The Rich Get Richer? Limited Learning in Charitable Giving on donorschoose.org

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Abstract

Crowdfunding websites allow anyone to raise money through many financial contributions from the 'crowd.' One commonly cited social benefit of crowdfunding is the *democratization* of access to capital. The degree of the democratization depends on how much ordinary people, who may not have financial access before crowdfunding, receive funding. Since many crowdfunders start out as a non-professional, learning is a critical factor for them to be successful. However, it is not clear that initially unsuccessful crowdfunders learn enough to prevent the rich get richer phenomenon. By analyzing a large dataset from donorschoose.org, we found that successful crowdfunders appear to learn more while unsuccessful crowdfunders frequently give up on crowdfunding. This result calls for design solutions that help crowdfunders learn from failure better.

Introduction

Crowdfunding websites allow anyone to raise money by soliciting the 'crowd' for donations. Crowdfunding is often believed to *democratize* access to capital by providing a handy online platform where an individual can ask internet users for small monetary contributions without having to go through the traditional financial institutions (Kim and Hann 2014). This democratization argument envisions the social virtue of crowdfunding as a platform that offers financial opportunities to ordinary people with socially beneficial ideas. Although frequently discussed in the business context, crowdfunding may democratize funding in a public good domain as well (Castillo, Petrie, and Wardell 2014; Althoff and Leskovec 2015). As an example, public school teachers have been able to raise $500 million to support their students through donorschoose.org since 2000.[1] Independent journalists and public media increasingly crowdfund their work as financial pressure on traditional media escalates (Jian and Usher 2014).

The alternative, though, is that people who already have access to funds and skills at fundraising are better able to raise money on crowdfunding websites. This is the "rich get richer" argument (Swart 2014). As Kim and Hann (2014) found out, people with higher education level and income take advantage of crowdfunding better than the other groups . As an extreme case, crowdfunding may simply provide the group of people who already had a good chance of fundraising with another source of funds.

The reality seems to lie between the two possibilities. For public goods, crowdfunding has already provided opportunities for individuals such as teachers and journalists to circumvent funding limitations of the organizations to which they belong (i.e. public school or media company). However, crowdfunders need to learn much to be successful, including marketing skills and crowdfunding-specific tools (Hui, Greenberg, and Gerber 2014). Project creators' level of knowledge and skills on crowdfunding often do not match the social benefit of their projects. Since ordinary individuals who need democratized financial access start out as a non-professional, their experience is an important means of learning.

If learning from personal experience is indeed an important path for a crowdfunder to successfully fund their ideas, it is natural to ask how well crowdfunders learn from their experience and whether the learning process works well for most of them. The democratization of capital would remain to be a mere possibility if people who initially lack fundraising skills do not have the opportunity to become successful. Conversely, better understanding of the learning process can help crowdfunders and platform designers so that fundraising through crowdfunding is more successful. Thus, it is valuable to gauge how crowdfunders learn from their experience. Further, if there is room for improvement, we can also ask what factors are currently impeding learning.

To tackle these tasks, we analyze a large data set from donorschoose.org, a crowdfunding website dedicated to educational projects. We show that crowdfunders who initially lack funding ability do not catch up much with skilled crowdfunders through repeated projects. Subsequently, we show that this limited learning is caused by learning from success but not from failure or repetition, and discouragement from previous failures. These results that rule out other types of learning process such as learning-by-doing and learning from failure imply that design solutions that help crowdfunders learn from unfunded projects are needed to make crowdfunding better serve democratization.

[1]See http://www.donorschoose.org/about/impact.html for a real time statistics. Last retrieved Jan 10, 2017.

Related Research

Crowdfunding researchers have found factors that make projects more fundable. By scraping and analyzing data from Kickstarter, Mollick (2014) found that asking for less money, having a larger social network, and including a video clip in a project description are positively associated with successful funding. For crowdfunders, those are important factors they need to learn. Hui et al. (2014) found that crowdfunders invest much time and effort in understanding feasible strategies; they frequently consult with other experienced crowdfunders and seek information from online tutorials and blogs as preparation.

Learning does not stop when crowdfunders create their first project. Focusing on failed projects and their relaunched counterparts, Greenberg and Gerber (2014) found that project goal of most relaunched projects decreases compared to previous attempts as a result of learning. According to their interviews, creators try to find why their project did not appeal beyond their social group, which leads to learning. In this paper, we generalize the analysis on crowdfunders' learning by expanding the analysis to a larger sample of crowdfunders and putting it in a broad scope of learning studies from the social sicences.

Efficiency of Learning in Empirical Research

Many researchers have been trying to create plausible theoretical learning models and empirically validate them. Although an experiment is often implemented to analyze behavioral learning (see Camerer (2003) and Salmon (2001) for surveys), researchers have also attempted to use observational data as a more realistic approach (Agarwal et al. 2008; Crawford and Shum 2005; Haselhuhn et al. 2012; Ho and Chong 2003). Our analysis of a large data set from a crowdfunding website can be located in the latter approach.

