Commitment vs. Flexibility in Information Disclosure: the Case of Kickstarter *

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Abstract

An important function of a crowdfunding platform is to mitigate information asymmetry between entrepreneurs and investors by transmitting private information from the former to the latter. But can the platform be trusted? Using data from Kickstarter, we estimate a dynamic model of cheap talk, develop a statistical test confirming that the platform's incentives undermine the credibility of its signals, propose regulations that would curb those incentives, and quantify their welfare consequences. These regulations enable the platform to commit to an information disclosure rule and lead to Pareto improvements. We show that the platform's long-run reputation concerns could substitute for commitment.

JEL: L15; L20; L51; D26; D82.

Keywords: Crowdfunding; Bayesian Persuasion; Information Disclosure; Dynamic Cheap Talk; Information Design.

*The views and opinions expressed in this paper are those of the authors and do not necessarily reflect the views and opinions of AlixPartners.

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1 Introduction

On a reward-based crowdfunding platform, entrepreneurs pre-sell their products to small investors (buyers).[1] Asymmetric information between entrepreneurs and investors about product quality, and insufficient incentives of investors to screen products individually create a role for a crowdfunding platform to serve as an information intermediary—facilitating information transmission from entrepreneurs to investors.

To study this role, we develop a theoretical framework and an empirical strategy with an application to the largest reward-based crowdfunding platform in the USA—Kickstarter.com. More specifically, we ask whether a crowdfunding platform can function as a credible information intermediary, model and quantify platform's incentives that may threaten its credibility, and study mechanisms that can discipline such incentives.

We start with two assumptions: (1) a crowdfunding platform is better informed about entrepreneurs' products than individual investors are, and (2) the platform is profit-motivated. Under these assumptions, it follows that if the platform tried to transmit information about products to investors, then it would have incentives to transmit only the information that would help it earn higher profits.

To formally examine the platform's incentives to misrepresent information, we study an interaction between a long-lived crowdfunding platform (Kickstarter in the data, henceforth, "it"), and a sequence of short-lived project creators (entrepreneurs, henceforth, "he") and investors (henceforth, "she"). At the start of each period, a creator may arrive at the platform and decide whether to post a funding request. Creators are characterized by the observable features of their projects and their privately known quality. If a project is posted, the platform observes its quality and communicates with investors through a cheap-talk message. Investors form expectations about the project's quality and decide whether to invest.

The platform's objective is to maximize expected discounted revenues under the All-or-Nothing (AON) funding mechanism.[2] Creators seek to maximize their likelihood of securing

[1] More specifically, reward-based crowdfunding involves funding of innovations/new products, where a large number of small investors contribute small amounts of money in return for non-financial rewards (often the product itself).

[2] Under the AON funding mechanism, a project is funded only if the total pledged investment meets or

funding but incur a cost when posting a funding request. Investors, in turn, weigh the project's quality against the opportunity cost of investing. The intensive margin of investors' decisions is modeled in reduced form.

At the start of period 0, we assume the platform announces a stationary rule outlining how it *promises* to transmit information about project quality (the information transmission or disclosure rule). This rule defines a joint distribution over project quality and the signals sent to investors. However, as a profit-motivated entity, the platform's revenues depend on the share of investments directed toward successfully funded projects. This creates an incentive for the platform to send signals that induce more favorable investor beliefs about a project's quality (i.e., higher posterior expected quality). Without mechanisms to discipline these incentives, the platform cannot credibly adhere to its *promised* information transmission rule, undermining its role as a reliable information intermediary.

There are at least two ways to mitigate a platform's incentives to misrepresent signals. The first is an exogenous mechanism that forces the platform to follow its promised rule. One such mechanism could be a regulator that makes sure that the platform sends signals according to the rule that was announced. The second way is via the platform's long-run incentives, *i.e.* if the platform violates the rule then there are consequences in the future. For example, the public may detect that the platform misrepresented a signal, leading the platform to lose credibility resulting in lower future revenues. Therefore, public monitoring can be another way to discipline the platform's incentives to misrepresent signals. If such mechanisms are in place to prevent the platform from altering the realized signals it privately observes, we say that the platform can *commit to information disclosure*.

We estimate the model outlined above to quantify the platform's incentives, assess the practical significance of commitment and public monitoring, and evaluate their substitutability. The data indicate that investors respond to Kickstarter's signals, suggesting that the platform's incentives to misrepresent signals are, to some extent, disciplined. But how effectively are these incentives controlled? To address this question, we develop a statistical test to determine whether the platform's incentives constrain it from achieving the commitment

exceeds the creator's goal within a specified timeframe. If these conditions are not met, investors reclaim their pledged amounts. The platform earns a fixed percentage of the funds raised from successfully funded projects.

outcome.

The logic of the test is as follows: we demonstrate that all necessary parameters of the model required to evaluate the platform's discounted revenues can be identified and estimated without relying on the platform's explicit optimization problem. Under commitment, the platform would maximize its revenues without facing incentive constraints, meaning the estimated transmission rule would be a global revenue maximizer. In contrast, without commitment, incentive constraints could bind, leading to the possibility that small perturbations of the estimated transmission rule might yield higher revenues. The null hypothesis assumes that small perturbations of the estimated rule do not increase revenues (indicating commitment). However, our test rejects this null hypothesis.[3]

Having established that the platform is unlikely to possess commitment power, we estimate the welfare effects of granting it such power. Our results indicate that commitment would benefit creators, investors, and the platform. Specifically, the platform's revenues would increase by 7 percent, creators' welfare by 4 percent, and investors' welfare by 0.5 percent.[4]

Next, we explores the role of public monitoring in addressing the platform's incentive issues. We solve the platform's dynamic optimization problem. We define *public monitoring technology* as the probability that the public (e.g., potential future investors) verifies a project's true quality independently across projects and over time. This probability is allowed to depend on the information transmission rule that the platform announces. Using the platform's optimality conditions, we estimate that the current public monitoring technology enables the public to verify a project's quality, on average, within 1.2 months. Finally, we demonstrate that if public monitoring technology were improved to reduce verification time, public monitoring could effectively substitute for commitment. In practice, one way to enhance public monitoring technology would be to create a forum where investors can exchange experiences with previous projects.

This paper advances the estimation of dynamic cheap-talk models and demonstrates how

[3] While our model offers a structured framework for testing the platform's commitment assumptions, its validity, like most theoretical models, depends on the correct specification of the model.

[4] The commitment outcome being Pareto-improving is not guaranteed a priori, as there are parameter values in the model under which this would not hold.

commitment power, in the sense of Kamenica and Gentzkow (2011), can be operationalized in practice, such as through regulatory oversight. It introduces an empirical strategy to test for commitment power and quantify its welfare effects. Additionally, the paper investigates whether public monitoring can effectively substitute for exogenous commitment.

The primary policy implications of this work are as follows: granting the platform commitment power is Pareto-improving, benefiting the platform, creators, and investors alike. A regulator could achieve this by ensuring the platform adheres to its promised information disclosure rules. In cases where such regulation is infeasible, the platform itself could enhance public monitoring mechanisms to approximate the commitment outcome.

Related Literature: The literature on reward-based crowdfunding has focused on studying the funding mechanisms on the platforms. One strand of the literature has argued for the ability of crowdfunding platforms to facilitate the learning of consumer-demand (Strausz (2017), Ellman and Hurkens (2019)). Entrepreneurs can learn about demand by observing the outcome of his listing on the platform, and the platform can affect the learning by its choice of a funding mechanism. Another strand of the literature has focused on social learning on crowdfunding platforms (Kim et al. (2022), Kuppuswamy and Bayus (2018), Marwell (2015)). Investors learn about some payoff relevant state by observing the history of the number of project backers (investors who have already invested) and pledged investment amount. Unlike this paper, the papers cited above either abstract away from the privately informed entrepreneur or model it in a reduced way. This paper tries to fill in this gap by explicitly modeling asymmetric information and studying a platform's potential for serving as an information intermediary.

This paper is also related to the literature studying information intermediation by financial institutions. It is believed that financial intermediaries can deal with information asymmetry between lenders and borrowers more effectively compared to individual lenders, and their role as information intermediaries has been well studied (Diamond (1984), Hirshleifer and Riley (1979), Leland and Pyle (1977)). The basic idea is that there is economies of scale in screening borrowers and if a financial intermediary has incentives sufficiently aligned with lenders then it can serve as an information intermediary. Similarly, reward-based crowdfunding platforms involve small investors who are not likely to be well incentivized to individually screen projects, suggesting that there might be a role for a platform to serve as an information intermediary. This paper tests this conjecture.

The structural model borrows its structure and assumptions from the literature on Bayesian Persuasion (Kamenica and Gentzkow (2011), Rayo and Segal (2010), Tamura (2016)) Avoyan et al. (2024) and dynamic cheap talk (Best and Quigley (2024), Margaria and Smolin (2018)). Most closely related to our model is Best and Quigley (2024). They study a repeated cheap-talk model with public monitoring in which a long-run sender tries to persuade short-run receivers to take certain actions and the state of the world is i.i.d. over time. They ask whether the sender's long-run incentives can substitute for full commitment a la Kamenica and Gentzkow (2011), in terms of sender's payoffs. In their framework, this is possible under certain types of optimal disclosure policies. To our knowledge, our paper is the first to address this same question empirically.

In addition to extensive theoretical work, there is relatively little empirical research on structurally estimating information design frameworks through Bayesian persuasion models. Xiang (2021) and Decker (2022) examine physician-patient interactions and Airbnb's rating system, respectively, using the Bayesian persuasion framework to analyze strategic information disclosure. While these studies take commitment as given, our paper focuses on testing the existence of commitment and evaluating the welfare effects of counterfactual scenarios under full commitment.

Our model structure as well as research question is related to the experimental work by Fréchette et al. (2022). They investigate commitment power in communication games with verifiable and unverifiable rules and find that increasing commitment power raises the amount of information conveyed under verifiable conditions but reduces it under unverifiable conditions. While we do not measure the amount of information, we add a real-world application by quantifying the welfare effects of increasing commitment power using empirical data.

Among other papers, summarized in Bar-Isaac and Tadelis (2008), the role of reputation on two-sided markets has been studied by Saeedi (2019). She estimates the value of reputation mechanisms on Ebay. She models sellers as having private information about their product quality, and buyers receiving signals about the product quality from the platform (Ebay) via existing reputation mechanisms. She does not have data that would directly measure quality and hence relies on a quality index that is recovered by estimating a structural model. Unlike us, Saeedi (2019) does not assume parametric distribution over quality. This constrains her in considering counterfactuals in which beliefs about quality change endogenously. Such counterfactuals are at the core of this paper.

