Competing Fundraising Models in Crowdfunding Markets

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Job Market Paper

November 13, 2015

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Abstract

The purpose of this paper is to study how different funding mechanisms affect donors’ and fundraisers’ incentives in crowdfunding markets— the Internet platforms that have revolutionized fundraising. In the first mechanism (All-or-Nothing), fundraisers receive the donations they raise only if it exceeds their funding target. Under the second mechanism (Keep-it-All), fundraisers receive the donations they raise regardless if it exceeds their funding target. I develop a model of donors’ preferences for crowdfunding that I estimate on a dataset that includes over a quarter-million fundraising campaigns collected directly from the two largest crowdfunding platforms. I then quantify the importance of donors’ incentives and fundraising sorting across the two platforms and the implications for platform revenues and market efficiency.

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1 Introduction

Crowdfunding markets are Internet platforms that have revolutionized fundraising. By reducing geographic frictions and leveraging social media networks, crowdfunding websites have allowed donors from all over the world to contribute billions of dollars to a range of creative, philanthropic, and innovative endeavors. In the last five years, these platforms have experienced rapid global growth, and it is estimated that in 2015 there will be over a thousand crowdfunding platforms projected to raise $30 billion (Massolution (2015)). Crowdfunding markets are credited with increasing lending to female entrepreneurs\(^1\) (Greenberg and Molllick (2014a)), reducing bankruptcy filings (Burtch and Chan (2015)), and addressing the difficulty of early ventures to raise small to medium amounts of capital.\(^2\)

An interesting feature of crowdfunding markets is the emergence of two competing fundraising mechanisms. In the All-or-Nothing mechanism (AoN), fundraisers keep the money they raise only if they reach or exceed their funding goal. In contrast, under the Keep-it-All mechanism (KiA) fundraisers keep the money they raise regardless if they reach their funding goal.

The main purpose of this paper is to quantify how these different mechanisms affect donors’ incentives to make contributions. To see why donors may behave differently under the two mechanisms, imagine an individual is deciding whether or not to donate to a fundraising campaign that has raised half its goal with a few days remaining. At the time of the decision, the individual does not know how much the project will raise by the end of the campaign since total donations depend on the arrival and contributions of future donors.

Under AoN, our donor faces two uncertain outcomes: either the campaign is successful in reaching its goal and the donor’s contribution is made, or it does not, in which case the fundraiser receives nothing and the donor’s contribution is returned. Under KiA, the donor knows that the fundraising campaign will raise at least half of its goal, but may fall short of actually reaching it. Regardless of how much is ultimately raised, though, the donor’s contribution is sunk. The different mechanisms thus affect both the costs and benefits of making contributions.

To investigate the role the AoN and KiA mechanisms play in crowdfunding markets, I develop an empirical model of donors’ preferences for contributing to crowdfunding campaigns under both the AoN and KiA mechanisms. I then estimate my model on a unique dataset collected directly from the two largest crowdfunding platforms: Kickstarter and Indiegogo. Kickstarter only allows the AoN mechanism, and while Indiegogo offers the choice of both, over 96% of fundraisers choose the KiA mechanism. My dataset covers a period of over two years and includes over a quarter-million fundraising campaigns.

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\(^1\)http://www.wsj.com/articles/kickstarter-closes-the-funding-gap-for-women-1407949759

\(^2\)https://hbr.org/2013/07/can-crowdfunding-solve-the-sta/
A major difficulty in modeling donors’ preferences for crowdfunding is determining their beliefs over how much the fundraiser will ultimately raise at the end of the campaign. Correctly specifying these beliefs is crucial to capturing how the different funding models affect donors’ incentives, since the final amount raised has different implications under the AoN and KiA mechanisms. The reason these beliefs are difficult to compute is donors’ decisions are interdependent: since donors care about how much the campaign ultimately raises, making a contribution to a campaign makes it more likely that a future donor also contributes. The distribution of the final amount raised is thus equal to the sum of a sequence of correlated random variables where the correlation structure is unknown. Solving directly for this distribution is computationally infeasible, as it requires delineating the full universe of every potential contribution path.

An important contribution of my paper is developing a method to overcome this computational hurdle and directly solve for donors’ beliefs over campaign outcomes. The method is based on a backward, iterative algorithm. The algorithm is easy to implement and computationally tractable: depending on the length of the campaign it can take under a second to run. Being able to quickly solve for donors beliefs is crucial since they must be computed at every parameter value in estimation. The algorithm can also be used in other applications where an expectation over the sum of correlated random variables must be computed without assuming the form of the correlation. With my method, I am then able to estimate the parameters of the donor’s utility function, which allows me to recover the distribution of the qualities of fundraising campaigns across both platforms and simulate how donations would change under alternative market scenarios.

My main finding is that higher quality fundraising campaigns select the AoN mechanism. The quality of the average fundraiser that selects Kickstarter is 30% higher than the average fundraiser on Indiegogo. This quality differential has a meaningful impact on platform revenues: if Kickstarter had the same distribution of qualities as Indiegogo, its average revenue per-project would decline by over 17%.

To understand what causes fundraiser sorting across the two platforms, I next simulate what each fundraiser would have raised had they chosen the opposite platform. I find that on average fundraisers receive more donations on Kickstarter but slightly less expected funding. However, the latter result only holds for lower quality fundraising campaigns: 67% of the projects in the top quantile of the quality distribution earn higher expected funding on Kickstarter, and the campaigns that both selected and raised more money on Kickstarter have an average quality that is over twice as high as campaigns that earn more on and selected Indiegogo. The reason for this result is intuitive: since fundraisers only receive the funding they raise on the AoN mechanism if it exceeds their funding goal, only the higher
quality campaigns can translate the increased donations induced by the AoN mechanism into higher expected funding. Hence, the finding that higher quality fundraising campaigns choose Kickstarter can be motivated in part by fundraisers selecting the mechanism that maximizes their expected funding.

Lastly, I find that over twice as many fundraisers on Kickstarter could have earned higher expected funding had they switched platforms than similar fundraisers on Indiegogo. This discrepancy suggests that fundraisers may have an innate preference for Kickstarter. I measure the magnitude of this preference by computing the amount that fundraisers are willing to forego in expected funding by choosing Kickstarter that maximizes the predicted platform choice. I find that fundraisers are willing to give up $1,340 on average by choosing Kickstarter, and that taking this preference into account can increase the rate of correctly predicting which platform each fundraiser chooses by 16%. That fundraisers are willing to forego expected funding to launch on Kickstarter is in line with the popular conception that Kickstarter is the premium crowdfunding platform.

My paper makes several contributions to a young but growing literature on crowdfunding. The current literature on crowdfunding has mostly focused on understanding market outcomes of specific platforms or funding models. Existing empirical work has investigated which project and creator characteristics are predictive of successful fundraising (Mollick (2014), Greenberg and Mollick (2014b), Zvilichovsky et al. (2014)), understanding patterns in contributions to projects over time (Kuppuswamy and Bayus (2014), Solomon et al. (2015), Burtch et al. (2012)), geographical relationships between project contributors and creators (Lin and Viswanathan (2014), Agrawal et al. (2015)) and traditional financing intermediaries (Kim and Hann (2014)), long term impacts of crowdfunding on project outcomes (Mollick and Kuppuswamy (2014), Kim and Viswanathan (2014)), and the degree to which crowdfunding donors’ and domain specific experts’ preferences are aligned (Mollick and Nanda (2015)).

A recent paper that asks a similar question is Cumming et al. (2015). The authors investigate the role that the choice of funding mechanism has on project outcomes on Indiegogo. Using regression methods, their paper finds that projects that select KiA have a lower probability of success. However, the authors treat the choice of mechanism as an exogenous regressor, where my results provide evidence that higher quality fundraisers are more likely to choose the AoN mechanism. Another recent paper that uses a similar methodology as this work is Li and Duan (2014). This paper is the only other one I am aware of that uses a structural approach to studying crowdfunding. The authors adopt a similar framework, but they assume a parametric form in modeling consumer expectations over project outcomes, and are only interested in studying consumer behavior on an AoN mechanism.
My paper is also related to the literature on fundraising and the private provision of public goods. There have been a number papers that have explored how introducing an AoN mechanism (also referred to as a “provision point mechanism”) affects donations in game theoretic settings. The papers in this literature generally find that introducing an AoN mechanism increases donations and eliminate inefficient equilibriums. In the theory literature, these results have been found in both static (Bagnoli and Lipman (1989); Andreoni (1998)) and dynamic settings (Admati and Perry (1991), Marx and Matthews (2000)). There is also empirical evidence that introducing an AoN mechanism can incentive donations. The majority of the empirical evidence is experimental - for example, a meta-analysis conducted in Croson and Marks (2000) finds that donations were higher in experiments where donations were refunded to donors if the total donation amounts did not exceed a threshold. In a large-scale field experiment, List and Lucking-Reiley (2002) find that refunding donations to donors has a modest effect in gift size but no discernible effect on participation. Whereas the focus of these papers is on how the AoN mechanism affect donor incentives, my finding that the choice of competing mechanisms can also result in fundraiser sorting is a new contribution to the literature.