The empirical learning studies based on observational data have commonly focused on efficiency of learning. They try to examine the extent to which individuals finally find out charateristics of their choice alternatives and their own preference to the alternatives. For example, Crawford and Shum (2005) consider a situation where a doctor tries to prescribe the most suitable drug for patients. By analyzing repeated prescriptions data, Crawford and Shum found that learning eliminates uncertainty about the patients fast, and that the realized choices are close to a simulated situation with complete information. However, conclusions are more skeptical in other cases. Haselhuhn *el al.* (2012) analyze video rental market and find out that renters tend to forget the fact that they paid a late penalty. Also, Agarwal *et al.* (2008) make a similar observation about a credit card penalty. Therefore, the question how well people learn from their previous experience is, for instance in crowdfunding, should be asked case by case.

Inequality by Learning

As learning from experience is one of the most recurring themes in the social sciences, there are multiple ways to conceptualize it depending on how a researcher thinks people learn in a context of interest. Learning-by-doing concept suggested by macroeconomic researchers and business scholars assumes that economic agents (e.g. workers or firms) learn from repetition (Lucas Jr 1988; March 1991). In this framework, knowledge and know-hows gained by experience are not differentiated by how successful the previous experience was. On the other hand, studies that focus on business organizations often emphasize learning from failure (Wildavsky 1988; Sitkin 1992; Arino and De La Torre 1998). For example, Wildavsky (1988) argues that, if a task involves a high degree of uncertainty and unknown processes, failure from experiment is an effective way to learn about the task. Learning from failure is also plausible in the crowdfunding context because projects creators the democratization argument focuses on are ordinary people who would not have much pre-existing knowledge about how crowdfunding works, and would not be trained for fundraising in general. Thus, these crowdfunders are likely to be in a great deal of uncertainty. Indeed, focusing on relaunched crowdfunding projects on Kickstarter, Greenberg and Gerber (2014) found that crowdfunders who experienced failure learn importance of marketing efforts and communication with potential contributors, and adjust some of their project material and monetary goal.

These learning concepts (learning-by-doing and learning from failure) seem to support the possibility that initially unsuccessful crowdfunders get better over their repeated experience or status quo at least. However, a few researchers noticed the possibility that learning from experience amplifies inequality that pre-exists on a variety of group levels. It has been long since psychologists identified *Matthew Effect* where productivity increases disproportionally depending on individual's initial success (Merton and others 1968). One suggested explanation for this widespread phenomenon in learning situations by Judge and Hurst (2008) is that people feel good about themselves when they succeed so that originally successful people draw a steeper learning trajectory in their career.

Amplification of inequality by learning is also observed in a broader scope. For example, sociologists have focused on a variety of paths through which economic inequality is widened (Voitchovsky 2009), and Mayer (2001) argues that education is one of the paths. According to his finding, children from high income families are more likely to reach good educational attainment, which in turn leads to even larger income inequality. A similar mechanism turns out to hold across countries. For example, Teulings and van Rens (2008) recently found out that wealthy countries with larger endowment can invest more on education, and it in turn leads to skill-based technological progress. This is suggested as one reason global inequality is worsened even though the standard neo-classical growth theory forecasted the opposite.

If initial success dominates the learning path in crowdfunding, we can suspect that the 'inequality by learning' mechanism explains the importance of the initial endowment that Kim and Hann (2014) noticed. In other words, if successful crowdfunders learn more than unsuccessful crowdfunders, initially competent crowdfunders with higher education levels and income will become even more successful disproportionately. This may be caused by differential information from success and failure. Successful crowdfunders have less uncertainty about success factors when they evaluate the previous experience because unsuccessful crowdfunders cannot match what they did with success. The success upon success is also possible by an emotional path as in psychological studies where successful crowdfunders self-evaluate themselves positively and are encouraged to invest more in next project.

One difficulty in examining whether learning upon success is actually present is that it is hard to distinguish differential learning that drives disproportionate growth of success rate from success due to crowdfunders' initial competence, which is a *proportionate* part. We will adopt a statistical technique to separate out the two parts in our empirical analysis.

Discouragement and Drop-out in Evolutionary Process

There is another path to the rich get richer phenomenon: an evolutionary path. Similarly to the aforementioned Matthew effect, some educational psychologists suggest emotional 'discouragement' as an impediment to learning. *Goal theory* states that if short-term goals are not achieved in the process of a task, it worsens an agent's performance through lowered motivation (Pintrich 2000). However, the lowered performance by discouragement is less plausible in the crowdfunding context because project creators are not forced into a next task as opposed to the educational setting and can at least post the same project if they decide to return.

Instead, discouragement may still have an impact on learning more through an evolutionary process. That is, even if crowdfunders do learn, an impatient person who is less motivated (or became less motivated) may refuse to learn on the same platform by quitting creating projects before she sufficiently learns. Whereas much learning literature posits that agents are given or consecutively enter in its model, it is often more natural to allow a theory to include agents' (metaphorical) death, or drop-out, as in evolutionary processes. To take a biological metaphor, a predator that keeps failing to hunt for any reason (maybe innate incompetence) will die out before it learns how to hunt from its experience. Social evolution theories explicitly take account of this aspect of social dynamics. For example, as opposed to traditional game theory based on rationally behaving individual actors, evolutionary game theory sets population as a unit of analysis and include death and birth of agents into the replicator dynamics to look at how a long term equilibrium differs conditional on a survival parameter (Sandholm 2010).

