Causal Inference Project Work

Executive Summary

Current Situation

Crowdfunding is a way to raise capital for a project or new business venture, where many small investments are made by many individuals. The industry is growing, with an estimated year-over-year growth rate of 31% in 2018[1]. With over $4 billion in raised funds since its launch in 2009[2], Kickstarter is the world's largest crowdsourcing platform, primarily focusing on creative projects.

Complication

The duration of a project can potentially indicate how successful the project will be. On Kickstarter's FAQ and support page, they state the following:

"We recommend setting your campaign at 30 days or less. Campaigns with shorter durations have higher success rates, and create a helpful sense of urgency around your project."[3]

Our goal is to test the assertion by Kickstarter. We will design an econometric approach that will allow us to detect and measure the potential causal effect, where our experimental treatment group is campaigns with durations less than or equal to 30 days.

Recommendation

Based on the results from our approach, we believe that Kickstarter's assertion is correct and that campaign durations should be no longer than 30 days. We observed in the data that keeping campaigns shorter than or equal to 30 days increased the probability of success of the campaign by 4%. There are still some effects that could be biasing our results; campaign quality, marketing, and campaign owner experience could be biasing our analysis, and we were unable to control for them in the experimental design. Regardless, we are confident in our results, and we have a large set of observations that strengthen the power of our analysis.

Background and Business Context

Crowdfunding is a convenient source of alternative for funding for business ventures of different types and niches, but it is also a great approach to raise funds for projects that are not solely traditional business oriented. Through the years, crowdfunding for creative projects and arts has been growing tremendously; the collective power of the crowd is shifting traditional business venture paradigms.

The creative and socially aware sectors are extremely important as they bring cultural value to the society, but they do not always exude obvious business or profit value to traditional investors. Crowdfunding plays a vital role in awakening the collective instinct of the people, and it allows multitudes of individuals to contribute to important solutions for ecological issues and social causes. It nurtures the culture of togetherness and allows one to feel like a part of something larger than oneself.

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[1] Businesswire Infograph
[2] investopedia.com--top-crowdfunding-platforms
[3] Kickstarter.com--What-is-the-maximum-project-duration?

Kickstarter has been one of the largest platforms to host campaigns which helps artists, musicians, filmmakers, designers, and other creators find the resources and support they need to make their ideas a reality. To date, over 150,000 creative projects — big and small — have come to life with the support of the Kickstarter community.

Our additional external research on length of crowdfunding campaign shows that the ideal length of a campaign should be 30 days or less, which was recommended by Kickstarter. In addition, according to voidacademy.com [4], crowdfunders have the belief that the longer the campaign, the less urgent the need is, and therefore might lead to supporters to procrastinate or forget about the campaign.

As users start a new campaign on the website, we see the Kickstarter gives a default recommendation to keep the duration of the campaign less than 30 days to increase the probability of success of the campaign[5]. For this project, we would like to test the veracity of the claim made by Kickstarter.

Experimental Design

Hypothesis

The causal effect we are interested in here is effect of the length of the campaign on the likelihood of success of the campaign. The overall hypothesis that we are testing is:

H_0: Campaign duration does not affect probability of success

H_α: Campaigns with durations $\leq$ 30 days have a higher probability of success

If we reject the null hypothesis through our econometric approach, we will accept the alternative hypothesis and agree with the assertion from Kickstarter's website.

Data Generating Process

The causal mechanism by which the length of the campaign interacts with the success of the campaign is as follows:

$$Y_i = \alpha + \beta_1 Treat_i + \gamma_1 Confound_i + \mu_i$$

$$\rho(Treat, Confound) \neq 0$$

Where:

Y_i = Outcome variable: success of the campaign

$Treat_i$ = Length of campaign ≤ 30 days

i = a campaign

μ_i = error with respect to a campaign

Unobserved Threats to Causal Inference

Omitted variable bias is the strongest potential source of endogeneity in our econometric approach, although we also could have some selection bias. We will address the potential confounders that are

[4] voidacademy.com--perfect-length-crowdfunding-campaign

[5] Kickstarter.com--What-is-the-maximum-project-duration?

measured in the data with our econometric approach. The following are sources of endogeneity that are not observed or controllable in our data.