The rest of the paper is organized as follows: the basic facts about the industry and Kickstarter are presented in Section 2; Section 3 sets up the model, discusses equilibrium selection strategy, and the key assumption of the model; in Section 4, we solve the model and present basic theoretical results; Section 5 describes the data set and provides some reduced form evidence on the ability of the platform to serve as an information intermediary; Section 6 proves the identification of model parameters; Section 7 discusses the estimation procedure. Finally, Section 8 presents all the main results in this paper. Proofs, estimation details, tables, and figures are relegated to the Appendix.

2 Kickstarter.com Background

Kickstarter.com was launched on April 28, 2009.[5] Currently, it is the largest reward-based crowdfunding platform.[6] Its revenue model is based on the All or Nothing (AON) funding mechanism and it takes 5 percent of the invested amount from the successfully funded projects.[7]

There are two important features that distinguish Kickstarter from a traditional venture capital firm:

1. The bulk of the investors on the Kickstarter are inexperienced and make only small stake investment decisions. Those investors are believed to have insufficient incentives or resources to conduct due diligence and screen the new ventures individually.[8]

[5] https://techcrunch.com/2009/04/29/kickstarter-launches-another-social-fundraising-platform/

[6] https://www.slintel.com/tech/crowdfunding/kickstarter-market-share

[7] https://help.kickstarter.com/hc/en-us/categories/115000499013-Kickstarter-basics

[8] http://www.finance-watch.org/hot-topics/blog/1182-take-care-of-the-crowd-crowdfunding

2. There are no regulatory measures that would help resolve asymmetry of information between project creators and investors. Because rewards are not classified as financial instruments or securities, reward-based crowdfunding does not fall under the securities law.[9]

Those two features create a space for Kickstarter to intermediate information transmission from project creators to investors and more importantly, to choose what information to transmit.

Currently, Kickstarter intermediates information transmission through "Projects We Love" - a way to feature projects that kickstarter deems promising. "Projects We Love" was launched on February 2, 2016 and is an evolution of a similar feature previously known as "Staff Pick".[10] The difference from the "Staff Pick" is that "Projects We Love" assigns a badge to the featured projects that cannot be falsified by the creators.[11]

The website claims that every project posted on it is pre-screened by either a complicated algorithm or a staff member.[12] Consequently, if a project meets certain quality standards, it is assigned a "Projects We Love" badge.

The structural model presented in the next section builds on the features of the Kickstarter outlined above.

3 The Model

The model has a one-period lived project creators, one-period lived investors, and long-lived crowdfunding platform. Time is infinite and discrete, indexed by $t = 0, 1, 2, ...$

[9] A candidate agency for regulating reward-based crowdfunding could be the Consumer Product Safety Commission. However, because crowdfunding is a form of pre-selling products to the investors, the product quality certification is required only after a project is funded.

[10] https://www.kickstarter.com/blog/introducing-projects-we-love-badges

[11] https://thenextweb.com/insider/2016/01/11/kickstarter-kills-staff-picks-in-favor-of-official-badges-to-avoid-confusion/

[12] https://www.kickstarter.com/blog/how-projects-launch-on-kickstarter

3.1 Creators

A creator has a project of type (q, m, l), where q stands for a quality of the project, m stands for the funding goal, and l stands for the length of the time during which the creator will be collecting funds from the investors on the platform (also referred to as the *length of the project*).

In a given period, the probability that a creator with a project type (q, m, l) arrives to the platform is denoted $f(q, m, l)$, and its CDF is denoted $F(q, m, l)$. We assume that the sets of all possible funding goals and project lengths, M and L, are finite. The set of all possible project qualities is normalized to be the $[0, 1]$ interval. Let $\oslash$ stand for the event in which no creator arrives; the probability of this event is $1 - \int_0^1 \sum_{(m,l)\in M\times L} f(q, m, l)dq$.

After arriving to the platform, a creator decides whether he wants to post his project on the platform or not. To post the project, he must incur the cost c_{cr} that is distributed according to CDF F_{cr}, independently across creators. He gets utility of 1 if his project is funded and 0 otherwise. A project is said to be funded if and only if the total amount invested in the project by investors, denoted x, is greater than or equal to the project goal, m. This mechanism is called All Or Nothing (AON) funding mechanism.

3.2 Investors

If a project is posted by a creator, the number of investors that view its web-page, k, is distributed Poisson with the mean n. The parameter n is also random and has a Gamma distribution with the shape parameter β and rate parameter α.[13]

After an investor views a project, she needs to decide whether to invest or not. Investor's payoff per dollar invested is $q - c_b$, whenever she invests and the project is funded, and 0 otherwise.[14] The opportunity cost of investing, c_b, is distributed according to CDF F_b. It follows that the probability that an investor viewing the project invests in it is $F_b(E(q|I))$, where E stands for the expectation operator and I is the information set of the investor. It further follows that the number of investors who invest into the project, k', has a Negative

[13] We provide an extended discussion regarding using mixture of Poisson and Gamma for modeling investor arrival process in Section 3.6.

[14] On a reward-based crowdfunding platform, investors are most often simply buyers of a product. Therefore, we denote the investor's side by b and avoid using i, as it might confuse the reader with the innovator.

Binomial distribution. Its density is denoted by $g(k'|F_b(E(q|I)))$, and is derived in Appendix A.1.

We model the intensive margin of investor's decision in a reduced form by assuming that the total investment amount pledged towards a project is drawn from an exponential distribution with the parameter $\lambda(m, l, k, E(q|I))$. It follows that conditional on k' investors investing in a project with the goal m, length l, and expected quality $E(q|I)$, the probability that the project is successfully funded is,

$$h(m, l, k', E(q|I)) = e^{-\lambda(m,l,k',E(q|I))m}$$

The following assumptions are maintained throughout the paper,

Assumption 1. *F_{cr} and F_b are continuous CDFs. $F(q, m, l)$ is continuous in q.*

Assumption 2. *$\lambda(m, l, k', E(q|I))$ is continuous in $E(q|I)$.*

Assumption 3. *$\lambda(m, l, k', E(q|I))$ is decreasing in k' and $E(q|I)$.*

Assumptions 1 and 2 are needed to prove the existence of an equilibrium. Assumption 3 implies that the expected amount invested into a project, $1/\lambda(m, l, k', E(q|I))$, must be increasing in the number of investors and in the expected quality of a project. In the estimation, we verify that assumption 3 holds.

3.3 The Platform

The platform maximizes discounted sum of revenues with the discount factor δ. It gets a share, r, of the invested amount into the funded projects (recall, a project is funded if the invested amount is greater than the goal amount). Hence, its revenue in a given period is simply rx if the project is funded and the invested amount is x, and 0 otherwise.

At the beginning of each period t, if a creator posts a project, the platform privately learns project's quality, q. The platform can communicate information about the project's quality to the potential investors. For this, we assume the platform has access to a fixed message space, $S = \{0, 1\}$, and can send a message, s, to the potential investors after learning the project's quality. Throughout the paper, message $s = 1$ is interpreted as assigning a badge to a project.

A rule determining how signals are correlated with the private information of the platform is announced by the platform at the beginning of period 0. Such a rule is called an Information Transmission Standard (ITS).

Definition 1. *Information Transmission Standard (ITS) is a threshold quality, q^*, such that a project is promised to be assigned a badge if and only if $q \geq q^*$.*

Even though the platform announces ITS at the beginning of period 0 and promises to adhere to it, such a promise should also be deemed credible by the investors, as otherwise the platform's signals would not be informative for the investors. Particularly, project creators' and investors' decisions depend on the beliefs about the platform's strategy. Since an investor does not observe q at the moment of making the decision, if the platform deviated from the announced ITS by sending a signal that is not supposed to be sent under the existing ITS such a deviation would not be verifiable by the investor. Investors understanding this, would deem signals sent by the platform uninformative unless the platform had sufficient incentives not to deviate from the announced ITS. To make such incentives possible, we introduce an imperfect public monitoring of project's quality.

A public monitoring technology maps ITS (q^*) to the probability with which a project's quality becomes public information (probability that the quality is verified) - independently across projects and over time. Formally, it is a function $\pi : [0, 1] \to [0, 1]$. This monitoring technology is one potential way to discipline the platform to adhere to the announced ITS: if the public verifies that the platform deviated from its announced ITS, then the platform may be punished by switching to an equilibrium that ensures lower long-run revenues (continuation value) to the platform.

We do not make parametric assumptions on $\pi(q^*)$ and hence allow for a wide range of ways in which a public monitoring could depend on ITS. Finally, we assume that $\pi(q^*)$ is continuous in q^*.[15]

[15] For instance, one mechanism could be that whenever q^* increases, that is ITS sets higher quality standard for a project to get badged, competitors of the Kickstarter decrease the efforts to verify badged projects' qualities as they expect that those projects are of pretty high quality - decreasing benefit from negative campaigning for the competitors. This would deteriorate public monitoring.

3.4 Timeline

At the beginning of period 0, the platform announces ITS. Within each period, t, the timeline of the game is depicted in Figure 1.