On a crowdfunding website, project creators may or may not successfully learn depending on how much they are willing to come back and create a next project. If they are not patient, they will not learn anymore. Further, if their patience is conditional on their previous success and failure, previous experience would have an additional impact on learning through this path. We will show that failure indeed induces early drop-out regardless of crowdfunders' ability with a statistical model.

Data Description

donorschoose.org is a crowdfunding website for educational projects created by school teachers. Since it was founded in 2000, it has successfully raised around $500 million for over 800,000 projects as of January 10^{th}, 2017. As for other crowdfunding websites, crowdfunders, namely teachers on donorschoose.org, create projects that require a certain amount of money (project goal). Donors search for projects that they are interested in and make a monetary contribution to the projects. A teacher describes purpose of the project she creates, a type of resources it needs and students who will be benefited to solicit donations.

A distinctive feature of donorschoose.org is that it is mainly for public education. Thus, crowdfunders' learning behavior we analyze may be different from small entrepreneurs' learning on Kickstarter. However, crowdfunding for public interest such as investigative journalism accounts for large portion of projects on a crowdfunding website. Our analysis seems generalizable to those people who solicit charity rather than private investment.

In addition, donorschoose.org adopts a specific rule known as *return rule* (Wash and Solomon 2014). According to this rule, all contributions made are refunded to donors if the monetary goal a creator sets for her project is not met. The return rule clearly defines success and failure of a project on donorschoose.org.

The data set analyzed in this study includes detailed information about every project and donation made from September 1^{st}, 2007 when donorschoose.org started providing a national wide service to February 17^{th}, 2012. During this period, 321,042 projects were posted by 131,757 teachers, and 224,262 projects were successfully funded. This makes a 69.85% completion rate. Among all projects created on donorschoose.org, 82.61% of them (264,209 projects) are for high poverty level schools.[2]

Teachers created 2.45 projects on average. This is larger than donors' average number of donations, 2.05. It tells us that teachers have more of an opportunity to learn than donors (Althoff and Leskovec 2015). However, the number of projects each teacher created varies enormously. 56.68% (79,603) created a project only once. On the other hand, the maximum number is 162.

Similarly, project goal widely varies across projects as well. While the mean and median of project goal are $446.6 and $376.8 respectively, the maximum value is $73,550. 97.14% (334,345 projects) falls into range of zero to $1,000. Within the range, the distribution is highly skewed to the right (bigger projects), which means many projects aim at less than $500 .

[2]Poverty level is defined on donorschoose.org based on the percentage of students at a given school who qualify for free and reduced lunch (`http://www.donorschoose.org/help/popup_faq.html?name=lowincome`). 1,744(0.52%) projects were for schools whose free and reduced lunch data are not available.

Limited Learning on DonorsChoose

In order to examine how efficient the learning is on donorschoose.org, we compare two groups: initially successful and initially unsuccessful teachers. On average, first projects created by the initially successful crowdfunders are likely to have more factors that appeal to contributors. They may have a reasonable project goal, a good description of the project, a visual presentation and so on. As both groups learn these factors along the repeated creation of projects, the possibility of funding is expected to change.

If the learning process is meaningful in a sense that crowdfunding democratizes access to capital (Kim and Hann 2014), even initially less competent project creators should be able to stay on the platform and have an opportunity to become more successful. To see if it is the case, Figure 1 shows the portion of creators who came back to post next projects *and* succeeded in funding to the original numbers of creators in the initially successful group and the initially unsuccessful group. For example, 33.64% of initially successful crowdfunders succeeded in their second projects whereas only 18.03% of the initially unsuccessful creators succeeded. If the lines of the two groups converge in an observable period, it means that crowdfunders who initially lacked fund-raising ability become as successful as their counterpart through their experience. In other words, the separation of the two lines indicates the inefficiency of learning.

The difference between the two groups is persistent. At the second attempts, the difference in the proportion of the successful returning crowdfunders between the two groups is 15.61% (33.64%-18.03%). And it stays at 7.32% (12.03%-4.71%) at the fourth attempts. Also, less than 10% of initially unsuccessful crowdfunders remained on the crowdfunding website to create their fourth projects, and only 4.71% managed to successfully make them funded. In addition, the data show that only 20.40% of the initially unsuccessful crowdfunders experience at least one success up to their forth projects whereas 38.05% of the initially successful group experience one or more successes *again*.

Considering that 89.11% of teachers created four projects or less, this persistence implies that large portion of the initially unsuccessful teachers lack learning opportunities to catch up with the other group. In other words, although crowdfunders may somewhat learn from their experience, they tend to give up while their initial incompetence in fund-raising is still in effect. Conversely, success in crowdfunding appears to still depend on existing knowledge on marketing and finance or an access to the knowledge that project creators gained beforehand. In this case, people who already have the financing skills would be more likely to achieve financial support from a crowdfunding website as on other financial platforms, and experience in crowdfunding would not fundamentally change the current picture.