1. **Marketing expense**: There could be variations in the marketing expense of the campaigns. We assume a positive correlation with marketing and success rate.
2. **Campaign quality**: Much like marketing, we would assume that the overall campaign quality, and the quality of the project or product, has a positive correlation with success rate.
3. **Experience of the campaigner**: This is a potential source for selection bias, where we might assume more successful campaigners might keep campaigning. A more experienced campaigner would have higher chances of success, regardless of campaign length.
4. **Leakage effect**: Campaigns can gain popularity and momentum through word of mouth. This would likely have a positive correlation with success rate.

Additionally, there are some confounders that are not measured in the data and would be non-trivial to measure in general:

1. **Sense of Urgency**
   The initial burst of excitement at the launch of your campaign can motivate your backers to get in on the ground floor and invest early. The drive to the finish line at the end of your campaign is another shot of adrenaline that will push your community to help you achieve your goal.
2. **Energy of the campaign**
   Crowdfunding is exciting, rewarding, and challenging. A well-run campaign has many moving parts: events to run, copy to write, backers to communicate with, rewards to plan, and video to produce. Ultimately this could be the distinguishing factor between your campaign and some of the other ones run by your peers. Many businessmen invest in people or the cause of the campaign rather than just being concerned about ROI. Showing energy is a great way to attract them, and it is difficult to measure.

Dataset and Initial Measurements

About the Dataset

The data set we will investigate is a Kaggle dataset[6] from the Kickstarter platform with information for over 375,000 Kickstarter campaigns. The dataset includes variables describing the timing size and characteristics of the campaigns. The unit of analysis is the Kickstarter campaigns.

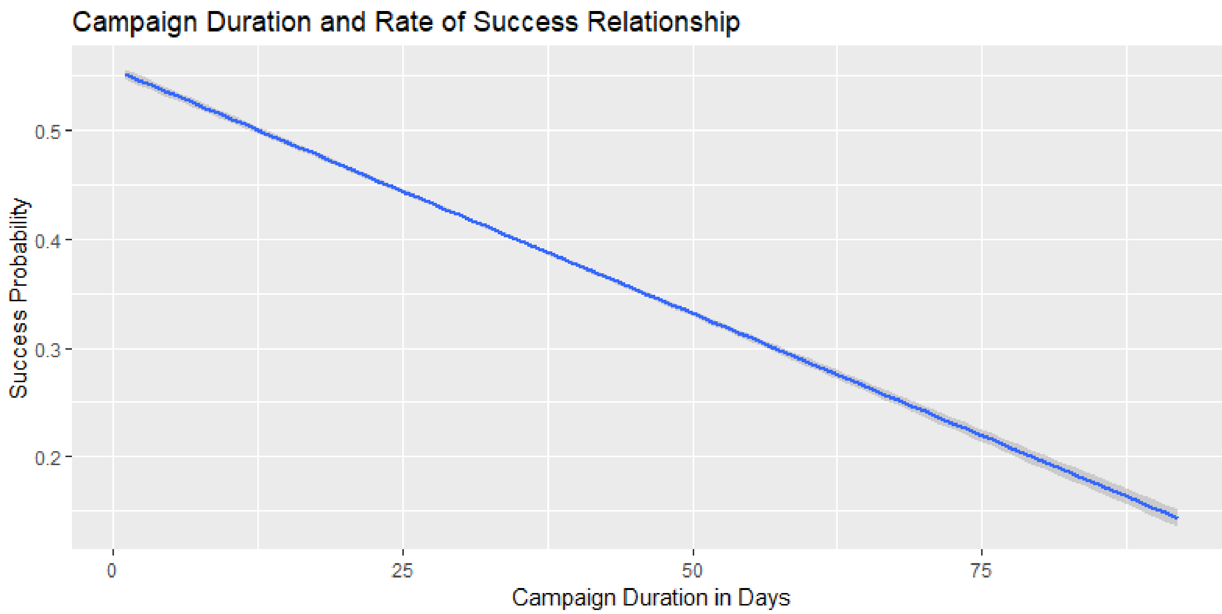
The data contains information about launch date and deadline of each campaign, which we used to calculate the duration of the campaign. There is also information regarding the category, goal, amount pledged, country and status of the campaign. The types of status are 'successful', 'failed' and some other intermediate or undefined states like 'canceled' or 'live'.