The remainder of this paper is organized as follows. Section 2 provides a brief history and background on crowdfunding markets. Section 3 describes the data used in the study. Section 4 presents a structural model for the demand for crowdfunding campaigns. Section 5 discusses identification and estimation of the model. Section 6 is the heart of the paper: it uses the estimates from the structural model to investigate the role that funding mechanism plays in crowdfunding markets. The paper concludes in section 7.

2 Industry Background

Crowdfunding platforms can generally be categorized by the type of financial incentives offered and by the type of funding mechanism used (i.e. - AoN v. KiA). The four main types of financial incentives offered are rewards-based, equity-based, debt-based, and donation-based. In rewards-based platforms, donors receive rewards or “perks” in exchange for donations, where the value of the reward is usually increasing in the donation amount. For example, a musician that launches a campaign to fundraise for a new album may offer donors an advanced copy of the CD for $10, a special-edition CD with additional material for $20, and a “producer” credit for $100.

In equity crowdfunding, the fundraisers offer equity stakes in their ventures in return for...
investments. Hence these platforms are much closer to traditional early stage investment entities, such as venture-capital, angel and seed investors. Until recently, these platforms were restricted in the US to accredited investors; however, in May 2015 new regulations were proposed by the SEC as part of the 2012 JOBS Act that would loosen these restrictions. In debt-based crowdfunding platforms, the donors receive fixed-income payments in return for contributions. Lastly, in donation-based platforms the donor receives nothing in return for their contributions. These platforms are mostly used by individuals that seek funding for medical and educational expenses. Since the focus of this paper is on rewards-based platforms, we restrict our attention to them for the remainder of the paper.

The first rewards-based crowdfunding platform is believed to be artistshare.com (Freedman and Nutting (2015)). Launched in October 2003, the goal of the website was to “connect creative artists with fans in order to share the creative process and fund the creation of new artistic works”\(^4\) The website, which is still operational, is mostly used by musicians to reward donors with various items. They could be physical items, such as CDs, or intangibles, such as being listed in the liner notes of the albums or receiving producer credits. This paradigm, where an artist offers a version of their content in exchange for a donation, would cast the mold for “rewards” based crowdfunding.

The market for rewards-based crowdfunding is currently dominated by two platforms: Kickstarter.com and Indiegogo.com. Indiegogo.com was launched in January 2008 originally as a platform to raise money for films. The site was launched around the philosophy of “DIWO - Do It With Others”\(^5\) In addition to acting as platform for fundraising, Indiegogo was organized as a marketing platform. Users were encouraged not only to make contributions, but also to rate, endorse, and comment on projects.

When the site first launched, the platform used an AoN model. However, by September of that year the site introduced an early precursor to the KiA model: if the project failed to reach its goal, consumers could now “choose to pass their contribution to the project or request for their funds to return to their account to fund projects later.”\(^6\) By January 2009, the site had completely abandoned the AoN model\(^7\). By March of 2009, the website also expanded beyond just film projects and allowed projects from an array of different categories. The site continued to only offer the KiA model until December 2011, when they introduced providing users with the option of selecting an AoN model.

When the site was first introduced, Indiegogo would collect 9% of the amount raised from all successfully funded projects. This then changed to collecting 9% off all donated funds,

\(^4\)http://www.artistshare.com/v4/About
\(^5\)https://web.archive.org/web/20080515085802/http://www.indiegogo.com/about/howitworks
\(^6\)https://web.archive.org/web/20080515085802/http://www.indiegogo.com/about/howitworks
\(^7\)https://web.archive.org/web/20090101010207/http://www.indiegogo.com/about/faqs?
before eventually changing again to the current fee structure: collecting 4% of funding raised from projects that successfully reach their goal, and 9% from projects that do not. Recently, the site has experimented with a few other innovations, including allowing projects to remain on the site after the campaign has ended if it successfully reaches its goal, and introducing a form of insurance for consumers if the projects have issues delivering their rewards on time\(^8\).

Kickstarter.com was launched in April 28, 2009. Unlike Indiegogo, the website initially allowed all types of projects to launch, and at first only limited access to the site via invitation only\(^9\). When it first launched, the company did not take any cut from the total amount raised, only charging users payment processing fees. It soon introduced a 5% fee on successful project, which it has maintained to this day. From the very beginning, Kickstarter has only used an AoN mechanism: on its website, it states that the “All-or-nothing funding is a core part of Kickstarter”\(^10\).

Outside of the choice of funding mechanism, there are a number of other differences between the two sites. First, Indiegogo allows people from all over the world to launch a project. Kickstarter on the other hand limits fundraisers from only a handful of countries, although they let anyone make a contribution and they are continually expanding the list of countries that can launch projects. Second, Indiegogo does not screen which projects use the site, allowing anyone to do so. Kickstarter, on the other hand, uses a two-tiered assessment process for every project before allowing them to launch. All projects are first evaluated by an algorithm, and depending on whether the algorithm greenlights release or not, it is then reviewed by the Kickstarter staff. Approximately 60% of projects submitted to Kickstarter are reviewed by Kickstarter staff\(^11\). Lastly, as stated earlier, the fee structure is different.

\(^8\)http://techcrunch.com/2015/02/18/indiegogo-testing-way-to-refund-money-if-crowdfunded-project-does-not-ship/


\(^10\)https://www.kickstarter.com/help/faq/kickstarter+basics

\(^11\)https://www.kickstarter.com/blog/how-projects-launch-on-kickstarter

### Table 1: Comparison of Indiegogo and Kickstarter

<table>
<thead>
<tr>
<th></th>
<th>Kickstarter</th>
<th>Indiegogo</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Mechanism</strong></td>
<td>AoN</td>
<td>AoN or KiA</td>
</tr>
<tr>
<td><strong>Fees</strong></td>
<td>5% if goal’s reached</td>
<td>4% if goal’s reached</td>
</tr>
<tr>
<td></td>
<td>0% if not</td>
<td>9% if not</td>
</tr>
<tr>
<td><strong>Screen Projects</strong></td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td><strong>Countries</strong></td>
<td>UK, CA, AU, NZ, DK, IE, SE, ES, DE</td>
<td>All</td>
</tr>
</tbody>
</table>
Table 1 summarizes the differences between the sites.

3 Data

The goal of this study is to understand how the two different fundraising mechanisms influence donors’ and fundraisers’ actions. To answer this question empirically, I have assembled a unique dataset consisting of over a quarter million fundraising campaigns launched on Kickstarter and Indiegogo. The data was collected by using a web scraper to directly obtain information from fundraising campaigns on the two platforms. Every day the scraper collects the full universe of projects currently raising money and iterates through them to obtain the relevant data. An example of the layout of a typical campaign page is shown in the Appendix; the project’s goal, the amount of time left, the amount raised, and the number of people who have made contributions are all featured prominently. Daily values for the number of contributors and the amount raised is then computed by taking the differences between days.

I first present summary statistics on campaign outcomes across the two platforms. Table 2 includes data from every campaign launched on Kickstarter and Indiegogo from when the platforms launched through September 2014.

There are a number of differences between the two crowdfunding sites, but a consistent finding is Kickstarter projects outperform those on Indiegogo across a number of metrics. Projects on Kickstarter are more likely to successfully reach their goal than Indiegogo, raise more money, and receive more contributions. Kickstarter itself has also earned over four times as much in revenue from project fees as Indiegogo. However, since projects that use the KiA model keep any funding they raise, Indiegogo projects that select this mechanism are 50% more likely to end receive any funding than projects on Kickstarter. Second, the vast majority of projects on Indiegogo choose to use the KiA mechanism - over 96% do so. Hence, even though Indiegogo chargers campaigners a lower fee than Kickstarter, only a minority select Indiegogo to launch an AoN campaign. Those projects that do choose an AoN mechanism on Indiegogo are less likely to reach their goals than those on Kickstarter but more likely than those on Indiegogo.

