Economics Letters 123 (2014) 391–394

Contents lists available at ScienceDirect

Economics Letters

journal homepage: www.elsevier.com/locate/ecolet

Non-profit differentials in crowd-based financing: Evidence from 50,000 campaigns

Stefan Pitschner[a,*], Sebastian Pitschner-Finn[b]

[a] *Universitat Pompeu Fabra. Ramon Trias Fargas 25-27, 08005 Barcelona, Spain*
[b] *Berlin Institute of Technology. Straße des 17. Juni 135, 10623 Berlin, Germany*

HIGHLIGHTS

- We assess empirically if non-profit crowdfunding projects are unusually successful.
- Within our database, we classify more than 2000 projects as non-profits.
- They receive higher average pledges and are more likely to reach their funding goals.
- Yet, they also obtain lower total funding amounts and have fewer funding providers.
- A small number of very successful for-profit projects is important for the results.

ARTICLE INFO

Article history:
Received 14 February 2014
Received in revised form
26 March 2014
Accepted 30 March 2014
Available online 8 April 2014

JEL classification:
G3
L2
L3

Keywords:
Crowdfunding
Non-profit
Entrepreneur
Startup

ABSTRACT

We use data from approximately 50,000 crowdfunding projects to assess the relative funding performance of for-profit and non-profit campaigns. We find that non-profit projects are significantly more likely to reach their minimum funding goals and that they receive more money from the average funding provider. At the same time, however, they have fewer funding providers and obtain lower total funding amounts. Our analysis shows that these results are driven by a small number of very successful for-profit projects. We argue that the findings are consistent with a simple selection mechanism in which entrepreneurs make the non-profit/for-profit decision based on expected project payoffs.

1. Introduction

Over the past 5 years, crowd-based financing has seen steady growth and also started to attract academic attention.[1] One of the most interesting findings of the existing literature on crowdfunding is reported by Belleflamme et al. (2013). Motivated by a model with contract failure, they collect data from 44 projects and show that non-profit campaigns appear to have above-average success at raising funds from the crowd.[2] This paper revisits their finding using a large dataset of approximately 50,000 crowdfunding campaigns, more than 2,000 of which we classify as non-profits. The total funding amount provided to the projects in our database sums up to more than 413 million US Dollars.

In terms of the average amount received per funding provider and the probability of reaching the desired funding goal, we confirm that non-profits are more successful. However, the picture re-

* Corresponding author. Tel.: +34 935421621.
E-mail address: stefan.pitschner@upf.edu (S. Pitschner).

1 For example Agrawal et al. (2011, 2013), Belleflamme et al. (2013), Gerber et al. (2012), Kuppuswamy and Bayus (2013), Lehner (2013) and Mollick (2014).

2 Read (2013) presents a similar finding considering 216 crowdfunding projects. In related work, Elfenbein and Fisman (2012) use data from eBay to show that charitable behavior of sellers can serve as a substitute for seller reputation. Also see McManus and Bennet (2011), who study how charitable product features can affect consumer demand.

http://dx.doi.org/10.1016/j.econlet.2014.03.022

verses when we consider the total number of funding providers and the total funding amount in dollars. We show that this reversed finding is driven by a small number of extremely successful for-profit campaigns, represented by the very right end of the success distribution. We argue that this is consistent with entrepreneurs running those projects for profit that have the highest expected overall payoffs.

The rest of the paper is organized as follows. Section 2 introduces the dataset and discusses how we identify non-profit projects. In Section 3, we present the empirical results. Section 4 concludes.

2. Dataset and definition of non-profit projects

The data used in this paper is from the public archive of the crowdfunding website kickstarter.com. We used the website's search function with 300 of the most common English words and considered the projects these searches returned. Overall, we use data from 50,861 crowdfunding campaigns that ended between 2009 and 2013. Out of these, we eliminate a small number of outliers and then keep all those whose location was within the US, and whose funding period had already ended.[3] This leaves us with a total of 46,888 campaigns.