History of Success and Dropout

Before a formal statistical analysis, a simple graphical analysis can give an intuition about how crowdfunders learn depending on their different experience, and complications that

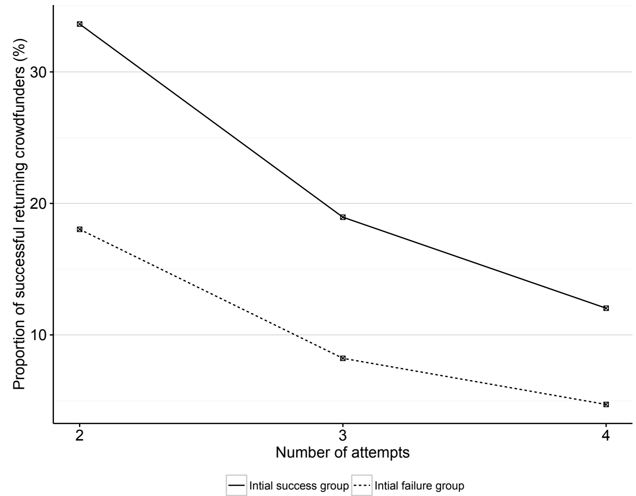


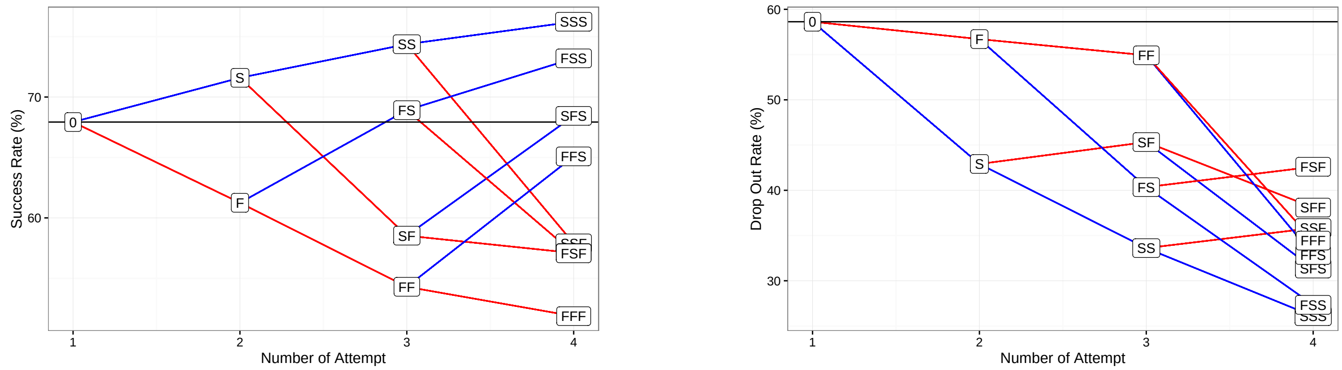
Figure 1: Proportion of crowdfunders who returned and succeeded to the original population of the initially successful and unsuccessful groups. Only 4.71% of initially unsuccessful crowdfunders succeeded in their fourth projects.

have to be dealt with to identify the learning with the statistical analysis. Figure 2 presents the average history of teachers on donorschoose.org along the sequence of success and failure.[3] Each node represents success rate (Figure 2a) and drop-out rate (Figure 2b) of teachers who previously experienced success and failure, which are represented by edges from their first projects (the leftmost node) to fourth projects (the rightmost four nodes). For example, among teachers who succeeded in their first project, failed next and decided to create third project (denoted as "SF"), 58.53% succeeded in funding their third projects and 45.33% did not create a fourth project.

First thing to notice from Figure 2a is that the diagram has the pattern where the average success rate increases and decreases conditional on previous success and failure. But there is one important caveat in interpreting this pattern as an evidence of learning upon success. Since success rate is a function of crowdfunders' initial competence *and* learning, it is possible that high success rate of the group with many successful experience solely comes from their initial competence, which is ubobservable from the data, rather than learning.

However, another pattern that success rate is higher when crowdfunders experienced success more recently given the same number of previous success appears to suggest that there is indeed learning upon success. For example, among teachers who succeeded only once up to third projects (i.e. succeed-fail-fail, fail-succeed-fail, fail-fail-succeed),

[3]We borrowed an idea for the graph from a blog post by Jim Albert on baseball data. `https://baseballwithr.wordpress.com/2016/05/09/graphing-pitch-count-effects/`



(a) Success rate

(b) Drop out rate

Figure 2: Crowdfunders' success rate and drop out rate conditional on their history of success and failure. Continual 'S' and 'F' in the nodes denote previous success and failure in crowdfunders' previous experience as ordered. The blue edge and the red edge denote one time success and failure.

the fail-fail-succeed group has far higher success rate for fourth projects than the other two groups (65.09% versus 57.09%, 57.07%). A similar pattern is observed in other cases such as two success groups (succeed-succeed-fail, succeed-fail-succeed, fail-succeed-succeed). That said, this anecdotal evidence does not generalize to longer histories that cannot be visualized in the diagram. Also, there are other factors that may change depending on previous experience, also affect success (e.g. project size) are not controlled in the graphical evidence. Thus a statistical modeling is required to verify whether crowdfunders learn from success.