Looking at Table 2, it’s clear that on average projects on Kickstarter projects raise more than those on Indiegogo. In Figure 1, we explore heterogeneity within and across the platforms by studying the distribution of a key outcome: the percentage of the goal the projects raise. With Kickstarter in blue and Indiegogo in red and restricting the sample to projects with non-zero contributions, we see the two distributions share a similar shape. There is a break in the distribution between projects that raise below and above their goal, but within
Table 2: Summary Statistics for Kickstarter and Indiegogo

<table>
<thead>
<tr>
<th></th>
<th>Kickstarter</th>
<th>Indiegogo-KiA</th>
<th>Indiegogo-AoN</th>
</tr>
</thead>
<tbody>
<tr>
<td>Avg. Goal ($)</td>
<td>16,108</td>
<td>22,470</td>
<td>33,905</td>
</tr>
<tr>
<td>Avg. Duration (days)</td>
<td>35.2</td>
<td>47.4</td>
<td>39.9</td>
</tr>
<tr>
<td>Avg. Total Donors (#)</td>
<td>97.9</td>
<td>22.2</td>
<td>56.3</td>
</tr>
<tr>
<td>Avg. Total Pledged ($)</td>
<td>7,562</td>
<td>1,783</td>
<td>5,480</td>
</tr>
<tr>
<td>% Projects reach goal</td>
<td>41.9</td>
<td>10.9</td>
<td>18.6</td>
</tr>
<tr>
<td>% Raise Any</td>
<td>41.9</td>
<td>62.9</td>
<td>18.6</td>
</tr>
<tr>
<td>% Total Backers=0</td>
<td>10.5</td>
<td>37.0</td>
<td>34.7</td>
</tr>
<tr>
<td>Avg. Profit per project ($)</td>
<td>343.9</td>
<td>106.7</td>
<td>192.4</td>
</tr>
<tr>
<td>Total Site Revenue ($)</td>
<td>54.3 M</td>
<td>13.2 M</td>
<td>0.98 M</td>
</tr>
<tr>
<td>Total # Projects</td>
<td>161,991</td>
<td>123,928</td>
<td>5,104</td>
</tr>
</tbody>
</table>

Note: The sample is limited to American campaigns in common categories through September 2014 with goals under 1 Million dollars

Each of these two groups the outcomes are skewed: it is more likely for a project to raise between 0-10% of its goal than 10-20%, more likely to raise between 10-20% of its goal than 20-30%, and so on. Further, projects tend not to raise much more than their goals: 64.5% and 75.6% of projects that reach their goal do not raise more than 25% of it on Kickstarter and Indiegogo respectively.

An interesting difference between the two platforms occurs in the section of the distribution where projects do not reach their goal. There appear to be fewer projects on Kickstarter that receive partial funding than those on Indiegogo; that is, Kickstarter projects seem more likely to either reach their goal or raise very little. For example, among those projects that receive at least one donor but fail to reach their goal, 83% of the projects raise less than a quarter of their goal on Kickstarter, compared to 74% of projects on Indiegogo. A natural consequence of this finding is that the jump in the distribution for projects that reach their goal is much more pronounced on Kickstarter than on Indiegogo. The ratio of projects that reach between 100-110% of their goal to 50-100% is 8.6 on Kickstarter and 1.1 on Indiegogo.

Since a primary goal of this paper is to understand how the different mechanisms affect donors incentives to make contributions, I next analyze whether donations are sensitive to the amount raised and time left during the life of the campaign. To do so, I create a 10x10 grid where the amount of time elapsed during the campaign is on the the X-axis and the percentage of the goal raised is on the Y-axis (the distribution plotted in Figure 1). I then compute the average number of donors in each cell of the grid for each platform.

Figure 2 graphs these grids as heatmaps: the brighter the cells, the larger the average
Figure 1: Distribution of the Percentage of Goal Raised

Note: The sample is limited to American campaigns common categories through September 2014 with goals under 1 Million dollars and have non-zero total donors. The blue histograms are Indiegogo projects and the red Kickstarter; the shaded purple regions represent areas where the histograms overlap. Projects that raise more than twice their goal are excluded.

The figure includes three different heatmaps: the one on the left for Kickstarter, the one in the middle for Indiegogo, and the one on the right shows the difference between the two. For this last heatmap, the red cells represent instances when average donations on Kickstarter are larger than on Indiegogo, and the blue cells the opposite.

The heatmaps reveal several interesting patterns in the data. In general, the data suggests that donors are sensitive to the amount raised and time remaining in the campaign. We see that across both platforms donations appear largest early and later in the campaign. Further, they show that donors on Indiegogo are more likely to make donations when the projects have raised a smaller amount of their goal than Kickstarter, while the reverse is true for projects that are closer to reaching their goal. This finding is consistent with the observed distribution of the final amount raised in Figure 2, where we see a larger fraction of projects receive partial funding on Indiegogo than on Kickstarter but a larger fraction of projects on Kickstarter reaching their goal.

These findings are indicative of two behaviors. First, it appears that donors are forward looking and care about how much the projects ultimately raise. For example, on Kickstarter we see that projects that raise a small fraction of their goal and hence are unlikely to get
fully funded receive a drop in donations as the campaign progresses. Similarly, we see a large increase in donations when the project appears “in reach” of becoming fully funded. And second, donors appear to value partially funded projects. Donations are higher on Indiegogo relative to Kickstarter in the regions where projects are unlikely to reach their goal.

Of course, the evidence from the heatmaps are only suggestive because projects that reach the lower right hand corner of the grid did not appear their at random. Rather, we would expect lower quality projects to both have lower donations and to raise lower amounts. In the next section, I present a model of donor preferences for crowdfunding that takes into account heterogeneity in project quality, has forword looking donors, and allows donors to value partially funded projects. The model will allow me to quantify the extent to which the differences in outcomes across the platforms are driven by differences in the types of projects across the platforms and differences in donor behavior within each platform.

4 A Model of Demand for Crowdfunding

In this section I develop a model of donor demand for crowdfunding projects on a rewards-based platform. Projects are defined by a quality $\delta_j$, a fundraising goal $G_j$ and a campaign length $T_j$. I consider narrow fundraiser categories (for example only Music campaigns), so that projects are only vertically differentiated. The parameter $\delta_j$ can then be thought of as the quality as perceived by the donor - for example, a bad versus good music album. Without loss of generality, I assume that there is no heterogeneity in the perception of this quality -
all donors agree on which projects are good and which are bad.  

Time is discrete and donors arrive sequentially in periods \( t = 0 \ldots T \) at an exogenous rate \( \rho(t) \). I assume that each period is short enough that no two donors arrive at the same time. When the donor arrives at a time \( t \), she observes the amount of time remaining \( T - t \) and the amount the project has raised so far \( X_t \). With this information, she forecasts how much the project is likely to raise at the end of the campaign \( \chi(X_t|\Theta) = X_t + \tilde{X}_{T-t}(\Theta) \), where \( \tilde{X}_{T-t}(\Theta) \) is the amount the donor believes will be raised between \( t \) and \( T \), and \( \Theta \) are parameters that affect the distribution of this amount. Upon arrival, the donor makes a one-time decision to donate to the project. I do not model the intensive margin – how much to contribute – and instead assume that donors receive an exogenous donation shock \( x_i \). Since donors are only considering whether or not to contribute to a single project, I drop the \( j \) subscript for notational convenience.

**Keep-it-All mechanism**

I assume donors receive the following utility from contributing to a project under a KiA mechanism:

\[
U^{KiA}(\delta, X_t, x_i, \Theta) = \delta \cdot h \left( \frac{\chi(X_t|\Theta) + x_i}{G} \right) - c_i
\]  

(1)

The function \( h(\cdot) \) determines the value of a project that raises \( p\% \) of its goal. I thus model a donor’s valuation of partially funded projects as the project’s latent quality \( \delta \) scaled by the fraction of the goal the project raises, where the degree of this scaling is determined by the function \( h(\cdot) \). \( \Theta \) are the parameters of the utility function.

The parameter \( c_i \) is the utility cost of making a contribution and is drawn from a distribution \( F_{c_i}(\cdot) \). One may wonder why this cost is not simply the donation amount \( x_i \). In addition to not observing the individual donation amounts (my data is aggregated to the day level), specifying a separate utility shock is useful for a few reasons. First, as described in the next section, when computing the probability that a donor makes a contribution, I need to integrate over the unobserved components of (1). Specifying a continuous distribution for the cost shock \( c \) is important because it adds smoothness to the choice probabilities. However, if the cost shock equaled the donation amount \( x_i \), then computing the choice probabilities would entail integrating over \( h \left( \frac{\chi(X_t|\Theta) + x_i}{G} \right) \) as well, which would typically not have a closed form expression except under restrictive assumption over \( h(\cdot) \). Hence, for computational reasons it will be helpful to model the utility cost as coming from a continuous distribution that

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12I have explored extending the model to include donor heterogeneity in quality perception; however, there is little in the data to differentiate this form of donor heterogeneity from heterogeneity in the donation cost
is separate from the donation amount $x_i$. Alternatively, one can think of $c_i$ as the donation amount with a random coefficient $c_i = \kappa_i \cdot x_i$, where $c_i$ has a known distribution.

I assume that the function $h(\cdot)$ has the form:

$$h(p) = \begin{cases} 
\alpha \cdot p^\phi & p < 1 \\
1 & o.w.
\end{cases}$$

The parameter $\phi$ determines whether donors valuation of partially funded projects is convex or concave in the final amount the project raises. As described in the data section, we may expect different values for this parameter for different project categories. Projects that require a large percentage of their goal in order to be successful would have larger values of $\phi$ than projects that require less of a their goal. The parameter $\alpha$ measures whether or not donors receive a discrete jump from completing the project. This two parameter specification is thus allows for a wide array of valuations for partially funded projects.