Our treatment is derived from the launch and deadline date from each campaign. While we are ultimately concerned with Kickstarter's claim about successful campaigns running for 30 days or less, we are more generally interested in how campaign duration affects probability for success. As we can see

[6] kaggle.com--kickstarter-projects

from Figure 1, campaign duration has a negatively and statistically significantly correlated relationship with success (p value ≈ 0).

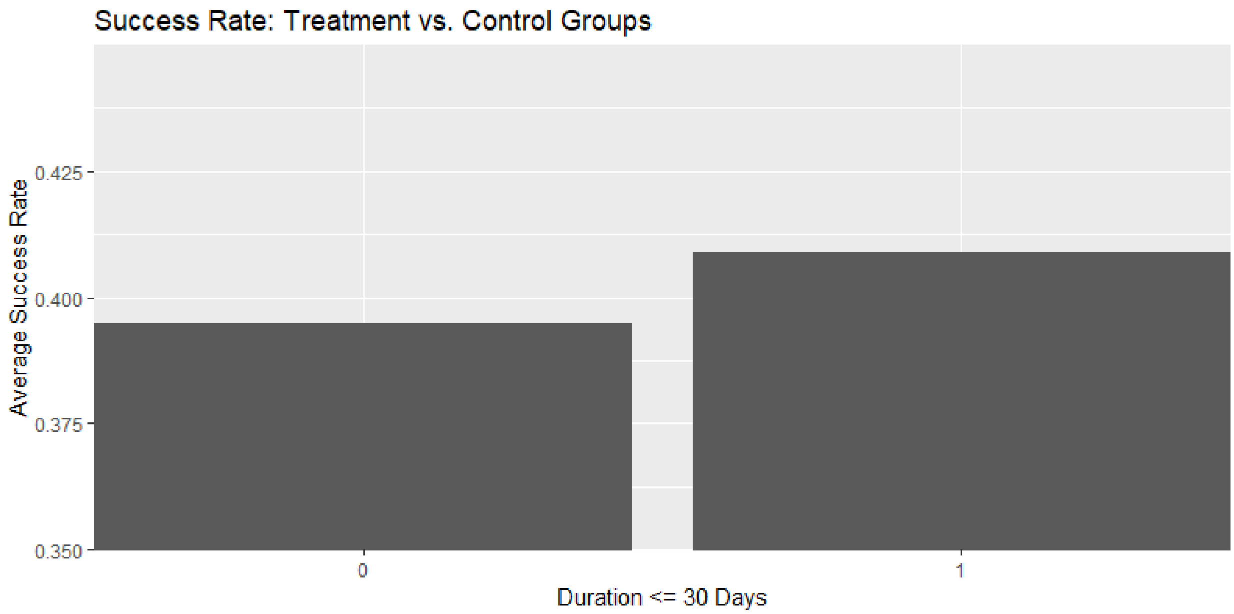
Figure 1



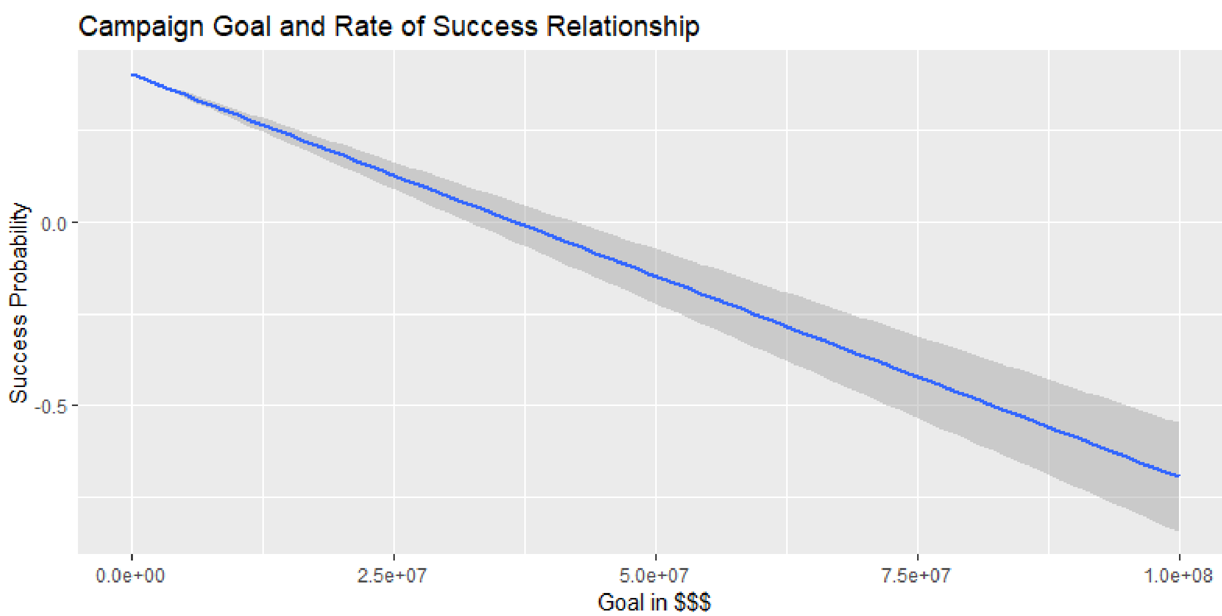
We also looked at the correlation coefficient between duration days and success rate. Thanks to the size of our dataset, we have a very sensitive test that detected a mild correlation coefficient of -0.11 between duration days and success. This is suggestive of a negative relationship between our treatment and outcome.