There is another complication in Figure 2a that makes the graphical analysis on learning harder. Each group with a different history may innately have a different drop-out rate or patience, and it may be correlated with learning efficiency. For example, the three success group in Figure 2a may be more patient than others, and these patient crowdfunders may learn better than others. In this case, crowdfunders with higher learning efficiency would generate more data because they tend not to drop out. Thus, the degree of learning can be over(under)-estimated if there is positive(negative) association between drop-out and learning efficiency. This possibility also calls for a statistical technique to control the potential bias.

Figure 2b shows that a crowdfunder who experienced failure is more likely to drop out than a crowdfunder who experienced success (red line is above blue line). To interpret this observation as an evidence for discouragement by failure, however, we should take account of a similar complexity. If crowdfunders who experienced failure more often are innately impatient in a sense that they would drop out early anyway regardless of previous experience, the observed different drop-out rate between crowdfunders who succeeded and failed may be larger than the real impact of previous success and failure. Also, it is necessary to control other factors that may affect crowdfunders' drop-out decision.

Learning upon Success

To understand why unsuccessful crowdfunders tend to remain unsuccessful, we first analyze their learning upon previous success and failure as well as learning-by-doing. This approach is invoked by the different conceptualizations of learning: learning-by-doing, learning from failure and learning upon success. We adopt statistical techniques to control out higher success rate directly from crowdfunders' unobservable initial competence so that we can identify learning from previous success.

Dynamic Hierarchical Probit Model

In order to generalize the observation from Figure 2a, we implement an autoregressive 1 (AR(1)) model in which current success is stochastically determined by past successes following Agarwal *et al.* (2008) who analyzed credit card penalty upon previous penalty. If previous success turns out to be positively associated with current success, we can interpret it as learning upon success.

Our AR model to describe the learning process can be expressed as:

$$y_{it} \sim Bern(\Phi(\beta_0 + \boldsymbol{y_{it-1}}\boldsymbol{\beta_1} + t\beta_2 + \boldsymbol{x_{it}}\boldsymbol{\gamma} + c_i + \epsilon_{it})) \tag{1}$$

where y_{it} is one if a teacher i succeeded in funding her t^{th} project and zero otherwise, $\boldsymbol{x_{it}}$ is a control variable vector that includes schools' poverty level (minimal, low and high), project goal (in dollar) and focus area of projects (applied learning, health & sports, history & civics, literacy & language, math & science, music & the arts and special needs), ϵ_{it} stands for an error, and c_i is an individual characteristic of a given crowdfunder. $\boldsymbol{y_{it-1}}$ denotes previous success. Therefore, its coefficient, $\boldsymbol{\beta_1}$ means association between previous success and current success. The function, Φ, is CDF of standard distribution, which makes our specification of the model probit.

If we do not consider the unobserved individual characteristic, c_i, then the model corresponds to the naïve interpretation of Figure 2a that the increase in average success rate after success is an evidence of learning upon success. However, the positive association between previous success and current success may simply mean that an innately competent teacher is likely to repeatedly succeed. A way to control out the innate ability is to model the distribution of the ability, c_i. Technically, we 'integrate out' c_i assuming that the initial competence follows the normal distribution, which is often called *random effect* model.

The problem arises from the possible correlation between patience and learning efficiency is called *attrition bias* in statistics literature. There are a variety of ways to control this bias, but we simply run the model for each attrition group. In other words, we separately run the models for teachers who created three projects throughout the data, for those who created four projects and so on. We did this because possibly differential learning upon success across different groups may contain useful information.

In addition to the attrition bias, a binary dynamic panel model with a lagged variable y_{it-1} with unobservable heterogeneity c_i such as ours may suffer from what is called *initial condition problem* (Wooldridge 2010). This occurs because initial success y_{i1} appears as a fixed value in a dynamic model although it may be also random. If y_{i1} is random, possible correlation between y_{i1} and an individual unobservable characteristic, c_i can cause bias. Wooldridge proposed a simple solution to the initial condition problem based on a model of c_i using the initial endogenous variable (y_{i1}) and the exogenous explanatory variables of the main model (Wooldridge 2005). In our model, we included average project goal as a possible predictor of c_i as following (Contoyannis, Jones, and Rice 2004):

$$c_i = \delta_0 + \delta_1 y_{i1} + \delta_2 \overline{\textit{project goal}}_i + u_i \qquad (2)$$

This approach allows us to simply run an AR model after substituting the above equation for c_i in the equation (1). Due to the presence of u_i (unmodeled crowdfunders' ability), we still have to take expectation of the likelihood function over distribution of u_i (random effect).