**All-or-Nothing**

In the AoN mechanism, the project is only funded if the amount raised it exceeds its goal; otherwise, the donor’s contribution is returned to her. The key challenge in modeling preferences under this mechanism is then specifying donors utility when the a campaign fails to reach its goal. I choose the following specification:

$$U^{AoN}(\delta_j, X_t, x_i, \Theta) = \begin{cases} 
\delta_j - c_i & \chi(X_t|\Theta) + x_i \geq G \\
-\gamma \cdot c_i & o.w.
\end{cases}$$

Equation 3 states that if the project reaches its goal and is funded, the donor’s utility is the project quality net the utility cost of contributing. Notice that this value is identical to the utility a donor would receive for a fully funded project under a KiA mechanism. Alternatively, if the project does not reach its goal, I assume the donor receives the utility cost scaled by the parameter $\gamma$. The parameter $\gamma$ can be thought of as representing a sunk component of the cost of making a contribution (for example, the time it take to set up an account and interact with the platform) or as a psychic cost incurred when a project fails to reach its goal.

**Expected Utility**

Under both mechanisms, donors preferences for crowdfunding are a function of the final amount the project raises $\chi(X_t|\Theta)$. Since this amount is a function of the (unknown) behavior
of future donors, I assume that donors contributions decisions depend on their expected utility:

\[ EU^{KiA}(\delta_j, X_{it}, \Theta) = \delta \cdot E_{\chi(X_{it} | \Theta)} \left[ h \left( \frac{\chi(X_{it} | \Theta)}{G} \right) \right] - c_i \] (4)

\[ EU^{AoN}(\delta_j, X_{it}, \Theta) = Pr(\chi(X_{it} | \Theta) \geq G) \cdot (\delta_j - c_i) - Pr(\chi(X_{it} | \Theta) < G) \cdot (\gamma \cdot c_i) \] (5)

where \( X_{it} = X_t + x_i \). Donors decide to contribute to the project if the expected utility is greater than 0. Conditional on the value of \( \chi(X_{it} | \Theta) \), the probability that a donor contributes is determined by the distribution of the cost shock \( c_i \). I assume this shock follows an Exponential distribution:

\[ c_i \sim Exp(\lambda_c) \] (6)

I assume \( c_i \) is Exponential for three reasons. First, it has the correct support for modeling a cost shock. Second, the CDF function can be computed quickly, which greatly increases the speed in which I can computationally solve the model. And lastly, it is closed under scalar multiplication. This last feature is crucial for it allows for an analytic expression for both choice probabilities. Rearranging 4 and 5, the choice probabilities are thus:

\[ q^{KiA}(\delta_j, X_{it}, \Theta) = F \left( \delta \cdot E_{\chi(X_{it} | \Theta)} \left[ h \left( \frac{\chi(X_{it} | \Theta)}{G} \right) \right] \right) \] (7)

\[ q^{AoN}(\delta_j, X_{it}, \Theta) = F_{\psi(X_{it}, G)}(\delta \cdot Pr(\chi(X_{it} | \Theta) \geq G)) \] (8)

\[ \psi(X_{it}, G) = \left( 1 + \frac{Pr(\chi(X_{it} | \Theta) < G)}{Pr(\chi(X_{it} | \Theta) \geq G)} \cdot \gamma \right) \]

In equation 8, we see the role that the parameter \( \gamma \) plays in affecting the choice probabilities in the AoN mechanism. If \( \gamma = 0 \), the donors contribution decisions would be unaffected by the probability that a project reaches its goal. In order to rationalize the behavior observed in the data section, \( \gamma \) would necessarily have to be greater than 0. In essence, \( \gamma \) determines how sensitive donors are to the probability that project reaches its goal.
Computing the Probability of Success $P(\cdot)$

In the previous sections, we see that the choice probabilities are a function of donors expectation over the final project outcomes: $Pr(\chi(X_i|\Theta) \geq G)$ and $E_{\chi(X_i|\Theta)}\left[h\left(\frac{X_i}{G}\right)\right]$. At first glance, computing these beliefs directly appears to be an intractable computational problem. To see this, notice that the probability that a project reaches its goal is the sum of all potential donors contributions. However, since each donors decision to contribute is a function of how much has already been contributed, these decisions are correlated. Hence, the distribution of the final amount raised is determined by the sum of correlated random variables.

A major contribution of this paper is the development of a method for explicitly computing these beliefs. The method is based on a backward-iterative algorithm. For convenience, I introduce the following notation. First, define the term $\tilde{G}_t \equiv G - X_t$; that is, $\tilde{G}_t$ is the amount a project needs to raise in order to reach its goal at time $t$. We then can rewrite the choice probabilities as $q^{AoN}(G, X_t, x_i) \equiv q^{AoN}(\tilde{G}_t, x_i)$. Second, we will detail how to compute the probability that a project reaches its goal, but algorithm is easily adapted to computed the expected value at the end of the campaign which is used in the KiA mechanism.

**Time T**

Since I assume that donors arrive in discrete periods, I first compute the probability that the project is successful in the final period\(^{13}\). For an unfunded project to reach its goal in this last period, three events must occur. First, a donor must arrive, which occurs with probability $\rho(T)$. Second, the donor must receive a donation shock that is large enough to complete reach the projects goal, which occurs with probability $1 - F_x(\tilde{G}_T)$. And lastly, utility from contributing must be greater than not contributing, which is simply the choice probability when the project is fully funded, or $F_c(\delta)$. Since we assume arrival, the contribution and cost shock are all independent, the probability that a project reaches its goal in the final period is simply:

$$P_T(\tilde{G}_T) = \rho(T) \cdot F_c(\delta) \cdot (1 - F_x(\tilde{G}_T)) \quad (9)$$

**Time T-1**

Having computed $P_T(\tilde{G})$, I now compute the probability that a project reaches its goal in the penultimate period. In period $T - 1$, a project is successful if the sum of the donations

\(^{13}\)Again, I define periods as short intervals of times - In our estimation, they occur every 3 minutes.
in periods $T - 1$ and $T$ exceeds the amount of the remaining goal $\tilde{G}_{T-1}$

$$P_{T-1}(\tilde{G}_{T-1}) = Pr(x_{T-1} + x_T \geq \tilde{G}_{T-1})$$

(10)

I can rewrite equation 7 by applying the law of iterative expectations.\(^{14}\)

$$P_{T-1}(\tilde{G}_{T-1}) = E_{x_{T-1}} \left[ Pr(x_T \geq \tilde{G}_{T-1} - x_{T-1}) \right]$$

(11)

Notice that the term inside the expectation operator in 11 is identical to equation 10. That is, after conditioning on the contribution in period $T - 1$, the probability of success in $T - 1$ is the probability of success in period $T$ taking into account that the amount the project needs to raise has been lowered by $x_{T-1}$. This observation is the central insight that forms the basis of the algorithm. Since we already solved for this probability in the previous step, computing 11 involves simply computing the expectation of a function over one variable $(x_{T-1})$ rather than the convolution of two random variables $(x_{T-1} + x_T)$

What remains then is characterizing the probability that the donor contributes in period $T - 1$. Again, this depends on the donor arriving $(\rho(T - 1))$ and the values of the cost and donation shocks.

$$P_{T-1}(\tilde{G}) = \rho(T - 1) \int_x \left[ \frac{P_T(\tilde{G}_{T-1} - x_{T-1}) \cdot q^{A_0N}(\tilde{G}_{T-1}, x_{T-1})}{\text{Donor contributes}} + \frac{P_T(\tilde{G}_{T-1}) \cdot \left( 1 - q^{A_0N}(\tilde{G}_{T-1}, x_{T-1}) \right)}{\text{Donor doesn’t contributes}} \right] \cdot f_2(x_{T-1})$$

$$+ \left( 1 - \rho(T - 1) \right) \cdot P_T(\tilde{G}_{T-1})$$

(12)

Donor doesn’t arrive

We see that Equation 12 can be thought of as the union of three independent events. The first event occurs if the donor arrives and makes a contribution,\(^{15}\) which occurs with probability $q^{A_0N}(\tilde{G}_{T-1}, x_{T-1})$ and lowers $\tilde{G}_{T-1}$ by the contribution $x_{T-1}$. The second event occurs when the donor arrives and decides not to make a contribution. And lastly, the third event occurs if the donor does not arrive. In both of these circumstances, the probability of success simply equals the probability that the project reaches its goal in the final period with $\tilde{G}_{T-1}$ remaining.

\(^{14}\)To see this, note that I can represent the probability as an expectation of an indicator variable instead:

$$Pr(x_{T-1} + x_T \geq \tilde{G}_{T-1}) \equiv E \left[ I(x_{T-1} + x_T \geq \tilde{G}_{T-1}) \right],$$

where $I(x_{T-1} + x_T \geq \tilde{G}_{T-1}) = \begin{cases} 1 & x_{T-1} + x_T \geq \tilde{G}_{T-1} \\ 0 & \text{a.w.} \end{cases}$

\(^{15}\)Note that $P_T(\tilde{G}_{T-1} - x_{T-1}) = 1$ if $x_{T-1} \geq \tilde{G}_{T-1}$. 