Given the large number of observations, we chose to identify non-profits by text-searching the descriptions of each project. More precisely, we set a non-profit indicator variable equal to 1 for all projects whose descriptions contain at least one occurrence of a variant of the word "non-profit".[4] Generally speaking, our dataset is constructed to contain only variables that can clearly be classified as either controls or outcomes. For example, the analysis does not use variables such as a project's number of social media followers or its number of project updates. Since such measures are likely influenced by both the initial set up of a given campaign and its success, their inclusion in our regressions could cause endogeneity problems. Our measures of funding success comprise a dummy variable for reaching the desired funding goal, the total number of funding providers, the total dollar amount provided, and the average dollar amount supplied per funding provider. The control variables are briefly discussed below. Table 1 contains some descriptive statistics of the dataset.

3. Empirical results

This section contains the empirical results. We begin with an introductory graphical analysis and then turn to multivariate regressions.

3.1. Graphical analysis

Our graphical analysis is based on the percentiles of three of the quantitative success measures. Since all three of these variables turn out to reach very large values at the right ends of their distributions, we display the percentile ranges 1–95 and 96–100 in separate plots. As Fig. 1 shows, for the percentiles 1–99 and all three measures, non-profit projects reach higher values than the for-profit ones. However, at the very right ends of the distributions this behavior changes. Here, for-profit projects outperform by very large margins. These findings suggest that non-profit projects do not consistently obtain more funding than for-profit ones.

3.2. Regression analysis

Next, we turn to the regression analysis. Apart from the three success measures already considered above, we now also use a dummy variable indicating that a project successfully reached the desired minimum funding goal. All of our specifications are estimated using OLS and of the following form:

$$s^i = c + \beta d^i_{non\text{-}profit} + \gamma X^i + \epsilon^i. \tag{1}$$

Here, s^i denotes the given success measure of project i, $d^i_{non\text{-}profit}$ is the indicator variable for non-profit projects and X^i is a vector of project-specific control variables. For those regressions using the funding goal dummy as the dependent variable, the specification corresponds to a linear probability model. Motivated by the findings from the graphical analysis above, we run two different regressions for each one of the success measures. While the first one always uses the entire sample of all 46,888 projects, the second one excludes the top 1% in terms of funding success.[5] This allows us to assess their role in the full sample results.

While our regressions do not warrant a causal interpretation, the control variables do account for many important characteristics that could be systematically different between for-profit and non-profit campaigns. In particular, we control for the funding goal, the minimum funding amount, the number of words contained in the project description, and the campaign duration in days. In addition, we also use dummy sets for the product categories, the campaign locations and the timing of the campaign ends.[6]

As Table 2 shows, we find that non-profit projects are more likely to reach their predefined funding goals and that their average amount received per funding provider is higher. For the other two success measures, however, the picture looks different. Here, our full sample regressions suggest that it is actually the group of for-profit projects that is more successful. On average, for-profit projects have more funding providers and receive higher total funding amounts in dollars. To understand this finding better, we can consider the regressions that exclude the 1% of most successful projects: given that the sign on the non-profit dummy is significantly positive in these regressions, we conclude that the apparent for-profit advantage is driven by a small group of very successful campaigns.

4. Concluding remarks

In this paper, we have used data from approximately 50,000 crowdfunding projects to assess the relative funding performance of for-profit and non-profit campaigns. Our results suggest that non-profit projects receive more money per funding provider and that they are more likely to reach their minimum funding goals. On average, however, they also have fewer funding providers and obtain lower total funding amounts. One possible explanation for

[3] We performed these searches in September 2013. Outliers are identified based on two criteria. First, we drop campaigns with extremely low or unrealistically high funding goals. For the upper and lower bounds we follow Mollick (2014) and use $100 and $1,000,000, respectively. Second, we eliminate all campaigns whose text descriptions contain fewer than 10 words. All results reported below are, however, qualitatively robust to the inclusion of these outliers.

[4] The variants we check for are "non-profit", "non profit", "nonprofit", "not-for-profit" and "not for profit". To assess the accuracy of this approach, we manually check random samples with $n = 50$ for each of the two automatically assigned categories. For these samples, we find that 46 out of 50 non-profit labels and 47 out of 50 for-profit labels were correctly assigned. This suggests that our non-profit variable captures the desired concept relatively well.

[5] We define these most successful products in terms of the number of funding providers, but the results are robust to using the total dollar amount of funding instead. Weighted specifications that take differences in the ratio of successful vs. unsuccessful campaigns into account also yield similar results.

[6] The location dummy set is defined at the level of US federal states, and the number of product categories is 51. The campaign ending times are captured by a set of year–month dummies. All of the main results are robust to excluding product categories that do not contain at least 20 non-profit projects.