To test our hypothesis of Kickstarter's assumption, we will define a binary treatment indicator that is derived from the continuous treatment of duration in days. If the duration is less than or equal to 30 days for a given campaign, we mark the campaign as treated. Our outcome variable is the rate of success. We subset our data to only include records that are clearly labeled with a 'successful' or 'failed' status, and we label successful campaigns with a 1 and failed campaigns with a 0. Our regression will be a linear probability model, where each predicted value is the probability of getting a 1 that indicates 'successful'. We can see from the Figure 2 that there is a difference between the test and control groups. We find from modeling this relationship that the difference is statistically significant, and we see that there is evidence of a decrease in probability of success when moving from treatment to control (p value ≈ 0).

Figure 2



In our observed data, the one of the biggest confounders to our causal effect is the goal of the campaign. Intuitively, we would assume a smaller goal is generally easier to attain. For an extreme example, a goal of $1 would presumably be easier to reach than a goal of $100,000, regardless of all other effects. When we plot the two and regress success rate on goal, our we can see our suspicions are valid:



The correlation coefficient for goal and success rate is -0.03, and our test returned a p value near 0. This is ultimately a mild level of correlation, but the significance of the p value suggests evidence of a negative relationship.

We are also concerned that campaign category and country will confound our causal inference. Certain campaign categories may generally have a higher likelihood of success. For example, campaigns in the Theater category have generally higher rates of success than campaigns in the Food category, regardless of duration. The same logic applies to country. For example, campaigns from Great Britain have higher average success rates than campaigns from Italy. We can observe both effects when plotting them (Figure 3 and Figure 4):