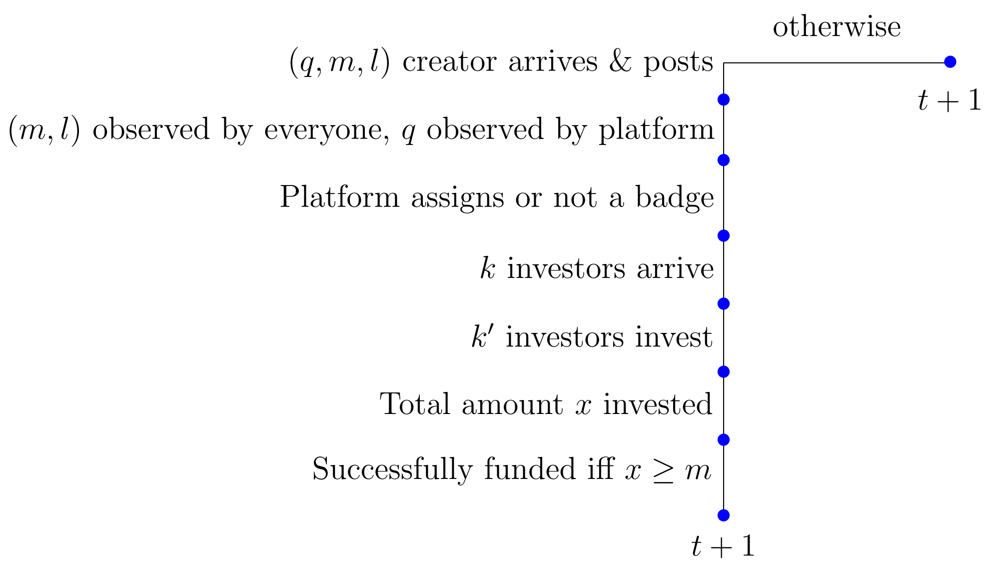

Figure 1: Timeline

3.5 Strategies and Solution Concept

Let h_t denote a public history at the beginning of period t. It includes the following information about each period up to time t: whether or not a project was posted; conditional on a project being posted, its goal amount, length, total investment amount pledged, total number of investors, and signal sent by the platform; whether or not a project's quality has been verified, and project's true quality if it has been verified. Let H_t denote the set of all period t public histories.

The platform, in addition to h_t, observes the realization of q for each project that was posted. A history observed by the platform is, $h_t^P = h_t \cup \{q_t\}_{t=0}^{t-1}$. We drop time subscripts whenever a reference to a specific time period is clear from the context.

A strategy of a creator who arrives at the platform is the probability of posting his project conditional on h_t, his project's type, (q, m, l), and cost of posting the project, c_{cr}. A strategy of an investor arriving at a posted project's page is the probability of investing conditional on h_t, current project's goal and length, (m, l), signal sent by the platform, s, and cost of investing, c_b. A strategy of the platform consists of the choice of q^* at the beginning of period 0, and a probability of sending $s = 1$ conditional on h_t^P and type of the current project, (q, m, l).

We study Perfect Bayesian Equilibria (PBE) that survive the intuitive criterion of Cho and Kreps (1987). For the estimation, we further narrow down the set of equilibria. We assume that the platform announces a two signal communication rule that is partitional (We refer to it as Information Transmission Standard (ITS) - see section 3.3), and history independent. We further assume the worst off-equilibrium punishment if the platform is detected to have deviated from the announced ITS. We elaborate on this punishment-phase selection further in the next section. Henceforth, we will refer to a PBE that survives intuitive criterion, involves history independent ITS, and prescribes the worst punishment for the platform (in case its deviation is detected) as an *equilibrium*.

3.6 Discussion of the Model

Project's Quality: we assume that a project's quality is exogenous (i.e. determined outside the model). Quality can be interpreted as something that is determined by the ability of a creator and uniqueness of his idea, and hence is difficult to change. Since quality differentiates projects on the vertical dimension, we estimate the model only for the projects in the technology category. In this category, quality has a more or less straightforward interpretation. For example, we could think about quality as an index of endurance, energy usage, size and other characteristics of a new technology piece.

Alternatively, we can consider two possible qualities, high or low, associated with each project. In this case, q can be interpreted as the probability of high quality. Here, we no longer need to assume that the platform perfectly observes the project's quality; instead, it is sufficient for our results that the platform observes the probability of the project being of high quality. This provides an observationally equivalent way of representing the model.

Finally, instead of thinking about the platform as observing certain signals about a product that investors do not, one could equivalently think about the platform as having an expertise in interpreting certain publicly observable signals about a product. In such a case, the signals that the platform transmits to investors would summarize information contained in the publicly observable signals (e.g. creator posts a blueprint and the platform interprets its content to the potential investors).

Project's Goal and Length: we abstract away from modeling creator's choice of project's goal and length. One would expect that a creator would choose those strategically if such choices signal something about his project's quality. One reason for why we do not model strategic choice of goal and length is that it would require us to answer very specific modelling questions. For instance, what would happen if a creator sets lower goal than he actually needs to develop the project? Would the project quality be affected by this? If so, how? Would this mean that the creator would be less likely to deliver his promises and do we translate this into the lower quality of the project? If so, how? If not so, do we explicitly model what it means to deliver promised project? To at least partially compensate for answering all these modelling questions, we allow project's quality distribution to depend on its goal and length.

Cost of Investment: The parameter c_b can be interpreted as the opportunity cost of a dollar invested. Ideally c_b would be modeled to be explicitly correlated with the actual amount invested, allowing for non-linearity of opportunity cost in amount invested. However we cannot afford this, as we do not observe the individual donation amounts (see Marwell (2015) for the similar modelling choice).

It is also noteworthy that an investor does not incur c_b in case she invests but the project ends up unfunded. The reason is that under the AoN funding mechanism if the project ends up unfunded all the invested amount is returned to an investor. In addition, since in theory the investor could wait up until the deadline of the project to make the investment decision, investing should be a costless action in case a project ends up unfunded.

While this paper assumes one-period lived investors for tractability, we acknowledge that long-lived investors could introduce reputational incentives for the platform. Such incentives may partially substitute for public monitoring by aligning the platform's interests with truthful reporting to incentivize investors to return.

Investor Arrival: we do not have data that would let us directly recover the investor arrival process. We assume that investor arrival is governed by a mixture of Poisson and

Gamma. Alternatively, we could have modeled arrival using only a Poisson distribution, which might seem to simplify the model, but we chose not to do so for the following reasons. First, since Poisson has only one parameter, while we could have allowed n to differ for projects with and without badges, we would have restricted variance to be equal to mean. By incorporating the Gamma distribution, the model becomes more flexible. Second, likely due to this added flexibility, these distributional assumptions provide a good model fit for the number of investors observed, conditional on the characteristics of a project. Finally, the mixture of Poisson and Gamma is mathematically equivalent to the number of investors following a Negative Binomial distribution, which is a simple distribution to work with.

The parameters α and β govern the arrival of investors. The investors' cost and belief parameters govern behavior of individual investors. Our identification strategy allows α and β to vary across projects based on whether a project has a badge or not. This allows us to capture the fact that projects that have badges are usually also on the front page, and easier for the investors to find - this can potentially affects arrival of investors on a badged project's page.

Information Transmission Standard: In general, a communication protocol could be a complicated rule involving more than two signals. ITS restricts communication protocols in two ways. First, by allowing for at most two signals. Second, allowing only for threshold rules. The first restriction is in line with the "Projects We Love" type of communication protocols. There are reasons why Kickstarter does not implement a protocol that is more complicated than "Projects We Love", and those reasons are out of the scope of our model. In the absence of such reasons, our model rationalizes the use of communications protocols that involve more than two signals (the platform could do better under such protocols). Since we do not observe Kickstarter implementing such types of protocols, our model is not relevant for investigating what would happen if the platform implemented more complicated protocols. The second restriction is due to making the analysis tractable. It is also intuitively appealing, as it means that if a project of a certain quality gets a badge then a higher quality project must also get a badge. In practice, violating this kind of monotonicity might lead to the public accusing the platform of showing favoritism.

Equilibrium Selection: we select equilibria in which announced ITS is history independent.

In general, ITS could be announced by the platform in any period and it could be history dependent. The model and identification strategy can be straightforwardly extended to Markovian or even richer history dependent ITSs. However, estimating such a model would be more data intensive.

One reason for why we do not consider history dependent ITSs is that, to our knowledge, there is no evidence of it being such. Kickstarter provides guidelines for becoming a "Project We Love."[16] Those guidelines discuss only the quality of a project that is determined by creativity, uniqueness of an idea and implementability. There is no mention that the decision of assigning a badge is history dependent. Moreover, there is no mention that project's goal or length determine the decision of assigning a badge. This leaves us with a simple communication protocol that depends only on the quality of a given project.

Another assumption that helps to reduce the number of potential equilibria is prescribing the worst punishment for the platform if it is detected to have deviated from its announced ITS. In the Appendix A.4, we provide a more detailed discussion of the theoretical foundation for our equilibrium selection strategy and show that the worst punishment for the platform arises naturally. At this point, we deem it sufficient to state that most of the results (including the main results) are insensitive to how we punish the platform off the equilibrium path or even what kind of public monitoring technology we assume. The reason is that all the parameters that are sufficient for reaching certain results can be estimated independently of the platform's dynamic problem. This point will become more clear when we get to the details of the model identification.

4 Solving the Model

Let $I_t = \{m_t, l_t, s_t, q^*\}$ be the information that an investor has about the period t project when making the investment decision. Note that q^* stands for the ITS that the players believe the platform is following.

We can write the probability that the posted project gets funded conditional on the

[16] https://www.kickstarter.com/blog/how-to-get-featured-on-kickstarter

information contained in I_t as,

$$Z(I) = \sum_{k'=1}^{\infty} g(k'|F_b(E(q|I)))h(m, l, k', E(q|I)) \tag{1}$$

Let I_+ denote I with $s = 1$ and I_- denote I with $s = 0$. The following probabilities follow from 1,

$$\begin{aligned} &\text{For } q \geq q^* \\ &Z(I_+) \equiv Z(I_+, q) = \sum_{k'=1}^{\infty} g(k'|F_b(E(q|I_+)))h(m, l, k', E(q|I_+)) \end{aligned} \tag{2}$$

$$\begin{aligned} &\text{For } q < q^* \\ &Z(I_-) \equiv Z(I_-, q) = \sum_{k'=1}^{\infty} g(k', |F_b(E(q|I_-)))h(m, l, k', E(q|I_-)) \end{aligned} \tag{3}$$

Expressions 2 and 3 are the probabilities of getting funded from the perspective of a creator. Note that, for a fixed (m, l), for all creators with $q \geq q^*$ the probability of getting funded is the same and similarly for all creators with $q < q^*$. The reasons is that, given (m, l), the only thing that differentiates projects in the eyes of investors is whether a project was assigned a badge or not. This would not be the case, for instance, if we allowed investors to get private signals on the top of whatever information the platform provides. However, since investors on reward-based platforms are usually unaccredited and have little incentive and ability to screen the projects on their own, we consider the assumption of not privately informed investors a good approximation to the reality.

