---|---|
| | success | | |
| | (1) | (2) | (3) |
| dream | $-0.259^{***}$ | | |
| | (0.040) | | |
| ma | | $0.099^{*}$ | |
| | | (0.058) | |
| dad | | | $-0.333^{*}$ |
| | | | (0.195) |
| lngoal | $-0.299^{***}$ | $-0.299^{***}$ | $-0.299^{***}$ |
| | (0.004) | (0.004) | (0.004) |
| totalduration | $-0.010^{***}$ | $-0.010^{***}$ | $-0.010^{***}$ |
| | (0.001) | (0.0005) | (0.0005) |
| Constant | $2.868^{***}$ | $2.865^{***}$ | $2.866^{***}$ |
| | (0.045) | (0.045) | (0.045) |
| Month | Yes | Yes | Yes |
| Day | Yes | Yes | Yes |
| Super Category | Yes | Yes | Yes |
| Observations | 150,011 | 150,011 | 150,011 |
| Log Likelihood | −93,973.360 | −93,993.070 | −93,993.030 |
| Akaike Inf. Crit. | 188,018.700 | 188,058.100 | 188,058.100 |
| *Note:* | | | $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01 |

Table 6: Regression results for use of particular words and success.

| | *Dependent variable:* | | |
|---|---|---|---|
| | success | | |
| | (1) | (2) | (3) |
| poor | $-0.582^{***}$ | | |
| | (0.181) | | |
| support | | $0.189^{***}$ | |
| | | (0.037) | |
| forgive | | | $-0.314$ |
| | | | (0.237) |
| lngoal | $-0.300^{***}$ | $-0.299^{***}$ | $-0.299^{***}$ |
| | (0.004) | (0.004) | (0.004) |
| totalduration | $-0.010^{***}$ | $-0.010^{***}$ | $-0.010^{***}$ |
| | (0.0005) | (0.001) | (0.0005) |
| Constant | $2.866^{***}$ | $2.860^{***}$ | $2.866^{***}$ |
| | (0.045) | (0.045) | (0.045) |
| Month | Yes | Yes | Yes |
| Day | Yes | Yes | Yes |
| Super Category | Yes | Yes | Yes |
| Observations | 150,011 | 150,011 | 150,011 |
| Log Likelihood | $-93{,}989.140$ | $-93{,}981.230$ | $-93{,}993.620$ |
| Akaike Inf. Crit. | 188,050.300 | 188,034.500 | 188,059.200 |
| *Note:* | | | $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01 |

Table 7: Regression results for use of particular words and over-funding.

| | *Dependent variable:* | | |
|---|---|---|---|
| | over | | |
| | (1) | (2) | (3) |
| ease | $-0.119^{***}$ | | |
| | (0.043) | | |
| father | | $-0.324^{***}$ | |
| | | (0.109) | |
| please | | | $-0.401^{***}$ |
| | | | (0.079) |
| lngoal | $-0.365^{***}$ | $-0.365^{***}$ | $-0.365^{***}$ |
| | (0.004) | (0.004) | (0.004) |
| totalduration | $-0.008^{***}$ | $-0.008^{***}$ | $-0.008^{***}$ |
| | (0.001) | (0.001) | (0.001) |
| Constant | $1.824^{***}$ | $1.820^{***}$ | $1.826^{***}$ |
| | (0.048) | (0.048) | (0.048) |
| Month | Yes | Yes | Yes |
| Day | Yes | Yes | Yes |
| Super Category | No | No | No |
| Observations | 150,011 | 150,011 | 150,011 |
| Log Likelihood | −65,686.190 | −65,685.450 | −65,676.080 |
| Akaike Inf. Crit. | 131,414.400 | 131,412.900 | 131,394.200 |
| *Note:* | | | $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01 |

Table 8: Regression results for use of particular words and over-funding.

| | *Dependent variable:* | | |
|---|---|---|---|
| | over | | |
| | (1) | (2) | (3) |
| thank | −0.086 | | |
| | (0.098) | | |
| every | | −0.039 | |
| | | (0.039) | |
| never | | | 0.038 |
| | | | (0.071) |
| lngoal | $-0.365^{***}$ | $-0.365^{***}$ | $-0.365^{***}$ |
| | (0.004) | (0.004) | (0.004) |
| totalduration | $-0.008^{***}$ | $-0.008^{***}$ | $-0.008^{***}$ |
| | (0.001) | (0.001) | (0.001) |
| Constant | $1.819^{***}$ | $1.820^{***}$ | $1.818^{***}$ |
| | (0.048) | (0.048) | (0.048) |
| Month | Yes | Yes | Yes |
| Day | Yes | Yes | Yes |
| Super Category | No | No | No |
| Observations | 150,011 | 150,011 | 150,011 |
| Log Likelihood | −65,689.800 | −65,689.690 | −65,690.050 |
| Akaike Inf. Crit. | 131,421.600 | 131,421.400 | 131,422.100 |
| *Note:* | | | $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01 |

Table 9: Regression results for use of particular words and over-funding.