---

16
Time $t$

The main insight from this approach is that one does not need to derive the distribution for the sum of individual donors contributions in order to compute the probability that a project will succeed. Rather, by solving backwards from last the period, one can “plug in” the probability of success from the next period into the current. To see the advantage of this method, let’s compute the probability of success for an arbitrary period $t$, having already solved for $P_{t+t}(\tilde{G}_{t+1})$. This probability equals the probability that the sum of donations from period $t$ to $T$ will exceed $\tilde{G}_{t}$:

$$Pr(\sum_{\tau=t}^{T} x_{\tau} \geq \tilde{G}_{t})$$

Deriving the distribution of $\sum_{\tau=t}^{T} x_{\tau}$ becomes computationally infeasible for even a small number of periods. However, since $P_{t+t}(\tilde{G}_{t+1})$ has already been computed, using LIE:

$$P_{t}(\tilde{G}_{t}) = E_{z_{t}} \left[ Pr(\sum_{\tau=t+1}^{T} x_{\tau} \geq \tilde{G}_{t} - x_{t}) | x_{t} \right]$$

$$P_{t}(\tilde{G}_{t}) = E_{z_{t}} \left[ P_{t+1}(\tilde{G}_{t} - x_{t}) | x_{t} \right]$$

Thus, by working backwards, one can solve for the probability of success for any period $t$. Once the probability of success has been computed for every period and possible value of $\tilde{G}$, I can compute the choice probabilities in 5, which can be used to form the basis of an empirical model. I use the same methodology for computing $E_{X} \left[ \left( \frac{X_{t} + z_{t}}{G} \right)^{\phi} \right]$ for the KiA mechanism.

5 Identification and Estimation

The parameters of the consumers utility function are the project qualities $\delta_{j}$, the parameters that determine how donors value partially funded campaigns ($\alpha$ and $\phi$), the sunk cost parameter $\gamma$, the mean of the cost shock $\lambda_{c}$, and the arrival rates $\rho(t)$. I will now discuss which parameters are identified in the data and which must be normalized. As a reminder, the unit of observation is day-project.

The project $\delta$’s are identified from the path of daily contributors to each project. Intuitively, projects with higher $\delta$’s will have more donors. A less obvious source of identification is when during the campaign the donations occur. For example, the model predicts that all
else equal donors are more likely to make contributions earlier in the campaign than later, since the probability that a project reaches its goal or raises more is higher\textsuperscript{16}. Hence, holding the goal amount and amount raised fixed, projects with higher $\delta$ are also more likely to receive donations later in the campaign\textsuperscript{17}.

The cost parameter $\gamma$ is identified by the covariance between daily donations and the amount of time and goal left in the campaign. As $\gamma$ increases, donations become more sensitive to these two variables. In the extreme, if $\gamma = 0$ then daily donations would be uncorrelated with how much projects have raised and any temporal variation in giving would driven exclusively by the arrival rate. A similar argument holds for identifying $\alpha$ and $\phi$. The parameter $\phi$ is identified by the correlation between the number of daily donations and the amount of time and goal left throughout the campaign, while $\alpha$ is identified by changes to this correlation as the project gets closer to reaching its goal.

To see this, consider a simplified example where a project receives either an additional 10% of its goal or no additional donations, with a fifty percent chance of either event occurring. The expected utility from contributing to a project that currently has raised 90% of its goal is then $0.5 \times (1 + \alpha \cdot 0.9^\phi)$, while the expected utility from contributing to a project that has raised 85% of its goal is $0.5 \times (\alpha \cdot 0.95^\phi + \alpha \cdot 0.85^\phi)$. The difference in the expected utility from contributing is then $0.5 \times ((1 - \alpha \cdot 0.95^\phi) - \alpha \cdot (0.9^\phi - 0.85^\phi))$. When $\alpha = 1$, this difference in utility is quite small and we would not expect to see any large changes in the number of donations as projects get closer to reaching their goals. As $\alpha$ decreases, though, this difference in utilities grows at a rate of approximately $0.95^\phi$. Hence, the smaller $\alpha$, the more donors are likely to contribute to a project as it gets close to reaching its goal.

The parameter $\lambda_c$ is set to 1 for a scale normalization, which is a standard normalization in discrete choice latent utility models.

**Arrival Rates $\rho(t)$**

If I had data on the number of people that arrived at each campaign every day then estimating the arrival rates $\rho(t)$ would be straightforward. One could model the arrival as poisson process and estimate the arrival rate through maximum likelihood or set $\rho(d) = \frac{N_d}{N}$, where $N_d$ was the number of donors arriving arriving on day $d$ and $N$ the maximum number of possible arrivals. Unfortunately, I do not have access to this data.

To address this issue, I use an estimate of arrival rates computed from campaigns that reach their goal early in the campaign. The idea behind this approach hinges on the assump-

\textsuperscript{16}With more time left in the campaign, there are more potential donors available to make contributions

\textsuperscript{17}The same argument applies to holding the goal amount and amount of time remaining fixed and instead varying the amount the project has raised.
tion that once a project reaches its goal, the only remaining driver that can account for variation in contributions is the arrival rate. To see this, notice that since 
\[
E[X_{it} | \Theta] \left[ h \left( \frac{\chi(X_{it} | \Theta)}{G} \right) \right] = Pr(\chi(X_{it} | \Theta) \geq G) = 1
\]
for successful projects, the choice probability is simply $F_c(\delta_j)$. The number of daily donors then follows a binomial distribution, with probability $F_c(\delta_j)$ and number of trials $N_d$ - the number of donors that arrive. The expected number of donors on day $d$ is thus

\[
b(d, \delta_j) = N_d \cdot F_c(\delta_j)
\]  

Using our previous definition, we can rewrite $N_d = \rho(d) \cdot N$. Hence, by dividing by \( \sum_{d\neq d_j} b(d, \delta_j) \), where the summation is over the days of the campaign after it has reached its goal, we have:

\[
\frac{b(d, \delta_j)}{\sum_{d\neq d_j} b(d, \delta_j)} = \frac{\rho(d)}{\sum \rho(d)}
\]  

From 15, we see that the relative arrival rates can be identified from within project variation in the number of daily donations for projects that have reached their goal.

Figure 3 plots the left-hand side of 15 for projects on both Kickstarter and Indiegogo.
The two plots are almost identical, showing a constant rate up until the very hand of the campaign after which the rate increases suddenly. There are a number of reasons why the arrival rate may increase drastically towards the end of the campaign. First is site visibility: on both Kickstarter and Indiegogo, donors can search for projects that are almost at the end of the campaign. Second, information about the campaign is likely to increase through the life of the campaign as donors and the fundraiser increase spread awareness of the campaign through traditional and social media. And lastly, donors may delay making decisions earlier in the campaign and wait until the very end to make a decision.

Explicitly incorporating these explanations would increase the complexity of the model, so for simplicity I will use the recovered arrival rates from projects that have already reached their goal. In doing so, I am assuming that all projects share the same arrival rate. This is a strong but necessary assumption. In a related paper where I have data provided directly from a different crowdfunding platform that includes arrival rates, I explore how making different assumption about the arrival process affects estimation of the project qualities. To recover the relative arrival rates, I run a panel regression on the number of daily donors for projects that reached their goal within the first five days of the campaign. The regressors are indicator variables for different periods of the campaign: for example, 5 – 10% of the campaign, 10 – 15%, etc. Each coefficient on these indicators thus provides an estimate to \( \rho(d) \).

**Likelihood**

I estimate the model by maximum likelihood. Denoting \( \Psi \equiv \{\gamma, \alpha, \phi\} \), \( \Delta = \{\delta_j\}_{j=0}^J \) the likelihood takes the following form:

\[
\mathcal{L} = \max_{\Psi, \Delta} \prod_j \prod_{d=0}^{T_j} \Pr(b(\Psi, \delta_j) = \hat{b}_{j,d} | X_{d-1,j})
\]

where \( \hat{b}_{j,d} \) is the number of donors who make a contribution to project \( j \) on day \( d \), and \( X_{d-1,j} \) is amount raised for project \( j \) at the beginning of day \( d \). To compute the probabilities of the likelihood function, I use a method for similar to the one used to compute the probability that a project reaches its goal (see the Appendix for more details). As stated in the model section, I assume that each day consists of a number of periods; in estimation, I set this number to 488, so each period corresponds to 3 minute intervals. I also discretize the amount raised \( X_{d-1,j} \) onto a grid of 200 spaces.

---

Since $\delta_j$ only enters the likelihood for project $j$, I am able to maximize the likelihood using a two step procedure. First, for a given value of $\Psi$, I find the value of $\delta_j$ that maximizes each sub-likelihood $L(j|\Psi)$. Once I maximize the sub-likelihood functions, I find the values of $\Psi$ that maximize the overall likelihood function
\[ L(j|\Psi) = \max_{\delta_j} \prod_{d=0}^{T_j} Pr(b(\Psi, \delta_j) = \hat{b}_{j,d}|\hat{X}_{d-1,j}) \] (17)
\[ L = \max_\Psi \prod_j L(j|\Psi) \] (18)

Estimation Sample

Selection Criteria

In this section I detail the selection criteria I use to select the sample of projects for estimation. First, I limit my analysis to projects in the Music category across both platforms. I do so because Music is one of the most popular categories the projects shared by both Kickstarter and Indiegogo and because the projects are most comparable to each other within this category. Music is also an industry that has been transformed by the advent of digital platforms and there has been considerable research devoted to the study of the music in the Internet era.