It follows that the probability that a (q, m, l) type creator posts a project with $q \geq q^*$ is $F_{cr}(Z(I_+))$ and for $q < q^*$ it is $F_{cr}(Z(I_-))$. We can further account for the equilibrium expectations of project quality, $E(q|I_+)$ and $E(q|I_-)$,

$$E(q|I_+) = \frac{\int_{q^*}^{1} f(m, l|q)f(q)q dq}{\int_{q^*}^{1} f(m, l|q)f(q) dq} \tag{4}$$

$$E(q|I_-) = \frac{\int_{0}^{q^*} f(m, l|q)f(q)q dq}{\int_{0}^{q^*} f(m, l|q)f(q) dq} \tag{5}$$

One more object that is useful to account for before turning to the platform's problem is the expected funds that a creator posting a (q, m, l) project obtains conditional on k' investors deciding to invest, $o(m, l, k', E(q|I))$,

$$o(m, l, k', E(q|I)) =$$

$$Pr(x \geq m|m, l, k', E(q|I))E(x|x \geq m, l, k', E(q|I)) =$$
$$e^{-\lambda(m,l,k',E(q|I))m}\left(m + \frac{1}{\lambda(m, l, k', E(q|I))}\right)$$

Note that $o(m, l, k', E(q|I))$ does not depend on q as the investors see s, not q.

Using the notation we developed so far, we can write down the platform's expected per period payoff before a creator posts a project and given that the creators and investors believe that the platform is using q^* as its ITS,

$$\begin{aligned} U(q^*) = r \sum_{(m,l)\in M\times L} f(m, l) \sum_{k'=1}^{\infty} \\ \Big[o(m, l, k', E(q|I_+))(1 - F(q^*|m, l))F_{cr}(Z(I_+))g(k'|F_b(E(q|I_+))) \\ + o(m, l, k', E(q|I_-))F(q^*|m, l)F_{cr}(Z(I_-))g(k'|F_b(E(q|I_-)))\Big] \end{aligned} \tag{6}$$

In the expression 6, $F(q^*|m, l) = \frac{\int_0^{q^*} f(q,m,l)dq}{f(m,l)}$.

Next, we account for the platform's payoffs after a project is posted on the platform. Recall that if a creator posts a project (m, l) becomes a public information, and in addition the platform privately observes q. Suppose the players believe that the platform is using the standard q^*. If the platform assigns a badge to the project, $s = 1$, its current period profits would be,

$$U_1(m, l, q^*) = r \sum_{k'=1}^{\infty} o(m, l, k', E(q|I_+))g(k'|F_b(E(q|I_+))) \tag{7}$$

If the platform does not assign a badge, $s = 0$, its current period profits would be,

$$U_0(m,l,q^*) = r\sum_{k'=1}^{\infty} o(m,l,k',E(q|I_-))g(k'|F_b(E(q|I_-))) \tag{8}$$

Comparing the payoffs from 7 and 8, one can see the platform's short-run incentive to always assign a badge to a project: note that for $q^* \in (0,1]$ we have $E(q|I_+) > E(q|I_-)$, which further implies that $G(k'|F_b(E(q|I_+)))$ first order stochastically dominates $G(k'|F_b(E(q|I_-)))$. In addition, assumption 3 implies that $o(m,k',E(q|I))$ is increasing in k' and $E(q|I)$. Based on those observations, we have $U_1(m,l,q^*) > U_0(m,l,q^*)$. Hence, if the platform did not have any dynamic incentives, then it would always assign a badge to a project, thus deeming any $q^* \in (0,1]$ non-credible. The only candidate for the credible behavior, on the part of the platform, would be $q^* = 0$ which is the uninformative one-stage equilibrium. This equilibrium involves $s = 0$ being off-path. Recall that we require equilibrium to be sequential and to satisfy intuitive criterion. In case of $q^* = 0$, these requirements select the unique equilibrium in which signal $s = 0$ is also uninformative.

Now we are ready to set up a dynamic problem for the platform. Recall that the platform's incentive to always assign a badge is potentially disciplined by the threat that the public will detect the deviation and punish the platform by switching to the worst equilibrium for the platform. The worst punishment that can be supported as an equilibrium is babbling (uninformative) equilibrium of a stage game played forever. In such an equilibrium, the public loses trust in the platform and deems all signals uninformative. This is an equilibrium because given that current investors expect that future investors will be regarding platform's signals uninformative, they know that the platform does not have any dynamic incentives (no reputation to lose), and hence cannot be disciplined to follow any ITS in the current period other than the uninformative one.

To see why babbling forever is the worst punishment for the platform suppose, by a way of contradiction, that there is a punishment that can be supported as an equilibrium and such a punishment generates lower value to the platform compared to the babbling equilibrium forever. Since the alternative punishment is different from babbling forever, after some histories the platform's signals must be informative. After such histories the platform could simply deviate to always sending a signal that induces expected quality higher than $E(q|m,l)$, and hence obtain higher expected revenue. Note that such a signal always exists after the histories where the platform is sending informative signals. This shows that the platform can always guarantee a payoff that is at least as large as the payoff from the babbling equilibrium.

Let $V(q^*)$ be the platform's discounted average expected revenues (value) evaluated at the beginning of period 0 and assuming that it never deviates from the announced ITS. The discounted average expected revenues is defined as the expected discounted revenues times $1-\delta$. We have,

$$V(q^*) = U(q^*) \tag{9}$$

Let $V(q^*, d)$ be the platform's value when the platform has deviated d times from its announced standard but has not been detected yet.

The platform's dynamic problem can be formulated as,

$$Max_{q^* \in [0,1]} U(q^*) \tag{10}$$

$$s.t.$$

$$\text{For } q^* > 0$$

$$\delta\big[U(q^*) - (1-\pi(q^*))V(q^*,1) - \pi(q^*)V\big] \geq (1-\delta)Max_{(m,l)\in M\times L}\big[U_1(m,l,q^*) - U_0(m,l,q^*)\big] \tag{11}$$

In 11, V stands for the platform's value in the permanent babbling equilibrium. Constraint 11 ensures that the platform does not want to deviate from its announced ITS. The right hand side is the best possible short-run gain from sending $s = 1$ whenever $q < q^*$, and the left hand side is the long run loss from doing so.

Given the values of the parameters, at this point, we already know how to evaluate all the quantities in the problem defined by 10 and 11 except for $V(q^*, 1)$. To evaluate $V(q^*, 1)$, we need to solve for the dynamic optimal deviation strategy of the platform given that it has already deviated once from the ITS. Note that one shot deviation principle does not hold in this model, as we have a privately informed long-run player. In appendix Evaluation of $V(q^*, 1)$ we characterize and prove the existence of unique $V(q^*, d)$ for any $d \geq 1$.

Consequently, to show that an equilibrium exists, it is sufficient to prove that the problem defined by 10 and 11 has a solution. Let q^{**} denote an ITS that solves the problem.

Proposition 1. *There exists a q^{**} that solves the problem defined by 10 and 11.*

The proofs of Proposition 1 can be found in the Appendix Proof of Proposition 1.

5 Data

The data are publicly available and include all projects posted on Kickstarter.com from its launch until February 15, 2018.[17]

We selected data from February 2, 2016 (when "Projects We Love" was started) to December 15, 2017. There are two reasons for restricting the data to this time frame. First, we refrain from considering projects that were posted under the "Staff Pick" regime, as some creators falsified the "Staff Pick" badges. Second, we need each project to be associated with one of the three outcomes, "funded", "not funded", or "canceled", in the data, so that we observe the final outcome of a project. Those outcomes are only assigned after the project's funding deadline. According to the Kickstarter rules, the funding period can last a maximum of 60 days.[18] As a result, all projects launched before December 15, 2017 have a definitive status recorded.

For each project, we observe its unique ID, category, creator's location, project launch time, funding deadline, goal amount, total investment amount pledged, number of investors, final funding status, and whether the project had a "Projects We Love" badge. We consider only projects in the technology category. Since quality differentiates projects on the vertical dimension, we need project quality to be comparable across projects. We drop all the project that have status "canceled", as we do not observe a reason why a project was canceled during a campaign. Anecdotal evidence (e.g. forums) suggests that a creator usually cancels a project if he wants to adjust the goal amount, or some other characteristics of his project. Because of this, we expect that the projects that are canceled in the data (10 percent of the data) are re-posted later.

[17] https://webrobots.io/kickstarter-datasets/

[18] https://www.kickstarter.com/help/handbook/funding

Finally, we limit the data to projects with goal amounts within $[5000, 50000]$ USD and number of investors within $[0, 800]$. This, along with canceled projects, leaves us with 47 percent of the original data. The projects with low goal amounts are dropped because they are likely to get funded from family and friends, while the project with high goals and a large number of investors may involve experienced investors and strong social learning effects. The final sample consists of 5411 projects. The sample is summarized in Table 1.

5.1 Evidence that Platform's Signals Affect Investors' Decisions

In this section, we provide suggestive evidence that badging may influence investors' beliefs about project quality. We begin by comparing the summary statistics of badged and non-badged projects.

The platform's badging decisions do not appear to rely on a simplistic rule of tracking real-time investment pledges. Table 1 highlights that 9 percent of projects are badged, yet 38 percent receive funding—over four times the proportion of badged projects. If badging decisions were strictly based on investment activity, the proportions of badged and funded projects would be expected to align more closely.

The distributions of investors and pledged amounts differ significantly between badged and non-badged projects, and badged projects are much more likely to be funded. Figure 2 shows the distribution of the number of investors, highlighting that about 55 percent of non-badged projects attract fewer than 20 investors, compared to only 3 percent of badged projects. This difference is statistically confirmed using the Kolmogorov-Smirnov test for the equality of distributions. Similarly, Figure 3 displays the distributions of total pledged amounts, and the Kolmogorov-Smirnov test rejects the hypothesis that these distributions are the same. Finally, 87 percent of badged projects secure funding, compared to 33 percent of non-badged projects.

These findings suggest that badged projects differ from non-badged projects in ways that could influence investment outcomes. In theory, if badging affects investors' behavior, it likely does so through two mechanisms:

(i) Badged projects are more visible on the platform, reducing search costs for investors;

(ii) Badges convey information that shapes investors' belief of project quality.

Identifying the source of the effect or quantifying how much of the observed difference is attributable to either channel requires richer data. However, we argue that we can provide suggestive evidence that the second channel is not entirely muted, implying that badging influences investors' beliefs about project quality.

Our approach to disentangling channels (i) and (ii) is as follows: if badges function solely to reduce search frictions for badged projects, their effect on investor behavior should not vary with project characteristics. This is because Kickstarter does not adjust the visibility of projects based on characteristics other than whether they are badged. Once badged projects are filtered on the platform, further sorting by other characteristics is effortless and vice versa. This suggests that any effect of badges on search costs should be similar across projects with different characteristics.