Figure 3

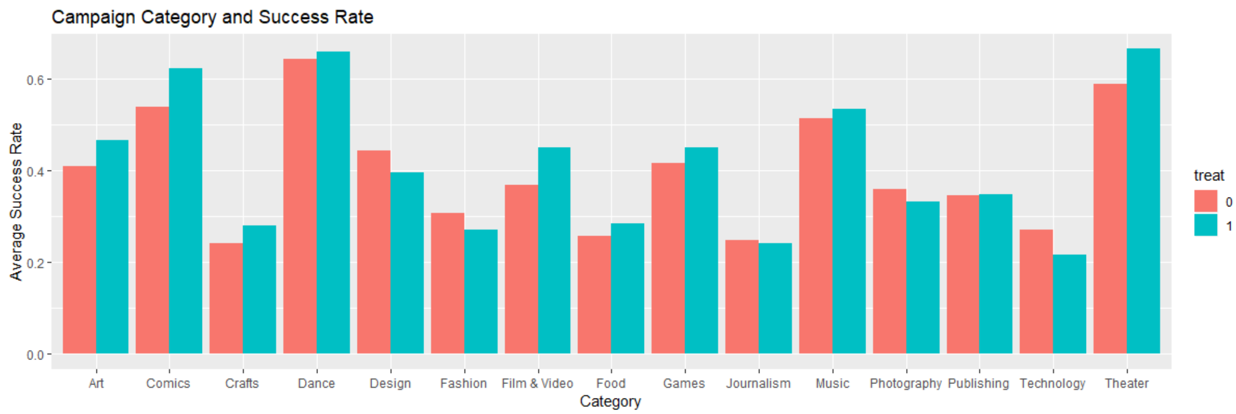
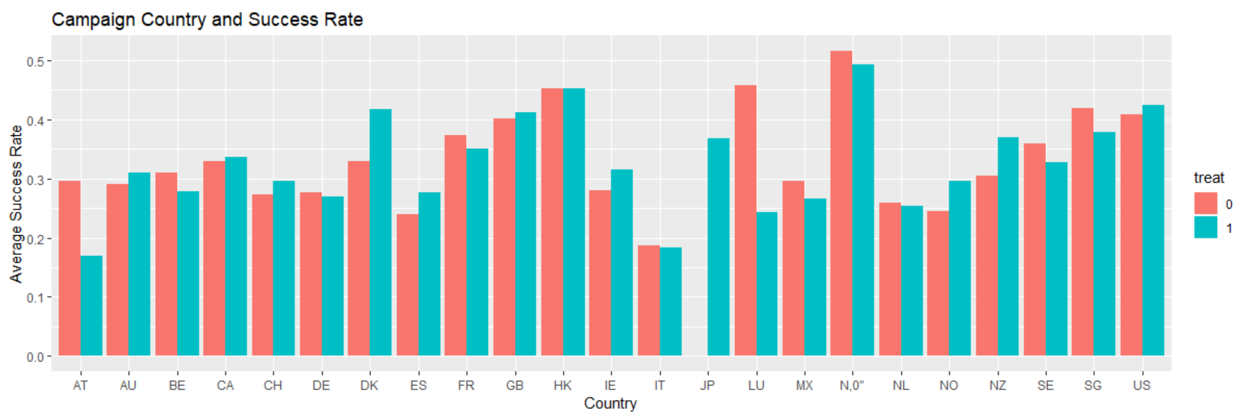
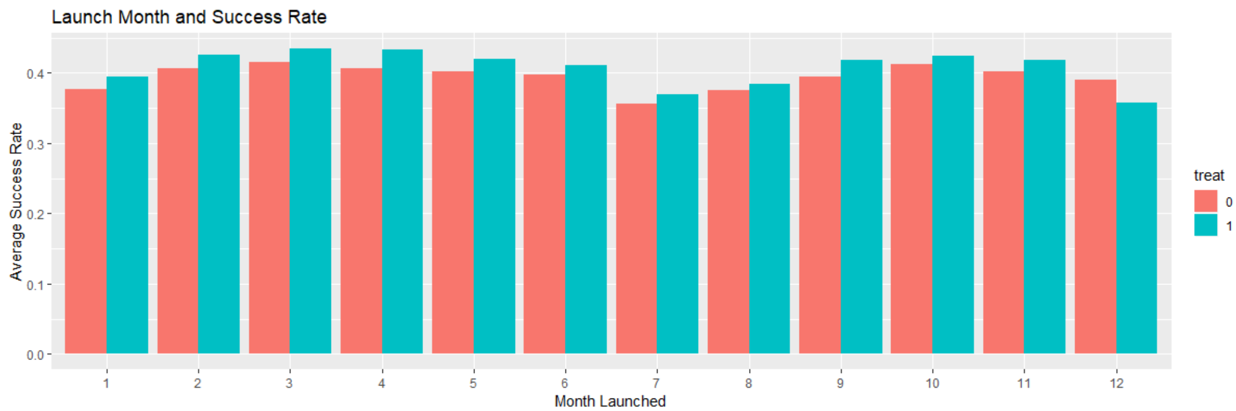