| | *Dependent variable:* | | |
|---|---|---|---|
| | over | | |
| | (1) | (2) | (3) |
| best | 0.040 | | |
| | (0.056) | | |
| est | | $0.121^{***}$ | |
| | | (0.030) | |
| child | | | $-0.528^{***}$ |
| | | | (0.055) |
| lngoal | $-0.365^{***}$ | $-0.365^{***}$ | $-0.364^{***}$ |
| | (0.004) | (0.004) | (0.004) |
| totalduration | $-0.008^{***}$ | $-0.008^{***}$ | $-0.007^{***}$ |
| | (0.001) | (0.001) | (0.001) |
| Constant | $1.818^{***}$ | $1.813^{***}$ | $1.822^{***}$ |
| | (0.048) | (0.048) | (0.048) |
| Month | Yes | Yes | Yes |
| Day | Yes | Yes | Yes |
| Super Category | No | No | No |
| Observations | 150,011 | 150,011 | 150,011 |
| Log Likelihood | −65,689.930 | −65,682.210 | −65,638.230 |
| Akaike Inf. Crit. | 131,421.900 | 131,406.400 | 131,318.500 |
| *Note:* | | | $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01 |

Table 10: Regression results for use of particular words and over-funding.

| | *Dependent variable:* | | |
|---|---|---|---|
| | over | | |
| | (1) | (2) | (3) |
| dream | $-0.503^{***}$ | | |
| | (0.059) | | |
| ma | | $-0.210^{***}$ | |
| | | (0.078) | |
| dad | | | $-0.839^{***}$ |
| | | | (0.311) |
| lngoal | $-0.365^{***}$ | $-0.365^{***}$ | $-0.365^{***}$ |
| | (0.004) | (0.004) | (0.004) |
| totalduration | $-0.007^{***}$ | $-0.008^{***}$ | $-0.008^{***}$ |
| | (0.001) | (0.001) | (0.001) |
| Constant | $1.827^{***}$ | $1.821^{***}$ | $1.820^{***}$ |
| | (0.048) | (0.048) | (0.048) |
| Month | Yes | Yes | Yes |
| Day | Yes | Yes | Yes |
| Super Category | No | No | No |
| Observations | 150,011 | 150,011 | 150,011 |
| Log Likelihood | −65,649.580 | −65,686.450 | −65,685.710 |
| Akaike Inf. Crit. | 131,341.200 | 131,414.900 | 131,413.400 |
| *Note:* | | | $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01 |

Table 11: Regression results for use of particular words and over-funding.

| | *Dependent variable:* | | |
|---|---|---|---|
| | over | | |
| | (1) | (2) | (3) |
| poor | $-0.634^{**}$ | | |
| | (0.255) | | |
| support | | $-0.146^{***}$ | |
| | | (0.048) | |
| forgive | | | $-0.635^{*}$ |
| | | | (0.361) |
| lngoal | $-0.365^{***}$ | $-0.365^{***}$ | $-0.365^{***}$ |
| | (0.004) | (0.004) | (0.004) |
| totalduration | $-0.008^{***}$ | $-0.008^{***}$ | $-0.008^{***}$ |
| | (0.001) | (0.001) | (0.001) |
| Constant | $1.820^{***}$ | $1.823^{***}$ | $1.819^{***}$ |
| | (0.048) | (0.048) | (0.048) |
| Month | Yes | Yes | Yes |
| Day | Yes | Yes | Yes |
| Super Category | No | No | No |
| Observations | 150,011 | 150,011 | 150,011 |
| Log Likelihood | −65,686.630 | −65,685.350 | −65,688.390 |
| Akaike Inf. Crit. | 131,415.300 | 131,412.700 | 131,418.800 |
| *Note:* | | | $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01 |

#### 3.2.3 Herding

We use a relatively simple method to detect herding. We segregate the data based on categories and summarise it by month of the project deadline. As a robustness check we use month of project launch date but our results remain similar. Once summarised, we use a rolling window regression to look at the effect of number of backers in a month on the number of backers in the previous 12 months. We also regress the amount of money pledged in a month on the amount of money pledged in the previous twelve months. There are 68 cases for regression in each category. We report aggregate results for all the categories. We use the following regressions:

$Backers_{13} = \alpha + \beta_1 Backers_{1-12} + \beta_2 Control + \epsilon$
$Sum_{13} = \alpha + \beta_1 Sum_{1-12} + \beta_2 Control + \epsilon$

#### 3.2.4 Readability

We use 26 different readability tests. It has an impact.

## 4 Results and Discussion

Readability affects the probability of success. Currency also contributes. Maybe due to familiarity. The time for which it is open is also a significant factor. The amount it wishes to raise. The use of certain words in the blurb. Month and category also have a role to play. Herding exists and the money contributed to projects in the previous months is a significant determinant.

## 5 Conclusion

In this study we show evidence of herding. Our hypotheses regarding emotion appeal is vindicated even after controlling for multiple factors. Since crowdfunding is in line with donations and appeals to the benevolence rather than to greed, a different lens is needed to look at the motivation of those who pledge money, beyond reciprocity. Change and all A general time control or something

- Difference between March and October is very high, in terms of proportion of projects successful to unsuccessful.
- Sunday is very high as compared to Monday.
- 

### 5.0.1 Correlation

- Mother/Mom: no, Ma: yes, but Ma has a mildly positive effect
- Dad/Pap: no, Father: yes but mildly positive
- Thank/Please: Positive
- Baby/Poor/Dream/Child/Kids/every/save/cancer: negative
- Love/student/together/story/fear/support: positive - Superlatives (est) help (Positive)
- Best and Prevent: Negative
- Worst: not significant
- Technology/Smart/Simple: no
- Ease/new: yes