Consider the following regression equation:

$$outcome_i = \gamma_0 + \gamma_1 \cdot Badged_i + \gamma_2 \cdot E(q|goal_i, length_i, Badged_i) + \epsilon_i \tag{12}$$

In this equation, *outcome* represents a variable capturing some aspect of investors' behavior (e.g., the number of investors in a project), and i indexes projects. The variable *Badged* is a dummy that equals 1 if a project is badged. The coefficients γ_0, γ_1, and γ_2 represent the intercept, the effect of badging, and the effect of expected quality, respectively, while ϵ is an error term independent of the regressors. Finally, $E(q|goal, length, Badged)$ denotes the expected quality of a project as perceived by investors, conditional on the available information.

As discussed above, Kickstarter does not adjust a project's visibility based on its characteristics other than whether it is badged. Therefore, γ_1 captures the entire effect of channel (i)—reducing search frictions. Our main interest lies in determining whether the effect of badging also operates through channel (ii)—shaping investors' beliefs about project quality. Although γ_2 cannot be directly identified, certain parameters of interest can still be derived from the regression equation. In what follows, we outline what can be identified and how these results contribute to our understanding of badging effects.

We note that $E(q|goal, length, Badged)$ can be approximated arbitrarily well using a polynomial expansion. To avoid over-parameterization, for this empirical exercise, we take a second-order polynomial expansion:

$$
\begin{aligned}
E(q|goal, length, Badged) \approx & \beta_0 + \beta_1 \cdot Badged + \beta_2 \cdot goal + \beta_3 \cdot length + \beta_4 \cdot goal^2 + \beta_5 \cdot length^2 \\
& + \beta_6 \cdot goal \cdot length + \beta_7 \cdot goal \cdot Badged + \beta_8 \cdot length \cdot Badged
\end{aligned}
$$

Substituting this expansion into regression equation (12), we can rewrite it as:

$$
\begin{aligned}
outcome_i = & (\gamma_0 + \beta_0) + (\gamma_1 + \gamma_2\beta_1) \cdot Badged + \gamma_2\beta_2 \cdot goal + \gamma_2\beta_3 \cdot length + \gamma_2\beta_4 \cdot goal^2 + \gamma_2\beta_5 \cdot length^2 \\
& + \gamma_2\beta_6 \cdot goal \cdot length + \gamma_2\beta_7 \cdot goal \cdot Badged + \gamma_2\beta_8 \cdot length \cdot Badged + \epsilon_i
\end{aligned}
$$

Most of the coefficients cannot be identified separately, but our data enables us to provide suggestive evidence that badging influences investors' beliefs about project quality. Since Kickstarter does not adjust project visibility based on their characteristics, any statistically significant estimate for either $\gamma_2\beta_7$ or $\gamma_2\beta_8$ would suggest that badges affect investors' decisions via channel (ii).

Table 2 presents results from two regression models. In the first, the outcome variable is the number of investors, and in the second, it is the total pledged investment amount. In both regressions, the coefficients on $Badged \times Goal$ are statistically significant. Additionally, an F-test was conducted to examine the joint significance of these variables, yielding significant results with a p-value < 0.000 in both models.

These findings suggest that the platform may influence investors' behavior by altering their beliefs about the quality of projects. Since our primary objective is to evaluate how specific counterfactual changes in beliefs might affect the behavior of investors, creators, and the platform, it is essential to structurally model each player's beliefs and behavior. Furthermore, this approach allows us to quantify the implications of "changing beliefs" within the context of the platform.

6 Parameterization and Identification

We set F_{cr} and F_b to be Frechet distributions with location parameters set to 0 and shape parameters set to 1. The scale parameters will be estimated and are denoted, β_{cr} and β_b.

The distribution of quality conditional on (m, l) project arriving, $F(q|m, l)$, is set to be truncated exponential on $[0, 1]$ with the parameter $\gamma(m, l)$. We normalize $\gamma(m, l) = 1$ for some $(m, l) \in M \times L$. Let such (m, l) be denoted $(\underline{m}, \underline{l})$.

We allow the parameters of Negative Binomial, α and β, to depend on whether a project is badged or not. The investor arrival parameters for the badged projects are denoted α_1 and β_1 and, α_0 and β_0 for non-badged projects. Let $\alpha = (\alpha_0, \alpha_1)$ and $\beta = (\beta_0, \beta_1)$.

Finally, we assume

$$\lambda(m, l, k', E(q|I)) = a_1 + a_2 k'^{a_3} + a_4 m + a_5 l + a_6 E(q|I)$$

Let $\theta = \{\theta_1, \theta_2, \theta_3\}$ where $\theta_1 = (q^{**}, \{\gamma(m, l)\}_{(m,l) \in M \times L \setminus (\underline{m}, \underline{l})}, \beta_b, \alpha, \beta)$, $\theta_2 = (a_1, a_2, a_3, a_4, a_5, a_6)$ and $\theta_3 = (\{f(m, l)\}_{(m,l) \in M \times L}, \beta_{cr})$. We need to identify θ and $\pi : [0, 1] \to [0, 1]$. In what follows, we argue that θ is point identified and develop our identification strategy. Even though we cannot identify the function $\pi : [0, 1] \to [0, 1]$, we discuss what information we are able to recover about this function.

6.1 Identification of ITS, Investors' Belief, Arrival, and Cost Parameters

The parameters in θ_1 are identified from the distribution of the number of investors conditional on the observable characteristics of the posted projects (goal amount and length) and badge assignment decision of the platform. We provide the proof of identification in the appendix Proof of Identification for Parameters in θ_1 and discuss only the sketch of what data contributes to which parameter here:

Step 1: Identify $(\alpha_0, \alpha_1, \beta_0, \beta_1)$ from the mean and variance of number of investors for badged and non badged projects;

Step 2: Identify q^{**} from distributional assumption on quality and normalized $\gamma(\underline{m}, \underline{l}) = 1$.

Step 3: Identify $\gamma(m, l)$ given q^{**} and distributional assumption on quality. Notice, identified $\gamma(m, l)$ is relative to normalized $\gamma(\underline{m}, \underline{l})$;

Step 4: β_b: With the distribution of quality already identified for each combination of (m, l) for badged and non badged projects, we can find the expected quality given the project characteristics and badging decision, therefore, from $F_b(E(q|I))$ only unknown to match actual number of observed investors is β_b.

6.2 Identification of the Parameters that Govern Intensive Margin of Investment Decision

Identification of θ_2 is straightforward. Variations in the goal, length, number of investors and $E(q|I)$ identify θ_2. The effect of beliefs on the intensive margin is captured by incorporating $E(q|I)$ in the definition of $\lambda(m, l, k', E(q|I))$. Alternatively, we could have used dummy variables for all combinations of (m, l, s) instead of using $E(q|I)$. However, we did not choose that route as the coefficients on those dummies would be fixed in our counterfactuals and we would not be able to capture the effect of changing beliefs on the intensive margin.

We allow the number of investors, k', to enter $\lambda(m, l, k', E(q|I))$ non-linearly. The data suggest that the expected investment amount pledges is increasing and concave in k'. The expected investment amount pledges implied by the model is $1/\lambda(m, l, k', E(q|I))$ and to make sure that it allows for the pattern observed in the data, we must allow k' to enter $\lambda(m, l, k', E(q|I))$ non-linearly.

6.3 Identification of Creators' Arrival and Cost Parameters

Creator's cost parameter, β_{cr}, is identified from the variation in the frequencies of the posted projects across badged and non-badged projects. We have already identified the probabilities of getting funded from the perspective of a creator - those probabilities depend only on θ_1 and θ_2. Those probabilities pin down creator's cost thresholds for badged and non-badged projects. Given the thresholds, the difference in the frequencies of projects across badged and not badged projects identifies creator's cost parameter.

After identifying β_{cr}, the arrival probabilities of (m, l) projects, $f(m, l)$, are identified by the variation in the frequencies of posted projects with different characteristics.

Formally, the probability that a creator with (m, l) project would post it, conditional on the project quality being above q^{**}, is $f(m, l)F_{cr}(Z(I_+))$ and conditional on his project quality being less than that threshold, it is $f(m, l)F_{cr}(Z(I_-))$. Recall that $Z(I_+)$ and $Z(I_-)$ are probabilities of getting funded. Then the probability of observing a posted project with the goal and length (m, l) that was badged by the platform is $f(m, l)F_{cr}(Z(I_+))(1 - F(q^{**}))$ and the joint probability of observing a posted project with the goal and length (m, l) that was not badged by the platform is $f(m, l)F_{c_{cr}}(Z(I_-))F(q^{**})$. From the data we can identify those two probabilities. We also know that $Z(I_+)$, $Z(I_-)$ and $F(q^{**})$ depend only on the parameters that we already identified, θ_1 and θ_2. This means that we can identify β_{cr} from the ratio, $\frac{(1-F(q^{**}))F_{cr}(Z(I_+))}{F(q^{**})F_{cr}(Z(I_-))}$. Consequently, $f(m, l)$ is identified from $f(m, l)F_{cr}(Z(I_-))F(q^{**})$.

6.4 Identification of the Public Monitoring Technology

So far, our identification strategy did not use the platform's optimality conditions, that is we have not used any information from the solution of the problem defined by 10 and 11. This means that any result that would depend only on the knowledge of θ_1, θ_2 and θ_3 would be insensitive to how one models the platform's incentives. This goes back to our earlier claim that some results in this paper would not change if we assumed any other public monitoring technology or off-equilibrium punishment for the platform.

The public monitoring technology function, $\pi(q^*)$, is the only object that requires us to solve the platform's problem. Even though $\pi(q^*)$ cannot be identified, we are able to identify certain bounds on the function. Those bounds have an economic content that will be discussed later in the text.

7 Estimation

The estimation procedure parallels our identification strategy and is comprised of four steps:

1. Estimate θ_1, calculate and save $E(q|I)$;
2. Estimate θ_2 (use $E(q|I)$ estimated from the previous step);
3. Estimate θ_3 using the parameters estimated in steps 1 and 2;
4. Solve the platform's problem using parameters estimated in the prior steps and recover needed information about $\pi(q^*)$.