I then further limit the sample to Music projects that set goals between $5,000 and $25,000. I do so because I want to limit my sample to fundraisers that are most likely to require contributions from donors outside of their social network. Friends and family play an important role in fundraising in general, and there is recent evidence that they also play an important role in crowdfunding as well. Since these donors are less likely to behave according to my behavioral model of donors preferences (one can imagine friends and family contributing to campaigns regardless of the expected outcome), my hope is that restricting the sample to projects with goals in this range minimize their influence. Similarly, I also restrict the sample to projects that have at least 5 and no more than 800 donors.

I next eliminate projects that became fully funded on the last day of the campaign. I do so to remove projects for which the fundraiser may have made a contribution to their own campaign. It is not hard to imagine that a fundraiser that is close to reaching his goal, especially having selected the AoN mechanism, would either make a donation to fund the project himself or appeal to a family member to do so\(^{20}\). This type of behavior would be one

\[^{19}\text{Since } \delta_j \text{ only affects project } j, \text{ I use cluster computing methods to solve equation } \# \text{ in parallel} \]

\[^{20}\text{The platforms have put policies to make it difficult for fundraisers to contribute to their own campaign.} \]
reason that you see so few projects on Kickstarter raising between 60 and 99% of their goals. Dropping projects that reached their goal in the last day does not eliminate the probability of fundraisers making donations to their own campaign, but it does reduce it.

Lastly, I limit my analysis to only the unfunded portion of each campaign. I do so because, as shown in the modeling section, this is the only period of the fundraising campaign that donors preferences differ under the two mechanisms. Hence, I care most about having the model fit the number of daily donations in the data during this period of the campaign. In order to have enough observations to identify the project δ and limit the bias of estimating the shared parameters due to the incidental parameter problem, I further restrict the sample to projects that have at least 20 days of being unfunded.

Limiting the sample to projects that started after January 1st and ended before September 1st 2015 and dropping projects with inconsistencies\textsuperscript{21} results in a sample of 555 projects on Kickstarter and 522 on Indiegogo. Table 3 provides sample statistics for this sample. The average project goals are very similar across the two platforms while the projects on Indiegogo are on average 8 days longer than those on Kickstarter. Since the sample conditions on projects receiving at least five donors the projects in the estimation sample receive more donations than the full sample described in Table 2, particularly for Indiegogo projects.

Since the computational time of maximizing the likelihood increases in the number of projects, I used a subsample of 200 projects from both platforms for to estimate the shared parameters (\(\gamma, \alpha, \phi\)), which I then use to estimated the distribution of project qualities for the entire sample.

Donation Distribution

The final component of my model that I need to specify is the distribution from which donors receive the exogenous contribution \(x_i\).\textsuperscript{22} While I do not observe the individual contribution levels, I can approximate this distribution with the distribution of average donations, which is computed by dividing the total amount given each day by the total number of donors.

The distribution of the average contributions for both platforms is displayed in Figure 7 in the Appendix. Both distributions are nearly identical across the two platforms: they are heavily skewed with a few mass points around $25, $50, and $100, which are popular values for the reward tiers. Donations from the estimation sample are also slightly larger on Kickstarter than on Indiegogo; the average contribution is is $89 and $71, while the median

\textsuperscript{21}For example, observing changes in the start and end dates or project category during the life of the campaign

\textsuperscript{22}Denoted \(F_x(\cdot)\) in equation 9
Table 3: Summary Statistics for the Estimation Sample

<table>
<thead>
<tr>
<th></th>
<th>Kickstarter</th>
<th>Indiegogo</th>
</tr>
</thead>
<tbody>
<tr>
<td>Avg. $ Goal</td>
<td>9,725</td>
<td>9,496</td>
</tr>
<tr>
<td>Avg. Duration (Days)</td>
<td>35</td>
<td>43.2</td>
</tr>
<tr>
<td>Avg. # Daily Donors</td>
<td>2.19</td>
<td>1.23</td>
</tr>
<tr>
<td>Avg. # Donors</td>
<td>72.2</td>
<td>49.1</td>
</tr>
<tr>
<td>%Goal Reach</td>
<td>48.5</td>
<td>9.50</td>
</tr>
<tr>
<td>%Goal Raised</td>
<td>65.6</td>
<td>38.1</td>
</tr>
<tr>
<td>$ Fundraiser keeps</td>
<td>3,976</td>
<td>2,709</td>
</tr>
<tr>
<td>$ Platform keeps</td>
<td>216.7</td>
<td>242.2</td>
</tr>
</tbody>
</table>

Note: The table presents summary statistics for the fundraising campaigns used in estimation. The selection criteria is detailed in the preceding section titled "Estimation Sample."

is $50 and $42 respectively. When I estimate the model, I use each platform's own donation distribution and discretize it on a grid of seven points.

Using the distribution of the average donations is advantageous because it drastically increases the computation speed of computing the likelihood. I should note, though, that I only observe an approximation to the distribution of donations conditional on donors making a contribution. A better approach would be to assume a parametric form for the unconditional distribution of contributions and then estimate the parameters of this distribution by fitting the sample moments of observed donations. Doing so adds an additional set of parameters to estimate, and since I maximize the likelihood on a grid it would greatly increase the computation time. Further, since I am only interested in modeling the extensive margin of donors contributions decisions, recovering the parameters that determine the distribution of donations is a second order concern. However, I am currently working on using a new approach to computing the likelihood that has the potential to greatly increase the computation speed and thus allow me to use the more robust approach to modeling donors contributions.

6 Results

Parameter Estimates and Model Fit

In Table 4 I present the MLE parameter estimates\(^{23}\). The main parameter from the AoN mechanism - the sunk cost parameter - is \(3.16 \times 10^{-4}\). The parameters \(\alpha\) and \(\phi\) mean

\[^{23}\text{The Hessian of the likelihood was computed using the standard numeric formula for computing the second derivatives: } f''(x) \approx \frac{f(x+h)-2f(x)+f(x-h)}{h^2}.\]
that donors value partially funded projects at 58% of fully funded projects, regardless of the amount raised. This finding suggests that, at least for Music projects, donors receive a discrete utility increase from fully funding a project, but otherwise are not sensitive to the total amount raised. The parameter estimates for $\alpha$ and $\gamma$ are statistically significant, while the value for $\phi$ is not. Since the value of $\phi$ that minimized the likelihood is 0, which occurs on the boundary of the parameter space, in order to compute a reliable estimate for the standard errors the Hessian was computed at $\phi = 0.0001$.

In Table 5 I compare the sample moments from the estimation sample and a Monte Carlo exercise where I simulate outcomes on each platform using the parameters from Table 4. In the exercise, I simulate a sequence of donors receiving donations shocks that “arrive” to each project with the same probabilities used in estimation. I then compute the donor’s choice probability according to (7) and (8) and draw a “choice shock” - a uniform random variable between 0 and 1. If the choice probability is greater than the choice shock then a contribution is made\(^{24}\). I then repeat this process 1,000 times and take the average over the simulated contribution paths.

The likelihood maximizes the probability of observing the number of daily donors and our model matches this moment closely, albeit slightly underfitting it on both platforms. This under-fitting poses more of a problem for matching the moments on Kickstarter than on

\(^{24}\)An alternative method would be to simply simulate costs shocks from an exponential distribution
Table 5: Model Fit: Sample Moments

<table>
<thead>
<tr>
<th>Avg. # Daily Donors</th>
<th>Kickstarter Data</th>
<th>Kickstarter Model</th>
<th>Indiegogo Data</th>
<th>Indiegogo Model</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>2.30</td>
<td>2.12</td>
<td>1.30</td>
<td>1.14</td>
</tr>
<tr>
<td>Avg. # Donors</td>
<td>65.3</td>
<td>68.9</td>
<td>48.1</td>
<td>47.8</td>
</tr>
<tr>
<td>%Goal Reach</td>
<td>47.9</td>
<td>36.1</td>
<td>9.00</td>
<td>9.32</td>
</tr>
<tr>
<td>%Goal Raised</td>
<td>57.6</td>
<td>57.1</td>
<td>35.8</td>
<td>38.7</td>
</tr>
<tr>
<td>$ Fundraiser keeps</td>
<td>4,042</td>
<td>2,906</td>
<td>2,772</td>
<td>2,912</td>
</tr>
<tr>
<td>$ Platform keeps</td>
<td>220.3</td>
<td>158.4</td>
<td>244.8</td>
<td>263.7</td>
</tr>
</tbody>
</table>

Note: The table presents the model fit of average values for a number of project outcomes across Kickstarter and Indiegogo. The column labeled "Data" refers to the data used in estimation; the column labeled "Model" refers to the moments computed by simulating outcomes on both platforms using the parameter values in Table 7.

Indiegogo. The model does most poorly matching the probability that a project reaches its goal on Kickstarter; in the data, nearly 48% of projects reach their goal, compared to only 36% predicted by the model. As a result, the model also under predicts the amount that fundraisers receive and Kickstarter earns in per-project revenues. In contrast, the model fits almost all the sample moments on Indiegogo.