Figure 4



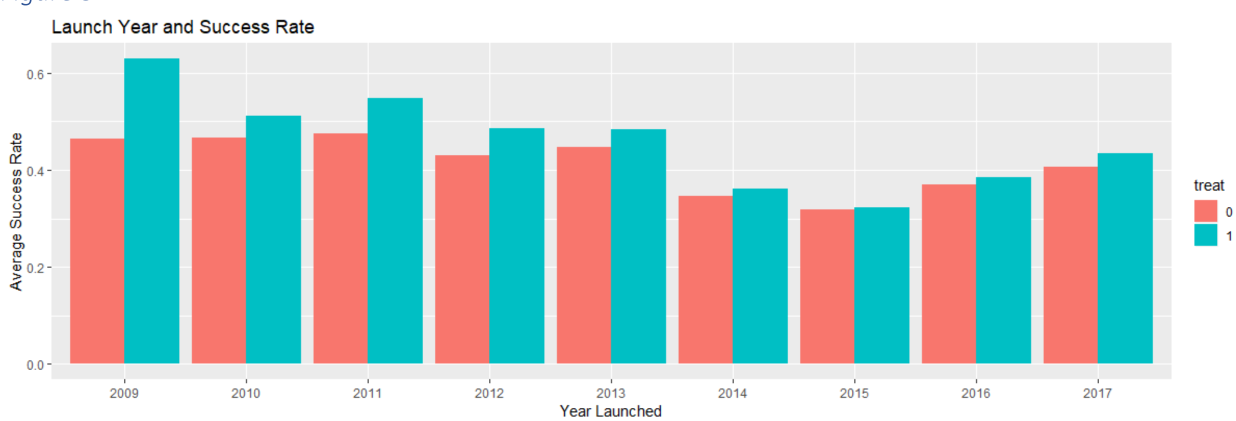
We also see a strong relationship between our variable for campaign launch year and launch month. Intuitively, we would expect certain times of the year to induce more fundraising than others. For instance, U.S. tax season is around March and April. Many Americans, especially younger taxpayers, will get a refund, and many people treat this refund like extra disposable income. We might assume that these people will use a portion of the refund to help push a few of their favorite Kickstarter projects past their fundraising goal. Additionally, money is a common holiday gift around December, and, like the tax refund, we might assume that taxpayers will pay part of their gift toward a project they are really interested in. See Figure 1 for a visual of the potentially confounding effect.

Figure 4



On a year to year basis, it is reasonable to assume that campaign success rate and average duration will change. It would likely be caused by several factors associated with the year, like total projects, total backers, and increased competition from other platforms attracting talented campaigners. We also don't have information about when Kickstarter released their assertion, as the site only shows how recently it was updated. Our hope is that the launch year variable captures these effects, in lieu of more robust measurements.

Figure 5



We believe that goal, category, country, and time are confounders to our causal inference, and we need to design our experiment around mitigating the effect they have on our experiment. We will use propensity score matching to handle the confounding effects of goal and country, and we will directly handle time and category with fixed effects regression.

Methods

Ideal Experiment Design

If the ideal experiment was possible it may be designed as follows. The unit of analysis would be the Kickstarter campaigns. An A/B test would be set up where each user that visits Kickstarter is randomly assigned to a control group or a test group. The control group would see one version of the campaign with the duration set at 30 days. Alternatively, the treatment group would see a separate campaign. The treatment campaign would be identical in all its content but would have a duration randomly chosen for between 31 and 90 days. Possible confounding issues include time of year, the category of the campaign and the level of the goal. By implementing this randomization at the individual campaign level, we can avoid confounding by the campaign specific issues. Additionally, running this test at different periods of the year and across many countries can help us avoid time or location related confounding issues. Interference is possible by users accessing the site from multiple IP addresses, or from campaigners setting up dummy accounts to artificially raise funds. If we are not able to identify the user, they may not see the version of the campaign that they are intended to see.

We do not have the resources to run this experiment. Instead, we will design a quasi-experiment with an econometric approach to detect the casual effect of campaign duration below or above 30 days on probability of success.

Matching

The first part of our design is propensity score matching, which will balance and recover 'as-good-as' random selection into treatment and control. We treated matching as a pre-processing for our further analysis. The basic idea behind doing it was to have propensity scores for each record matched with another propensity score. Each matched record should have almost identical profiles, except with different binary treatments. For each record, we built the matching profile on the campaign goal and country.

Assumptions and Downsides

With matching alone, we would only be able to recover treatment effect on the campaigns in the dataset. We could not generalize the results to the population. We are also assuming that the success or failure of the campaign depends on the variables that we are matching on. We have acknowledged that we do not have measurements for a few unobserved variables, but we have measurements for others and we can use them for matching and further analysis.

Benefits

The benefit of matching is that we have a dataset that has recovered 'as-good-as' randomization between treatment and control with respect to goal amount and country. Our assumption now is that goal and country will no longer confound our causal effect.

Fixed Effects

The second approach in our analysis was Fixed Effects. After we have preprocessed the dataset using matching, we can now directly address the static confounders that affect our causal inference. We used fixed effect analysis on time (year & month) and category.