The way we allow prior beliefs about project's quality to depend on (m, l), implies that finer partition of $M \times L$ space would require us to estimate more parameters. To avoid the incidental parameter problem, we partition M in two subsets - projects with goals in $(0, 25\,000)$ and projects with goals in $[25\,000, 50\,000]$. The reason for choosing this partition is that it roughly divides the sample in equal parts and at 25 000 there is a peak in the distribution of goal amount (see Figure 5). We also partition L in two subsets - projects with length in $(0, 30]$ days and projects with length in $(30, 64]$ days. About 50 percent of the projects choose 30 days length. The other peaks in the distribution of project length occur above 30 days (see Figure 6). In what follows, we denote a project from the lower part of a partition as lo and from the upper part as hi. For example, a project with $m \in (0, 25\,000)$ and $l \in (30, 64]$ is denoted as (lo, hi) project. We choose to normalize $\gamma(lo, lo) = 1$.

We also need to choose a unit of time because for estimating θ_3 we need to calculate frequencies with which projects with different characteristics are being posted and need to assume how often the platform makes decisions when solving its dynamic problem. We choose one second as a unit of time because there are several projects in the data that were posted one second apart.

In what follows, we will discuss some details of the estimation procedure outlined above. The parameters, θ, are estimated using the three stage conditional maximum likelihood estimator. In the first stage, we calculate the probability of observing k' investors conditional on observing a project with certain characteristics (including, whether it is badged or not) posted on the platform (note that conditional on project not being posted, probability of observing $k' = 0$ is always 1). Let the natural logarithm of that probability be denote

$L_{1i}(\theta_1) \equiv L_1(k'_i, s_i, m_i, l_i, \theta_1)$ where i indexes observation. We need to solve,

$$\max_{\theta_1} \sum_{i=1}^{n} L_{1i}(\theta_1)$$

The solution gives us the estimate of θ_1 denoted, $\hat{\theta}_1$.

In the second stage, we construct log-likelihood using the distribution of investment amount pledged to a project conditional on observing a posted project with a certain goal, length, number of investors and whether it is badged or not. This likelihood depends on $\hat{\theta}_1$ via $E(q|I)$ that enters the parameter of the distribution of pledges, $\lambda(m, l, k', E(q|I))$. Let this log-likelihood for observation i be denoted $L_{2i}(\hat{\theta}_1, \theta_2)$. We need to solve,

$$\max_{\theta_2} \sum_{i=1}^{n} L_{2i}(\hat{\theta}_1, \theta_2)$$

The solution gives us the estimate of θ_2 denoted, $\hat{\theta}_2$.

In the third stage, we construct log-likelihood using the probability of observing a posted project with the goal, length and signal (m, l, s). Let this log-likelihood for observation i be denoted $L_{3i}(\hat{\theta}_1, \hat{\theta}_2, \theta_3)$. We need to solve,

$$\max_{\theta_3} \sum_{i=1}^{n} L_{3i}(\hat{\theta}_1, \hat{\theta}_2, \theta_3)$$

The solution gives us the estimate of θ_3 denoted, $\hat{\theta}_3$.

Finally, using $\hat{\theta}$ and setting the annual discount rate to 2 percent, we solve the platform's problem defined by 10 and 11. For each $\pi(\hat{q}^{**}) \in [0, 1]$, we find $V(\hat{q}^{**}, 1)$ using value function iteration. Then, we check whether 11 is true. We know that 11 becomes more relaxed as $\pi(\hat{q}^{**})$ increases. Intuitively, better public monitoring induces platform to abide to its announcement as otherwise, it can lose its future value easily. We find the threshold, $\bar{\pi}(\hat{q}^{**})$, such that whenever the probability with which the public verifies project's quality is below that threshold, 11 is violated - meaning that the platform does not have an incentive to follow its announced ITS and hence, $\hat{q}^{**}$ could not have been an equilibrium ITS. So, any $\pi(\hat{q}^{**})$ above that threshold is rationalized by the model and no $\pi(\hat{q}^{**})$ below that threshold is rationalized. We do the same exercise for the counterfactual ITSs that are of interest and discuss the economic content of the results.

In order to find the global maxima of the likelihoods, we use Mesh Adaptive Direct Search Algorithm (MADS) from Audet and Dennis Jr (2006) along with the Simplex Search Method from Lagarias et al. (1998). We use those methods for various initial points and then choose the parameters that achieve the highest objective value.

8 Results

8.1 Estimates of Model Parameters

The estimates of θ_1, θ_2 and θ_3 are presented in Tables 3,4 and 5, respectively. Standard errors are in parenthesis and are calculated using the estimator that is a generalization of Murphy and Topel (2002) two-stage estimator and is derived in the Appendix. To compute reliable estimates of standard errors, we set $\beta_{cr} = 0$ as the estimated β_{cr} is $1.431e - 15$, that is close to zero. Such a low value for β_{cr} means that the cost of posting a project is virtually zero i.e. creator's cost distribution is concentrated around zero. This is in line with what one would expect because once a creator has developed his idea to some extent, posting it on the Kickstarter does not require much effort - he just needs to register, upload few photos, describe his project and set goal and length of the project. Moreover, there is no fee for posting a project.

The estimate of investors' cost parameter, β_b, is 1.624. This suggests that investors are responsive to their beliefs about project's quality. The estimates of $\gamma(m, l)$ imply that the quality distribution of (hi, hi) projects first order stochastically dominates (FOSD) the quality distribution of (lo, hi) projects which FOSD the quality distribution of (hi, lo) projects which FOSD the quality distribution of (lo, lo) projects. The ranking of quality distribution means that high goal projects are of better quality (in terms of FOSD) than low goal projects, and high length projects are of better quality than low length projects. This ranking, implied by the model, is consistent with the ranking, implied by the data, of the share of badged projects across projects with different characteristics. In the data, 12.6 percent of (hi, hi) projects are badged, and this number is 9.8 for (lo, hi) projects, 8.3 for (hi, lo) projects and 7.3 for (lo, lo) projects.

In Table 6, we calculate first two moments of the distribution of the number of investors from the data and compare them to the same moments as implied by the model. In the data, mean and variance of the number of investors are always higher for badged projects compared to the non-badged projects. This same pattern is also replicated by the model. To further elaborate on the model fit, in Figure 7 we visually show how the model implied distribution of the number of investors fits the distribution in the data. For the non-badged projects, the model does a good job in matching the shape of the distribution except for consistently overestimating the probability of observing zero investors. For the badged projects, we see spikes in the data. Note that the number of badged projects is relatively small in the data. It varies from the minimum 78 for the (hi, lo) projects to the maximum 159 for the (lo, hi) projects. The abundance of the spikes of the same height in the distributions for the badged projects is due to a given number of investors being observed at most 3 times (usually only once).

The estimated values for a_2, a_4, a_5 and a_6 are negative meaning that expected pledged amount is increasing in the number of investors, expected quality (validating assumption 3), goal and length. However, note that the parameters on expected quality, goal and length are not statistically different from zero. Table 7 compares mean pledges from the data to the mean pledges as implied by the model for each $(m, l) \in \{lo, hi\} \times \{lo, hi\}$ project. Figure 8 plots mean pledges against the number of investors, for each $(m, l) \in \{lo, hi\} \times \{lo, hi\}$ project. One can see that the fitted curves are convex up to roughly 50 investors and then concave.

Finally, the estimates of $f(m, l)$ (investor arrival rates) are very close to the probability of observing a posted project (see Table 8). This is not surprising given that estimated value of β_{cr} is close to zero implying that creator's decision to post a project is insensitive to his private information. Hence, whenever a creator arrives, he posts a project with probability close to one leading to the arrival rate being close to the probability of observing a posted project.

8.2 Commitment vs. Flexibility

The main objective of this paper is to quantify the welfare effects of granting the platform commitment power to information disclosure.

To see how commitment to information disclosure can arise, think about a regulator who decides to form a committee that closely monitors the process through which the platform evaluates the projects and assigns badges on the grounds of information it obtains. Given the ITS announced by the platform, the committee would make sure that the platform follows the announcement. The platform's incentive to misrepresent information, would no longer be a threat to the platform's reputation. Hence, any ITS announced by the platform would be credible. In terms of the formal model, platform having the commitment power is equivalent to solving the relaxed version of the problem defined by 10 and 11 i.e. the constraint 11 is dropped.

Comparing commitment outcome involving at most two signals to no commitment outcome (flexibility) is appealing at least for four reasons. First, we have a clear understanding of what incentives are curbed under commitment. Second, we have an idea of how commitment can be implemented through regulation. Third, we do not require the platform to design complicated information transmission rules in order to implement commitment outcome involving two signal realizations.[19] Lastly, this exercise empirically addresses the question of whether the outcomes under commitment, in the sense of Bayesian Persuasion (see Kamenica and Gentzkow (2011)), can be achieved in a dynamic cheap talk setting in which exogenous commitment is replaced by the platform's long-run incentives (reputation concerns).

8.2.1 Testing for Commitment

Before comparing commitment to flexibility, we investigate which one is more likely to be the factual world. Given that information intermediation by Kickstarter is not regulated, we should expect that the factual world is a flexibility world. To check for this claim,

[19]Unlike here, if we were quantifying welfare effects of asymmetric information, we would need to see what would happen if we provided the investors with complete information about projects. While this is a viable counterfactual exercise, in practice, providing complete information may be too time consuming in terms of communicating it to the investors, requiring us to consider modeling such details.

we construct a statistical test to check whether the platform's incentives to misrepresent information are binding it to achieve higher revenues.

Recall that if the factual is commitment then the platform solves,

$$_{q^* \in [0,1]} U(q^*)$$

If the *argmax*, q^{**}, is interior (which should be the case according to the data, as we observe both badged and unbadged projects) then the necessary condition for an optimum is,

$$\frac{\partial U(q^{**})}{\partial q^*} = 0$$

If the factual is no commitment, then 11 may bind at an optimum and it may be the case that,

$$\frac{\partial U(q^{**})}{\partial q^*} \neq 0$$

The test is as follows:

$$H0 : \frac{\partial \hat{U}(\hat{q}^{**})}{\partial q^*} = 0$$

$$H1 : \frac{\partial \hat{U}(\hat{q}^{**})}{\partial q^*} \neq 0$$

Under the alternative hypothesis, the test rejects that the factual is commitment.