In Figure 4 we see how the model fits the distribution of the fraction of the goal raised - the variable graphed in Figure 1. We see that the model does a good job fitting the distribution of project outcomes on Indiegogo. For Kickstarter, the model fits the general shape of the distribution, but over predicts the number of projects raising between 60 and 100% of its goal.

Lastly, we test how well the model can predict donations during the campaign. We replicate the heat map from Figure 2 showing how sensitive donors are to the amount of time left and amount of raised during the campaign. The left hand side of Figure 5 reproduces the heat map from Figure 2, and the right hand side shows the analogous heat map from donor behavior simulated by the model. We see that the model matches the same patterns in the data almost exactly. Donations on Indiegogo are higher in regions where projects are less likely to reach their goal, while the opposite is true for Kickstarter.

In summary, the model does a good job fitting both the sample moments and the general patterns in the data. It captures the main shape of the distribution of the final amount the projects raise and reproduces the general patterns of donor behavior during the life of the campaign.
Figure 4: Distribution of Goal Raised - Model Fit

Note: The figure plots the model fit for the distribution of the percent of goal raised from Figure for both platforms and compares them to the model fit. The graph on the left are projects on Kickstarter; the graph on the right Indiegogo.

Figure 5: Heatmap of Donations: Model Fit

Note: The figure compares the model fit for heatmap of variation in average donations by how much the project has raised and how much time has elapsed. The figure on the left is reproduced from Figure 2; the figure on the right is the model fit analogue. The red cells represent instances where average donations are higher on Kickstarter; the blue on Indiegogo.
A central question in this paper is to what extent are the different outcomes between projects that use the AoN and KiA explained by different types of projects sorting across funding mechanisms. In this section I provide an answer. Figure 6 displays the distribution of project qualities across the two platforms. It is clear that distribution of project qualities on Kickstarter is shifted to right of Indiegogo; the average project on Kickstarter is 30% higher than the average project on Indiegogo. On both platforms, we see that the distribution of project qualities is also skewed with a “long” tail commonly found in demand data on digital platforms (Anderson 2006). However, there is more mass in the tail of these distributions on Kickstarter than Indiegogo; this difference can clearly be seen by looking at the CDF in right hand side of the figure. Hence, our first finding is that fundraisers sort across the two platforms based on quality, with the distribution Kickstarter is shifted to the right of those on Indiegogo.

One way of quantifying the affect of this sorting is to see what would occur if the distribution of project qualities across the two platforms were reversed. That is, we can simulate outcomes on Kickstarter if it had the same distribution of projects that chose Indiegogo and vice versa. Table 6 presents the results of this experiment. As expected, we see that if the distribution of projects were reversed that project outcomes on Kickstarter would decline and Indiegogo would increase. If the same projects that selected Indiegogo instead launched on Kickstarter, the average number of donors on Kickstarter would decline by 4.4%, while if the reverse happened the average number of donors on Indiegogo would increase by 11.9%. These changes translate into a 17.3% decline in Kickstarter’s and a 4.8% increase in Indiegogo’s
Table 6: Counterfactual 1 - Fix Platform, Change Projects

<table>
<thead>
<tr>
<th></th>
<th>Kickstarter Baseline</th>
<th>Kickstarter IGG δ</th>
<th>Indiegogo Baseline</th>
<th>Indiegogo KS δ</th>
</tr>
</thead>
<tbody>
<tr>
<td>Avg. # Donors</td>
<td>68.9</td>
<td>65.8</td>
<td>47.8</td>
<td>53.5</td>
</tr>
<tr>
<td>%Goal Reach</td>
<td>36.1</td>
<td>33.5</td>
<td>9.32</td>
<td>12.5</td>
</tr>
<tr>
<td>%Goal Raised</td>
<td>57.1</td>
<td>60.2</td>
<td>38.7</td>
<td>40.8</td>
</tr>
<tr>
<td>$ Fundraiser keeps</td>
<td>2,906</td>
<td>2,404</td>
<td>2,912</td>
<td>3,212</td>
</tr>
<tr>
<td>$ Platform keeps</td>
<td>158.4</td>
<td>131.0</td>
<td>263.7</td>
<td>276.3</td>
</tr>
</tbody>
</table>

Note: The table presents the results from simulating outcomes on Kickstarter and Indiegogo when the distribution of project qualities on the two platforms are reversed.

average per-project revenue respectively.

The reason that the drop in Kickstarter’s revenue is larger than the increase in Indiegogo’s can be attributed to the differences in how many projects reach their goal and the fee structure across the two sites. If Kickstarter had Indiegogo’s projects, then the fraction of projects that reach its goal would decrease by 2.6 percentage points, while if the reverse were true, the number of projects that reach their goal on Indiegogo would increase by 3.2 percentage points and average fraction of goal raised would increase by 2.1%. Further, Indiegogo’s transaction fee is 9% of the amount raised by projects that don’t reach their goal and 4% of the amount raised by projects that do. Since Kickstarter uses the AoN mechanism, the drop in projects that reach its goal has a more substantial affect on the platforms revenues than the increase in the amount raised does on Indiegogo.

Why do projects sort? The role of expected funding

Having documented that project sorting on quality occurs and quantifying its importance, we next explore the causes of this sorting. My goal is to understand why higher quality projects choose Kickstarter, and my approach is to simulate each project’s outcome had they chosen the alternative mechanism. In the previous exercise, I held the mechanism fixed and simulated outcomes by changing the distribution of projects. In this exercise, I do the opposite: I hold the distribution of projects fixed and changed the platform. By doing so, I can see how key outcomes would change if each fundraiser had selected the opposite mechanism, and then by comparing these outcomes to those on the actual platform chosen, I can infer which outcomes drive platform choice.

Table 7 presents the results from this counterfactual. The first column shows the baseline outcomes across the two platforms while the second column lists the results from simulat-
There appear to be two important changes that result in fundraisers choosing different platforms. First, we see that on average, fundraisers raise more using the KiA mechanism than they do using the AoN mechanism. Had Kickstarter projects instead chosen to launch on Indiegogo, their expected revenues would increase by 9.8%; similarly, Indiegogo’s expected revenues would decrease by 22% had they switched. At the project level, nearly 70% of Kickstarter fundraisers could have earned more expected revenues by choosing Indiegogo, while almost 33% of Indiegogo projects would have earned more switching to Kickstarter. This pattern - that the majority of fundraisers could have increased their revenues by switching platforms - is reversed when looking at the other outcomes. Projects are much more likely to reach their goal using the AoN mechanism than using the KiA mechanism; fewer than 1% of the projects that launched on Kickstarter would have been more likely to reach their goal had they switched to Indiegogo, while close to 60% of projects on Indiegogo would have improved the probability of reaching their goal had they switched. Similarly, only 17% of Kickstarter projects would receive more donors by switching to Indiegogo, while the reverse is true for over 86% of Indiegogo projects.

Table 7 shows that on average, projects raise more using the KiA mechanism but are more likely to reach their goal using the AoN mechanism. Since we observe higher quality projects sorting to Kickstarter, the next question is to see how the differences shown in Table 7 vary by quality. I first group projects by whether or not they would have earned higher expected revenue had they switched platforms and then see if there are differences in the average quality across these groups. Table 8 presents a 2x2 matrix, where the rows refer
Table 8: Quality Differences by Expected Earnings

<table>
<thead>
<tr>
<th>Choice</th>
<th>Maximize Fundraising</th>
<th>Kickstarter</th>
<th>Indiegogo</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>0.055 [172]</td>
<td>0.018 [383]</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.038 [172]</td>
<td>0.015 [350]</td>
</tr>
</tbody>
</table>

Note: The table groups projects based on whether earnings would have been higher or lower and computes the average project quality. The row labeled "Choice" refers to projects that chose the platforms on the left-hand side, while the column labeled "Maximize Fundraising" refers to projects that raised more money on each platform. Project counts are presented in brackets.

We clearly see that projects that raised more on Kickstarter are of higher quality than those than raise more on Indiegogo. Projects that both choose Kickstarter and had higher expected earnings on Kickstarter have an average project quality of 0.055, compared to an average project quality of 0.015 for projects that choose Indiegogo and earned more money on Indiegogo. Similarly, 67% of the projects in the top quantile of the quality distribution earn higher expected funding on Kickstarter.

How well can the differences in expected earnings rationalize the observed choices of fundraisers? Assuming that projects select the mechanism that maximizes expected fundraising can correctly predict platform choice 48% of time. Fundraisers choosing the platform that maximizes expected funding thus provides a plausible explanation for why higher quality projects sort onto Kickstarter.

Do fundraisers prefer Kickstarter? Calculating a “platform” effect.

In Table 8, I show that 48% of the observed choices of fundraisers can be predicted by fundraisers choosing the platform that maximizes expected funding. However, a closer examination shows that far more campaigns on Indiegogo select the platform along these lines than on Kickstarter: 67% compared to 31% respectively. These observed choices suggest that fundraisers may have an innate preference for Kickstarter “outside” of how the AoN mechanisms affect outcomes.