Assumptions and Downsides

We are assuming that the confounding effects we are fixing are not varying across time or category. The downside to this approach is that we cannot control for confounders that vary across time or category. Thankfully, our biggest threat that varies across time and category is goal, and we used matching to handle this confounder.

Benefits

Fixed Effects gives us the ability to directly address our static confounders. We observed earlier that there is unaccounted for variation across categories, and we can also safely assume that there is likely some variation across time.

Results and Conclusions

Our recommendation is to keep campaigns at or below 30 days, as we found strong evidence in support of Kickstarter's claim. Our conclusion from our econometric approach using matching and fixed effects is that the treatment effect is 4%. In other words, if a campaign is run for 30 days or less, it increases the probability of success for that campaign by 4%. Our treatment effect has a significant p value that is nearly 0, so there is almost no chance of detecting this effect if there truly was none. See Figure 6 for the regression results.

Now that we have strong evidence indicating that duration has a causal effect on success rate, we can start to investigate other similar relationships. We model success on duration, to understand the marginal causal effect that each day has on rate of success, and we found that each additional day reduces the rate of success by 0.5%.

We are no longer using our binary treatment variable here, so we cannot justify using the matched set as the input to our fixed effects regression. We will use the pre-matched data in the same fixed effects model to recover the marginal treatment effect, but we should also try including goal and country in the model to ensure they are not confounding this relationship. Our iterations show that adding goal and country creates statistically significant $\hat{\beta}$ estimates, they do not affect our estimate of the treatment effect in a meaningful way. Our model with continuous treatment only includes our original fixed effects (see Figure 7).

We can also repeat this process to understand how our binary and continuous treatment effects impact the pledged to goal ratio. We might be interested in campaigns that are trying to exceed their goal, as many campaigns are run with a goal of $1, $10, or some small and easily cleared hurdle. These campaigners are not simply interested in success or failure, and we have the observations and approach in place to capture pledge to goal ratio.

For our pledged to goal on binary treatment regression, we see a treatment effect of 5%. Running a campaign for 30 days or less increases your expected pledge to goal ratio by 5%. This is in line with our outcome when modeling success rate (see Figure 8 for regression output).

We run into the same issue regarding our matched dataset when modeling pledged to goal ratio on our continuous treatment variable. We find that increasing the duration of a campaign by one day decreases the expected rate of success by 0.5%. We again see that, when we add goal and country into the model, our $\hat{\beta}$ estimate for our treatment effect is not affected in a meaningful way (see Figure 9 for regression output).

Our final results and business interpretations can be summarized as follows:

- Setting a campaign duration to 30 days or less increases the probability of success by **4%**
- Increasing campaign duration by 1 day decreases the chance of success by **0.5%**

- Setting a campaign duration to 30 days or less increases the Pledged/Goal ratio by **4%**
- Increasing campaign duration by 1 day decreases the Pledged/Goal ratio by **0.5%**

Appendix: Regression Outputs

Figure 6

Fixed Effects: Success

	Dependent variable:
	success
	Success on Treatment
treat1	0.039***
	(0.002)
Observations	238,164
R2	0.053
Adjusted R2	0.053
Residual Std. Error	0.478 (df = 238129)
Note:	*p<0.1; **p<0.05; ***p<0.01

Figure 7

Duration Effect on KS Success

	Dependent variable:
	success
	Success on Duration
duration.days	-0.005***
	(0.0001)
Observations	331,664
R2	0.073
Adjusted R2	0.073
Residual Std. Error	0.472 (df = 331629)
Note:	*p<0.1; **p<0.05; ***p<0.01

Figure 8

Fixed Effects: Pledged/Goal Ratio

	Dependent variable:
	log(pledged.goal.ratio + 1)
	Pledged/Goal on Treatment
treat1	0.050***
	(0.002)
Observations	238,164
R2	0.046
Adjusted R2	0.046
Residual Std. Error	0.588 (df = 238129)
Note:	*p<0.1; **p<0.05; ***p<0.01

Figure 9

Fixed Effects: Pledged/Goal Ratio

	Dependent variable:
	log(pledged.goal.ratio + 1)
	Pledged/Goal on Duration
duration.days	-0.005***
	(0.0001)
Observations	331,664
R2	0.061
Adjusted R2	0.061
Residual Std. Error	0.554 (df = 331629)
Note:	*p<0.1; **p<0.05; ***p<0.01