It is worthwhile to note that the test does not use any particular information about 11, that is, we just need to know that there are some incentive constraints under no commitment - exactly what those constraints are is irrelevant for this test. In addition, all the parameters, including $\hat{q}^{**}$, are estimated without any reference to either 10 or 11. These imply that the result of this test would be insensitive to assumptions on public monitoring technology or off-equilibrium path punishments.

To conduct the test, we need to know the asymptotic distribution of $\frac{\partial \hat{U}(\hat{q}^{**})}{\partial q^*}$. Since $\frac{\partial \hat{U}(\hat{q}^{**})}{\partial q^*}$ depends only on $\hat{\theta}$ and we already derived the asymptotic distribution of $n^{1/2}(\hat{\theta} - \theta)$, which is normal with mean 0 and variance-covariance matrix Σ (see the Appendix), applying the delta-method we have,

$$n^{1/2}\left(\frac{\partial\hat{U}(\hat{q}^{**})}{\partial q^*}-\frac{\partial U(q^{**})}{\partial q^*}\right)\xrightarrow{D}\mathcal{N}\left(0,\left(\frac{\partial^2 U(q^{**})}{\partial q^*\partial\theta}\right)'\Sigma\frac{\partial^2 U(q^{**})}{\partial q^*\partial\theta}\right)$$

Using the above distribution, we conduct a Z-test. The resulting p value is 0.0272, meaning that we can reject the commitment assumption at 2.72 percent significance level.

It is important to emphasize that the test for commitment essentially evaluates whether the empirical badging threshold coincides with the solution to the first-order conditions (FOC) derived from our model. This approach implicitly assumes that the model is correctly specified. In other words, the rejection of the commitment hypothesis might be because of misspecified model not because of luck of commitment.

8.2.2 Welfare effects of Commitment

So far, we have argued that we have reasons to think that the platform does not have commitment power, and we have an idea of how to grant it commitment power through regulation. Before we present welfare effects let's discuss potential impact of commitment to each side, platform, creator and investor.

Commitment results in an increase in the announced ITS because the platform can uphold higher quality standards for badging. For the platform, the impact on its revenues is positive, as commitment removes constraint (11) and allows the platform to optimize the objective function (10) instead. In other words, if ITS in the absence of commitment is the best for the platform, it remains available when the constraint is removed.

For creators, we can consider three categories: (1) those who receive a badge under the current system and retain it under the commitment system (these are creators with relatively higher quality projects), (2) those who receive a badge under the current system but would not receive it under the commitment system, and (3) those who do not receive a badge under either system. The welfare effect for the first and third groups is positive, as both benefit from higher expected quality under the commitment system compared to the current system. However, for the third group, the welfare effect is negative. This is because they are now pooled with non-badged projects rather than badged ones, reducing their expected quality.

Similarly, for investors, there can be a trade-off. We could have direct and indirect effects working against each other. Specifically, the increase in ITS makes it more informative about project quality. Consequently, expectation of $q - c_b$, conditional on the event that a project was posted, increases. However, there is also an indirect effect: as ITS increases, as mentioned above, the likelihood of receiving a badge decreases from the creators' perspective. This might reduce the probability that a project will be posted (as welfare effects for creators is unclear as discussed above). Ultimately, welfare effects of commitment for the investors depends on whether indirect effect is positive or negative and how it compares to the direct effect. We now present the welfare effects of commitment from the counterfactual exercise.

Table 9 provides percentage change in the welfare of the platform (which is its present value of revenues), investors and creators from granting the platform commitment power. It is noteworthy that everyone benefits from commitment, even though this is not clear before estimating the model parameters (except for the platform). If the platform had commitment power, platform's revenues would increase by 7.4 percent, investors' welfare would increase by 0.5 percent, and creators' - by 4 percent. This result implies that a regulation that pushes the platform towards commitment should be well-received by everyone.

8.2.3 Further Regulation

In practice, in addition to making sure that an intermediary abides to a disclosure rule, a regulation of disclosure rule involves regulator dictating such a rule. For example, Securities and Exchange Commission regulates disclosure requirements (rule) on the equity-based crowdfunding platforms by requiring a platform to make sure that certain information is transmitted from entrepreneurs to the investors. In this section, we estimate the additional value of such a regulation on the top of commitment power. In this model, such a regulation would mean that a regulator is choosing an ITS, q^*. What are the potential gains of regulating q^* after the platform's commitment problem is resolved?

We start by finding the best ITS for the investors and the best ITS for the creators. For example, if a regulator is maximizing only investors' welfare, it would be willing to set investor-best ITS on the top of granting the platform commitment power.

Tables 10 and 11 provide welfare changes due to going from flexibility to commitment power, in addition to regulator setting investor-best ITS (table 10) and creator-best ITS (table 11). The platform's revenue gain is 6.9 percent under the creator-best ITS and 1.6 percent under the investor-best ITS. This means that under any regulation the platform is better-off compared to the factual. The investor is also better-off under any regulation compared to the factual with the 0.7 percent improvement in investors' welfare under the investor-best ITS. Creators' welfare is reduced by 5.5 percent under the investor-best ITS.

It is noteworthy that compared to the platform-best ITS, the investor-best ITS increases investors' welfare further by only 0.2 percent and creator-best ITS increases creators' welfare further by only 0.5 percent. These numbers suggest that if one granted the platform commitment power to information disclosure, more stringent regulation would not be necessary, as investors' and creators' welfare would already be near their global optima.

Figure 9 depicts investors', creators' and platform's welfare as functions of q^*. Platform's and creators' welfare functions have similar shapes. For the creators, this shape is driven by the probability that a project gets funded. This is so because creators' project posting costs are concentrated near zero and the shape of the creators' welfare function is driven only by the benefits which come about in the form of the probability that a project gets funded. The shape of the platform's revenue function is also driven by the probability that a project gets funded, in addition to the intensive margin of investment.

The shape of the investors' welfare function is driven by how well an ITS can partition quality space in order to maximize expectation of $q - c_b$, conditional on the event that a project was posted; and the probability that a project is posted on the platform. The latter is the channel through which investors' welfare depends indirectly on creators' welfare. As one increases the probability with which a project gets successfully funded, creators expect higher benefits from using the platform and this encourages more creators to post projects. Consequently, everything else equal, more projects posted translates into higher investors' welfare. However, this effect turns out to be approximately non-existent since β_{cr} is close to zero.

8.3 Public Monitoring

In this subsection, we discuss the role of public monitoring for curbing the platform's incentives to misrepresent information.

To start with, we ask whether public monitoring can substitute for commitment. This same question was asked by Best and Quigley (2024), who posed it in a repeated cheap-talk model with public monitoring in which a long-run sender tries to persuade short-run receivers to take certain actions, and the state of the world is i.i.d. over time. They ask whether the sender's long-run incentives can substitute for full commitment a la Kamenica and Gentzkow (2011), in terms of sender's payoffs. They provide conditions on optimal disclosure rules under which this would be true. Even though the question we are asking in this section is the same, we do this under the restricted strategy space of the sender, special case of monitoring, and quantitatively.[20]

To see whether public monitoring could substitute for commitment, we set $\pi(\hat{q}^{**}_{comm}) = 1$, where $\hat{q}^{**}_{comm}$ denotes the estimate of platform-optimal ITS under commitment, and see if 11 holds. It is easily verified that this is so. Hence, under extremely good public monitoring, the platform has reputation concerns strong enough to let it achieve commitment outcome. We can go further and ask what is the weakest public monitoring technology that could still substitute for commitment?

To answer the question, we can recover a threshold, $\bar{\pi}(\hat{q}^{**}_{comm})$, such that public monitoring substitutes for commitment for all $\pi(\hat{q}^{**}_{comm}) \geq \bar{\pi}(\hat{q}^{**}_{comm})$ and does not substitute for commitment for all $\pi(\hat{q}^{**}_{comm}) < \bar{\pi}(\hat{q}^{**}_{comm})$. We recover this threshold to be $2.53e-7$. Since this number is the probability with which the public verifies project's quality in a given second independently over time and across projects, we can calculate the average time that the public would need to verify the quality of a project at this threshold. It turns out to be 1.5 months.

Since the observed ITS is not the same as $\hat{q}^{**}_{comm}$, we know that under the true $\pi(\hat{q}^{**}_{comm})$ it would not be credible for the platform to announce $\hat{q}^{**}_{comm}$ implying that under commitment,

[20] In our model, Best and Quigley (2024) results imply that there exist combinations of discount factor and public monitoring technology for which public monitoring can substitute for commitment. This is mainly due to restricting the platform to use threshold disclosure rules.

on average, more than 1.5 months would be needed for the public to verify quality. Hence, if the public monitoring was such that it required, on average, less than 1.5 months for a public to verify project's quality - the reputation concerns would substitute for commitment.

We also recover the threshold under the factual, $\bar{\pi}(q^{**})$, which is $3.1e-7$, meaning that currently, on average, less than 1.2 months is needed for the public to verify quality. Taken together, the thresholds under commitment and factual imply that there is a better public monitoring (in the sense of higher true π) under factual ITS compared to what would have been under the commitment-ITS, $\hat{q}^{**}_{comm}$. To improve public monitoring under the commitment ITS, in practice, Kickstarter could create a special web-page/forum on which investors would share their experience with the projects. This would likely increase the probability that a project's quality is verified by the public after people invest in it.

Rationalizing the result, that in the factual world the platform is not achieving its commitment payoffs, depends on how one models the platform's long-run incentives. Our model suggests that the public would be more restricted or reluctant to conduct monitoring on its own under the commitment ITS compared to the factual ITS.

9 Conclusion

This paper elaborates a theory and an empirical strategy to study information intermediation, with an application to crowdfunding. We identify incentives of an intermediary that might be detrimental to this role, and propose mechanisms that could mitigate such incentives.

Using the data from Kickstarter, we estimate a repeated cheap talk model and develop a statistical test to confirm that incentives to misrepresent information are present and that they are constraining the platform in achieving better outcomes for itself, entrepreneurs and investors. Complete annihilation of such incentives can be achieved via granting the platform commitment power to information disclosure. Regulation is one way to grant this power. Another way turns out to be public monitoring.

Public monitoring creates long-run reputation concerns for the platform and disciplines platform's incentives to misrepresent information. We show how strengthening public monitoring can substitute for commitment.