How large is this preference? One way to quantify it is to compute how much fundraisers are willing to forego in expected fundraising by choosing Kickstarter over Indiegogo. Denoting
this amount $\Delta_{KS}$, we can compute the size of this preference by solving:

$$
\max_{\Delta_{KS}} \sum_j I_j(\text{Choose KS}) \cdot (\pi_j(KS) + \Delta_{KS} > \pi_j(IGG)) \\
+ I_j(\text{Choose IGG}) \cdot (\pi_j(KS) + \Delta_{KS} < \pi_j(IGG)) 
$$

Equation (19) defines the preference for Kickstarter as a dollar amount added to the expected funding received on Kickstarter that maximizes fundraisers predicted platform choice. From table 8, we see that setting $\Delta_{KS}$ to 0 results in 19 equals $172 + 350 = 522$, or 48% of all projects. In contrast, the solution to 19 is $\Delta_{KS} = 1,340$, which correctly predicts 605 choices, or 56% of all projects. This increase in the prediction rate results in a 16% increase over the baseline of setting $\Delta_{KS}$ to 0. Further, $\$1,340$ represents a large percentage of fundraisers average profits - around 46%.

7 Conclusion

Crowdfunding platforms are new markets for individuals and firms to fundraise. When deciding whether to use crowdfunding, fundraisers must decide which type of fundraising mechanism to use. This paper builds a model of donors preferences for crowdfunding and investigates how these different mechanisms affect both donors and fundraisers incentives.

My main finding is that fundraisers sort across the two mechanisms by quality. On average, projects on Kickstarter are of almost 30% higher quality than those on Indiegogo. This quality differential is economically meaningful; if Kickstarter had the same distribution of projects as Indiegogo, its revenues would decrease by 17%. By simulating what would happen if projects chose the opposite mechanism, I explore how the different mechanisms affect project outcomes, holding project characteristics fixed. I find that most outcomes – such as total donations – increase on Kickstarter. I also find that higher quality projects are more likely to earn higher revenues on Kickstarter than on Indiegogo, and that nearly half of all projects select the mechanism that maximizes their expected revenues. My findings suggest that the sorting of higher quality projects onto Kickstarter can thus be in part rationalized by fundraisers selecting the platform that maximizes their expected earnings. Further, I provide suggestive evidence that fundraisers may also choose Kickstarter because of an innate preference for it, and quantify this preference as $\$1,340$ to fundraisers. This finding is in line with anecdotal evidence that Kickstarter is the premium branded platform in the market.

Given my findings, it is natural to ask what is gained by having both platforms available
to fundraisers. On the one hand, we see that the AoN can act as a screening mechanisms to attract higher quality projects. On the other hand, more projects on Indiegogo receive any funding, and my estimates suggest that donors find value in these partially funded projects at close to 60% of fully funded ones. Hence, from a social welfare perspective it is not obvious which mechanism is “better.” I am currently working on formalizing and solving how a social planner would allocate funding across projects, and determining how close each mechanisms gets to achieving this socially optimal allocation. The results from this future research will help shed light on the extent to which fundraisers and donors benefit from having both mechanisms in the market.

As firms increasingly turn to crowdfunding markets to introduce new products, it is crucial to understand the factors that influence market outcomes. This paper is the first to study how different fundraising mechanisms affect both donor and fundraisers incentives, and develops a set of tools that can be used by future researchers to continue to study these new and exciting markets.
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Appendix

Screen Shots

Kickstarter Screenshot

16 year old singer/songwriter, Eli Pfumi, finally has the opportunity to cut his first EP this summer in Ashville, NC.

Indiegogo Screenshot

Help Pacific Public finish their EP!

We have already begun tracking our first EP, but we need your help to finish it.
Likelihood Function

Our goal is to construct a likelihood function that predicts the number of people that make contributions on every day of a project’s campaign. Given my data, this entails computing the probability that a project that begins the day having raised $X_{d-1,j}$ ends the day with $\hat{b}$ donors raising $X_{d,j}$ dollars. To do so, I use a similar backward-induction algorithm used to compute the probability that a project will reach its goal developed in Section 3.

Again dividing each day $d$ into discrete periods and denoting each period during each day $t_d$, define $\iota_{t_d}$ as an indicator variable that equals one if a contribution is made in period $t_d$. Conditional on beginning that day having raised $X_d$, the probability that the total number of contributions made in day $d$ equals $\hat{b}$ is:

$$Pr\left(\sum_{t=0}^{T_d} \iota_t = \hat{b} | X_d\right)$$

(20)

Defining $B_r = \sum_{t=0}^{T} \iota_t$, I can rewrite 20 as simply

$$Pr\left(B_{T_{d-1}} + \iota_{T_d} = \hat{b} | X_d\right)$$

(21)

Computing 21 is straightforward. The distribution of $\iota_{t_d}$ is equal to the choice probability derived in Section 3:

$$1 \ w.p \ \rho \cdot q(X_d + x, x)$$

$$0 \ w.p \ \rho(1 - q(X_d + x, x)) + (1 - \rho)$$

(22)

With 22, I can compute 21 conditioning on different values of $B_r$. Note that 21 equals 0 for any value of $B_{T_{d-1}} < \hat{b} - 1$; hence, I only need to compute 21 for $B_{T_{d-1}} = \hat{b} - 1, \hat{b}$. Hence, I have:

$$Pr\left(\iota_{T_d} = 1 | X_d, B_{T_{d-1}} = \hat{b} - 1\right) = \rho \cdot \int_x q(X_d + x, x)$$

(23)

$$Pr\left(\iota_{T_d} = 0 | X_d, B_{T_{d-1}} = \hat{b}\right) = \rho \int_x (1 - q(X_d + x, x)) + (1 - \rho)$$

(24)

Note that I can directly compute equations 23 and 24, since they are simply a function of the underlying choice probabilities which I computed in Section 3. Having solved 21, I next compute the following:
Using the law of iterated expectations, I can rewrite 25 as:

\[
Pr \left( B_{T_d-2} + \nu_{T_d-1} + \nu_{T_d} = \hat{b}|X_d \right)
\]

(25)

\[
Pr \left( B_{T_d-2} + 1 + \nu_{T_d} = \hat{b}|X_d, \nu_{T_d-1} = 1 \right) \cdot Pr \left( \nu_{T_d-1} = 1 \right) + Pr \left( B_{T_d-2} + 0 + \nu_{T_d} = \hat{b}|X_d, \nu_{T_d-1} = 0 \right) \cdot Pr \left( \nu_{T_d-1} = 0 \right)
\]

(26)

Note that equation probabilities I and II are simply equal to those computed in 23 and 24. For example, if \( B_{T_d-2} = \hat{b} - 2 \), then the term II in equation 25 is zero\(^{25}\) and the term I is simply

\[
Pr \left( \hat{b} - 2 + 1 + \nu_{T_d} = \hat{b}|X_d, \nu_{T_d-1} = 1 \right) \rightarrow Pr \left( \nu_{T_d} = 1|X_d, \nu_{T_d-1} = 1 \right)
\]

(27)

which is exactly what I derived in 23. I can also compute 25 for \( B_{T_d-2} = \hat{b} - 1 \) instead; then term II becomes:

\[
Pr \left( \hat{b} - 1 + 1 + \nu_{T_d} = \hat{b}|X_d, \nu_{T_d-1} = 0 \right) \rightarrow Pr \left( \nu_{T_d} = 0|X_d, \nu_{T_d-1} = 0 \right)
\]

(28)

which exactly what I have computed in 24. Computing 25 for \( B_{T_d-2} = \hat{b} \) is simply equal to term II. Hence, I have shown how I can compute 25.

Following this same procedure, I can continue to compute equation 25 for values of \( B_\tau \) for fewer and fewer period \( \tau \). For example, solving 25 for \( B_{T_d-3} \) equals:

\[
Pr \left( B_{T_d-3} + \nu_{T_d-2} + \nu_{T_d-1} + \nu_{T_d} = \hat{b}|X_d \right)
\]

(28)

I can again rewrite 28 using LIE:

\[
Pr \left( B_{T_d-3} + 1 + \nu_{T_d-1} + \nu_{T_d} = \hat{b}|X_d, \nu_{T_d-2} = 1 \right) \cdot Pr \left( \nu_{T_d-2} = 1 \right) + Pr \left( B_{T_d-3} + 0 + \nu_{T_d-1} + \nu_{T_d} = \hat{b}|X_d, \nu_{T_d-2} = 0 \right) \cdot Pr \left( \nu_{T_d-2} = 0 \right)
\]

(29)

As in the previous section, I see that the terms I and II are identical to the probability I computed in 25. Hence, I see that by proceeding backwards, I can continue to compute

\(^{25}\text{If a contribution is not made, then it would only be possible for project to receive } \hat{b} - 1 \text{ backers}\)
the probabilities like 28 for $B_{T_d - \tau, \tau} = 0 \ldots T_d$. In the last period, $B_0$ simply equals $\iota_t$, which equals 20, the probability that builds the likelihood.
Distribution of Average Contributions

Figure 7: Distribution of Average Contributions

Note: The figure graphs the distribution of average contributions made to the fundraising campaigns in the estimation sample described in section 5