Running a maximum likelihood (ML) algorithm was not computationally plausible particularly for teachers who created small number of projects because there are many individual characteristics to model compared to data points. Thus, we used a Bayesian update using Gibbs sampler implemented by JAGS. It is well known that ML estimation and Bayesian update produce similar results with large data like ours. Each coefficient started from a vague prior, $N(0, 0.0001)$, and the unobserved individual characteristics u_i started from hierarchical prior, $u_i \sim N(0, 1/\sigma^2)$ and $\sigma \sim unif(0, 100)$.

Finally, our data set may suffer from a *right-censoring* problem because it includes both teachers who truly stopped creating projects and those who came back after the end of observation. Data from the latter group is right-censored in that their subsequent behavior up to their true last period was not observed within the observation period. The simplest solution to this problem is to only include fully-observed data from teachers who dropped out within the observation period. However, the situation becomes more complicated in our case because it is hard to decide which teacher will not come back (*i.e.* dropped out) based on our observation. We took a heuristic way to define drop-out, in which we consider a teacher who did not come back to create another project more than 180 days to be a drop-outs.[4] We applied different standards, but they did not change the result qualitatively. In addition, we excluded teachers who have a project that has not expired in the observation period. The first subsetting gives us 191,370 projects among 344,196 cases, and the second subsetting further excludes one teacher with only one project creation history. We also excluded data that lack school poverty level information. As a result, we have 190,661 projects created by 98,331 crowdfunders as base data. Lastly, we used data from only teachers who created three and more projects because it is not possible to run a dynamic random effect model on teachers who created only two projects. These teachers generate only one data point in the dynamic model. Thus it is not possible to distinguish individual characteristic, u_i, and the error term, ϵ_{it}. This last subsetting gives us 73,733 projects created by 17,376 crowdfunders.

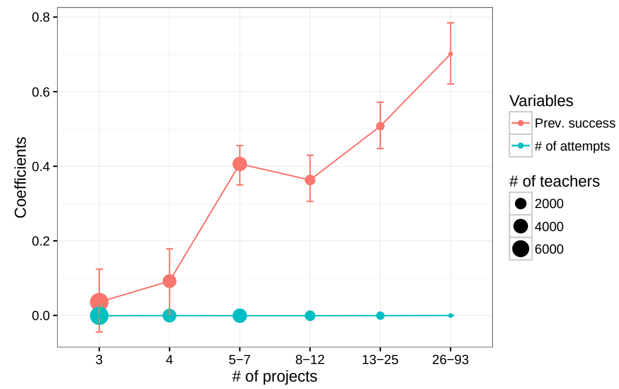


Figure 3: Coefficients for the previous success variable and the number of attempts variable depending on the number of projects crowdfunders create in the data. The size of points indicate the number of teachers fall in to each group.

Statistical Results

Figure 3 shows the impact of previous success and the number of attempts on current success (β_1 and β_2 in equation (1)).[5] The positive coefficients for the previous success for all the groups suggest that teachers learn to succeed from the previous success rather than failure. This result tells us that initially successful crowdfunders will disproportionately learn more than initially unsuccessful crowdfunders, i.e. the steeper learning trajectory for them.

Also, persistent teachers who create many projects learn even more from the previous success. This result provides a even stronger support for the rich get richer hypothesis com-

[4] In DonorsChoose data, 3^{rd} quarter of interval between two projects is 142 days, and a typical period a project stay alive is 150 days.

[5] Including more lags does not change the result qualitatively.

Table 1: APM of Probit Models and Results from LPM for 8-12 Projects Group

	Pooled	Random	LPM
Previous success	0.2257	0.1445	0.0993
	(0.0116)	(0.0111)	(0.01152)
Project goal	-0.0001	-0.0002	-0.0001
	(0.0000)	(0.0000)	(0.0000)
Number of attempt	-0.0086	-0.0109	-0.0136
	(0.0008)	(0.0008)	(0.0014)

bined with drop-out followed by failure (next section). According to the result, initially successful crowdfunders not only become more successful, but also remain to create another project and learn even more efficiently from previous success.

Another important observation is that the estimated effect of repetition (number of attempt) is negative although the magnitude of the effect is very small (Figure 3). For all groups, the coefficient for the number of attempt variable is within -0.0007 to -0.0002. It means that crowdfunders do not learn simply by creating projects repeatedly. This result rejects the simple learning-by-doing hypothesis where crowdfunders simply learn from repetition. Combined with the previous finding on learning upon success (rather than failure), this result provides a strong support for the possibility of inequality by learning on donorschoose.org, which seems to dominate other potential learning process such as learning-by-doing and learning from failure.

To validate whether the random effect assumption to control the effect of initial competence on the current success is proper, we compare the result from the random effect model to that from a more robust model. In particular, we use a linear probability model (LPM) which assumes a linear relationship between previous success and current success. The linearity is not desirable as a *full* description of a zero-one (success-failure) event as in our case because a predicted success rate may be over one or under zero. However, LPM has two advantages compared to non-linear models such as probit. One is that LPM does not necessarily depend on the distributional assumption to control the unobserved crowdfunders' ability. In that sense, LPM is more robust. In particular, we adopt the standard Arellano-Bond GMM estimator (Arellano and Bond 1991) which utilizes the moment conditions between the error term and lagged variables.

Another advantage of LPM is that it is known to produce a good approximation of *average* effect estimated by nonlinear models. One major drawback of non-linear models as probit is that estimates cannot be directly interpreted into an intuitive meaning. To better interpret the size of the effect, we derived the *average partial effect* (APE) of the nonlinear models, $E_{c_i}[\frac{\partial E(y_{it}|x_{it},c_i)}{\partial x_{tj}}]$ using maximum likelihood estimation (MLE). APE is an average effect size across the sample. But in LPM, the estimated coefficients are APE itself. It is well known that LPM coefficients are a good approximation of the true APE (Wooldridge 2010). Therefore LPM gives a good comparison point to see if the random effect probit model properly control the unobservable ability.

Table 1 compare APEs from probit, random effect probit and LPM for crowdfunders who create 8 to 12 projects. Unlike the pooled probit (first column), the estimated learning upon success from the random effect probit (0.1445) is close to the results from LPM (0.0993). Thus, the random effect probit model seems to handle the individual difference. According the results, when a crowdfunder in this group succeeded in the previous project, it will increase the probability to succeed this time by $10-15\%$ on average. This result makes the steeper learning trajectory story even clearer. On average, competent crowdfunders who starts out with 70% success rate will hit 87% (applying $s_{t+1} = 1.10s_t^2 + (1-s_t)s_t$ where s_t is the success rate at t^{th} attempt) after three attempts whereas initially less competent crowdfunders who start out with 40% success rate will remain at 45% success rate even when we choose a conservative learning rate, 10%.

Drop-out by Failure

If a crowdfunder does not learn much from failure, what does failure do in crowdfunders' dynamic behavior? To understand the effect of failure, we move our focus on drop-out this time. Similarly to the learning upon success model, we regress success on drop-out using the hierarchical probit model. Formally,

$$drop_{it} \sim Bern(\Phi(\beta_0 + \boldsymbol{y_{it-1}\beta_1} + t\beta_2 + \boldsymbol{x_{it}\gamma} + c_i + \epsilon_{it})) \tag{3}$$

where $drop_{it}$ is an indicator variable, which is 0 if a crowdfunder comes back to create t^{th} project and 1 if she does not. y_{it-1} is the previous success and t is the number of projects as in equation (1). x_{it} is a vector of explanatory variables, which include project goal (in dollar), total amount to donated to the project relative to the project goal (continuous within 0 to 1, 1 being funded), schools' poverty level (minimal, low, high) and focus area of projects (applied learning, health & sports, history & civics, literacy & language, math & science, music & the arts and special needs).

This model is simpler to estimate than the learning upon success model because it does not contain a lagged dependent variable as an explanatory variable. However, there is an unobservable characteristic issue similar to the previous model. That is, if crowdfunders who experienced failure more often innately have a tendency to drop out early, the estimated coefficient for the previous success may exaggerate the impact of failure on drop-out. Accordingly, we ran both a simple probit model and the random effect model that takes account of the unobserved individual difference. Similarly to the learning upon success model, we used Gibbs sampler as an MCMC algorithm to estimate the posterior distribution of coefficients starting with vague prior $N(0, 0.0001)$. Also, we use the same hierarchical prior for individual characteristics, $c_i \sim N(0, 1/\sigma^2)$ and $\sigma \sim unif(0, 100)$. Lastly, we used the same sample with the teachers who created more than three projects, and the same definition of drop-out.

Table 2: Results from Drop-out Models

	Probit	Multilevel
Previous success	-0.7989	-0.6051
	(0.0164)	(0.0506)
Number of attempt	-0.0037	-0.0302
	(0.0020)	(0.0016)
Project goal	-0.0000	0.0000
	(0.0000)	(0.0000)
Ratio	0.3736	0.0136
	(0.0519)	(0.0522)
Low poverty	0.1149	0.0351
	(0.0155)	(0.0154)
Minimal poverty	0.1390	0.0579
	(0.0382)	(0.0383)
N	73,733	73,733
Teachers	17,376	17,376

Table 2 reports the result of the vanilla probit model and the hierarchical random effect model. The models yield expected results: previous success decreases drop-out rate. Conversely, previous failed crowdfunders are more likely to drop out. This corresponds to our hypothesis that initially unsuccessful crowdfunders would not have a chance to learn from success because they give up. Compared to the probit model, the effect size from the random effect model (-0.6051) is significantly smaller than the estimated coefficient from the vanilla probit model (-0.8009), which means that there is correlation between innate tendency to drop-out rate and success.

The number of attempts has a significantly negative impact on drop-out (-0.0302). This means that crowdfunders become less likely to give up as they create more projects. This implies a second hand advantage for initially successful crowdfunders. They tend to stay to create another projects not only because they are less discouraged, but also because they become more persistent as they create more projects than discouraged initially less successful crowdfunders.

Ratio in Table 2 is the total amount of donation relative to the project goals. In the random effect model, the ratio does not seem to have a significant effect on drop-out because the estimated coefficient (0.0136) is small compared to its standard error (0.0522). This means that crowdfunders' drop-out decision depends on dichotomous success and failure, but does not depend on the degree to which the fund-raising was successful if they fail to meet the goal. This emphasizes the role of success in crowdfunders' learning along the path.

Discussion

Using almost five years of data from donorschoose.org, we examined one way that crowdfunding websites might be able to democratize accesses to funding: helping people learn how to raise money effectively. We found that many people don't seem to improve at being funded as they create additional projects; the learning that does happen mostly occurs because of successes rather than failures, and that initial failure can cause people to drop out before having the opportunity to learn. This result provides a strong support for the inequality by learning on crowdfunding, which other forms of learning such as learning-by-doing and learning from failure would not produce.

This potentially contradicts previous findings from Greenberg and Gerber (2014). Studying mostly Kickstarter, they found that people actively try to learn about crowdfunding by talking to others and reading advice online, and that people report failure as a positive experience because it encourages them to learn more. There are several possibilities for this discrepancy. First, crowdfunders' perception of their previous experience may be different from the real effect. Second, the interviewees in Greenberg and Gerber's research may be a group that is more motivated than population. They only interviewed people who were still active in crowdfunding who relaunched their failed project, and the discouragement by failure we found would not be captured from this sample.

Finally, we studied donorschoose.org, which focuses mostly on charitable giving, while Greenberg and Gerber focused on the business-like context of Kickstarter. It is possible that public good crowdfunding, which includes donorschoose.org, sites like Spot.Us that focus on journalism, sites that support scientific research (Hui and Gerber 2015), and other non-reward based crowdfunding, have very different motivations for both donors and project creators than business-like crowdfunding websites like Kickstarter or IndieGoGo.

Our findings suggest that crowdfunding websites still have a long way to go to democratize access to funding. However, they also help point toward ways that we can improve the websites. For example, many people do not learn because they are over-ambitious in their initial project, ask for too much money, fail to receive enough funding, and then are discouraged. Goal theory suggests that users are less likely to be discouraged, and more likely to learn, if they set reasonable and achievable goals (Pintrich 2000). We suggest using the prior research that can predict crowdfunding success (such as research by Mollick (2014) and Mitra and Gilbert (2014)) to estimate the success of a proposed crowdfunding project and help set realistic goals. The finding that people do not learn from repetition and failure also implies that we can improve crowdfunders' learning by helping them evaluate their failed projects. For instance, a functionality that compares failed projects with successful similar projects as adopted in reverse auction websites like priceline.com would help this evaluation, and mitigate the discouragement from the failure by suggesting a way for an improvement.

Conclusions and Limitations

Crowdfunding has rapidly become a legitimate financial platform that complements or partially substitutes traditional funding institutions, particularly for innovative ideas. Easy entry that crowdfunding allows makes creators' learning an important and peculiar issue to understand. On crowdfunding websites, many non-professional people come and go with their innovative ideas and learn from their repeated experience, while bigger organizations or professional individuals raise more money by conducting more systemic and institutionalized effort through tradition funding mechanisms. Thus, we tried to explain the unique features of dynamics on a crowdfunding website that comes from crowdfunders' learning.

What we found out is a little disappointing compared to the picture of democratization of access to capital may envision. Crowdfunders who start out with strong competence will be more successful because they learn from their success whereas initially unsuccessful crowfunders are likely to drop out without learning much. Our finding corresponds to the rich get richer phenomenon in that successful ones will be more successful. But it is partially beyond that to resemble the natural selection where less competent members even die out. Although other sources of learning can help, it does not seem to be working well either because our finding shows the success rate is not improved as crowdfunders try again. This suggests that democratization through crowdfunding requires both learning from own experience and that from outside to be enhanced.

The present research is limited in that donorschoose.org is a peculiar type of crowdfunding website based solely on charity. Since a reward to contributions is common and turned out to be helpful for funding on the generally purposed crowdfunding websites such as Kickstarter and Indiegogo (Mollick 2014), crowdfunding is understood in an investment framework in some cases (Belleflamme, Lambert, and Schwienbacher 2013). To apply our result to the generally purposed crowdfunding websites, one needs to consider possible differences from charity-based crowdfunding. For example, projects on Kickstarter may involve more private interest. Private incentive may enhance efficiency of learning (less decay of information and less discouragement) and increase role of skills. However, it is not definite that charitable intent provides a weaker incentive to learn than the private interest does. Even if it does, there may be other elements that offset the stronger incentive to learn in a private interest setting. For instance, success rate in Kickstarter is much lower than that of donorschoose.org, which may intensify the discouragement effect. Thus, learning on the generally purposed crowdfunding websites is still up for empirical examination.

However, this limitation does not necessarily mean that our research is too narrowly focused. Crowdfunding has drawn attention also as a new financial source to serve public interest. Crowdfunding public media or independent journalism is a leading example (Carvajal, Garcia-Aviles, and Gonzalez 2012). Our result seems generalizable to these growing cases involved with public interest where charitable give is more prevalent.

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