The paper contributes to the existing literature by taking a step towards the identification and estimation of dynamic cheap talk and information design models; posing the question of whether information intermediation is possible in the context of crowdfunding; exposing how commitment power, a la Kamenica and Gentzkow (2011), can come about in practice through regulation; empirically examining whether public monitoring could substitute for exogenous commitment. The paper introduces two questions in the empirical industrial organization literature - What is the value of commitment to information disclosure? How can one extract that value? - and shows that it is feasible to empirically answer those questions, and provides a framework for doing so.

The summary message of the paper to a policy maker is as follows. Granting the platform commitment power would be Pareto improving. A regulator could accomplish this by verifying that the platform follows a promised information disclosure rule. If such a regulation is not feasible, then the platform could try to improve public monitoring and achieve the commitment outcome. A traditional meaning of regulating disclosure requirements on the financial markets is that a regulator chooses information that has to be transmitted from entrepreneurs (borrowers) to investors (lenders). As long as the platform is granted commitment power to information disclosure, regulation of disclosure requirements in the traditional sense would not be of much additional value.

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A Technical Appendix

A.1 Distribution of the Number of Investors

We have, the number of investors who view the project, k distributed Poisson with mean n:

$$\frac{e^{-n}n^k}{k!}$$

and n itself is distributed Gamma with the shape parameter β and rate parameter α, so the distribution of number of investors viewing a project becomes:

$$\int_0^\infty \frac{e^{-n}n^k}{k!}\frac{\alpha^\beta}{\Gamma(\beta)}n^{\beta-1}e^{-\alpha n}dn$$

Since each investor who views the project independently decides to invest or not, the probability that k' out of k will invest is:

$$\binom{k}{k'}F_b(E(q|I))^{k'}(1-F_b(E(q|I)))^{k-k'}$$

To find the probability of k' investors investing, we need to consider all k such that k' investors investing is possible, so we sum up probabilities for all $k \geq k'$. As a result, we can write distribution of k' as:

$$g(k'|F_b(E(q|I))) =$$

$$\sum_{k=k'}^{\infty}\int_0^\infty \frac{e^{-n}n^k}{k!}\frac{\alpha^\beta}{\Gamma(\beta)}n^{\beta-1}e^{-\alpha n}dn\binom{k}{k'}F_b(E(q|I))^{k'}(1-F_b(E(q|I)))^{k-k'} =$$

$$\int_0^\infty \left[\sum_{k=k'}^{\infty}\frac{e^{-n}n^k}{k!}\binom{k}{k'}F_b(E(q|I))^{k'}(1-F_b(E(q|I)))^{k-k'}\right]\frac{\alpha^\beta}{\Gamma(\beta)}n^{\beta-1}e^{-\alpha n}dn =$$

$$\int_0^\infty \frac{e^{-nF_b(E(q|I))}(nF_b(E(q|I)))^{k'}}{k'!}\frac{\alpha^\beta}{\Gamma(\beta)}n^{\beta-1}e^{-\alpha n}dn =$$

$$\frac{F_b(E(q|I))^{k'}\alpha^\beta}{k'!\Gamma(\beta)}\int_0^\infty n^{k'+\beta-1}e^{-(\alpha+F_b(E(q|I)))n}dn =$$

$$\frac{\Gamma(k'+\beta)}{\Gamma(k'+1)\Gamma(\beta)}\frac{F_b(E(q|I))^{k'}\alpha^\beta}{(\alpha+F_b(E(q|I)))^{k'+\beta}} =$$

$$\binom{k'+\beta-1}{k'}\left(\frac{\alpha}{\alpha+F_b(E(q|I))}\right)^{\beta}\left(\frac{F_b(E(q|I))}{\alpha+F_b(E(q|I))}\right)^{k'}$$

Here $\Gamma(\cdot)$ is the gamma function. For the third equality see Myerson (1998). In the fifth equality we integrate out the density of Gamma distribution. The final expression is the probability mass function of the Negative Binomial distribution.

A.2 Evaluation of $V(q^*, 1)$

To evaluate $V(q^*, 1)$ we need to keep track of the number of times that platform deviates from its standard, denoted d. This is because more times the platform deviates, the probability that at least one deviation will be detected by the public increases. Hence, the number of times the platform deviates becomes payoff relevant private information for it.

Consider some $d \geq 1$. Suppose the platform learns that the type of the creator who posted the project in the current period is (q, m, l) with $q \geq q^*$. The platform sends $s = 1$. By doing so it does not increase the probability that at least one of its deviations will be detected in the future and in the current period gets higher expected profits compared to sending $s = 0$. The platform's value in this case is,

$$W_1(m,l,q^*,d) = (1-\delta)U_1(l,m,q^*) + \delta[(1-(1-\pi(q^*))^d)V + (1-\pi(q^*))^d V(q^*,d)] \quad (13)$$

If $q < q^*$, then the platform needs to decide whether it wants to deviate from its standard by sending $s = 1$ and increasing the probability that its deviation will be detected in the future, or sticking to the standard and not increasing that probability. Platform's value in this case is,

$$\begin{aligned} W_0(m,l,q^*,d) =_{j\in\{0,1\}} \Big\{ &(1-\delta)U_j(l,m,q^*)+ \\ &\delta[(1-(1-\pi(q^*))^{d+j})V + (1-\pi(q^*))^{d+j}V(q^*,d+j)] \Big\} \end{aligned} \quad (14)$$

If a creator does not post a project then the platform's value is,

$$W(q^*,d) = \delta[(1-(1-\pi(q^*))^d)V + (1-\pi(q^*))^d V(q^*,d)] \tag{15}$$

Using 13, 14 and 15 we can write $V(q^*,d)$ as,

$$\begin{aligned} &V(q^*,d) = \\ &\sum_{(m,l)\in M\times L} f(m,l)\Big[(1-F(q^*|m,l))F_{cr}(Z(I_+,q^*))W_1(m,l,q^*,d)+ \\ &F(q^*|m,l)F_{cr}(Z(I_-,q^*))W_0(m,l,q^*,d)\Big]+ \\ &\Big[1-\sum_{(m,l)\in M\times L} f(m,l) + \sum_{(m,l)\in M\times L} f(m,l)\big[(1-F(q^*|m,l))(1-F_{cr}(Z(I_+,q^*)))+ \\ &F(q^*|m,l)(1-F_{cr}(Z(I_-,q^*)))\big]\Big]W(q^*,d) \end{aligned} \tag{16}$$

We have the following lemma,

Lemma 1. *There exists unique $V(q^*,d)$ that solves equation 15. $V(q^*,d)$ is continuous in q^* on $[\epsilon,1]$ for any $1>\epsilon>0$, decreasing and convex in d.*

Proof. Under the assumptions 1 and 2, $F_{cr}(Z(I))$, $F(q|m,l)$, $U_1(m,l,q^*)$ and $U(q^*)$ are continuous in q^*. However, $U_0(m,l,q^*)$ is discontinuous at $q^*=0$. This is due to $E(q|I_-)$ jumping to $\frac{\int_0^1 f(m,l|q)f(q)qdq}{\int_0^1 f(m,l|q)f(q)dq}$ at $q^*=0$. For this reason, we show continuity of $V(q^*,d)$ only on $[\epsilon,1]$ for any $1>\epsilon>0$. The arguments for why the unique $V(q^*,d)$ satisfying 16 exists and is continuous in q^* are then standard (see, Stokey and Lucas Jr (1989)). Here we sketch the arguments. First, we define the operator T as follows,

$$T(V'(q^*,d)) =$$
$$\sum_{(m,l)\in M\times L} f(m,l)\Big[(1-F(q^*|m,l))F_{cr}(Z(I_+,q^*))W_1'(m,l,q^*,d)+$$
$$F(q^*|m,l)F_{cr}(Z(I_-,q^*))W_0'(m,l,q^*,d)\Big]+$$
$$\Big[1-\sum_{(m,l)\in M\times L} f(m,l)+\sum_{(m,l)\in M\times L} f(m,l)\big[(1-F(q^*|m,l))(1-F_{cr}(Z(I_+,q^*)))+$$
$$F(q^*|m,l)(1-F_{cr}(Z(I_-,q^*)))\big]\Big]W'(q^*,d)$$

In the last equation, W_1', W_0' and W' depend on $V'(q^*,d)$ and are given by the expressions 13, 14 and 15. We can easily verify that T satisfies Blackwell's sufficient conditions for contraction and maps bounded and continuous functions in q^* to bounded and continuous functions in q^*. This proves that unique $V(q^*,d)$ satisfying 16 exists and is continuous in q^*.

Further, we show that $V(q^*,d)$ is decreasing in d. Again, replicating the arguments from the Stokey & Lucas 1989, we need to show that if we have $V'(q^*,d)$ decreasing in d then $T(V'(q^*,d))$ is also decreasing in d. Inspecting 13, 14 and 15 we can easily verify that this is indeed the case.

To show that $V(q^*,d)$ is convex in d we need to verify that if $V'(q^*,d)$ convex in d then $T(V'(q^*,d))$ is also convex. Take a convex $V'(q^*,d)$. If we verify that W_1', W_0' and W' are all convex in d then this will imply the result. Let's first investigate W_1'. We need to show that $W_1'(m,l,q^*,d)-W_1'(m,l,q^*,d+1)\geq W_1'(m,l,q^*,d')-W_1'(m,l,q^*,d'+1)$ for all $(q,m,l)\in[0,1]\times M\times L$ and $d'>d$. Evaluating the inequality, this is equivalent to showing that $(1-\pi(q^*))^d(V'(q^*,d)-(1-\pi(q^*))V'(q^*,d+1)-\pi(q^*)V)$ is decreasing in d which is further equivalent to showing that $V'(q^*,d)-V'(q^*,d+1)+\pi(q^*)V'(q^*,d+1)$ is decreasing in d. By assumption $V'(q^*,d)$ is convex and decreasing in d, implying that the last expression is decreasing in d.

The same arguments apply to show that W' is convex. As for the W_0', it is the maximum of convex functions and hence is also convex.

□

A.3 Proof of Proposition 1

Proof. Lets first make $U_0(m, l, q^*)$ continuous at $q^* = 0$ by setting $E(q|I_-) = 0$ whenever $q^* = 0$. Note that under such a modification none of the quantities in 11 are affected for $q^* \neq 0$. This claim is obvious for $U_1(m, l, q^*)$, $U(q^*)$ and $U_0(m, l, q^*)$. As for $V(q^*, d)$, note that q^* is a fixed parameter of the dynamic problem so changing something for certain values of q^* does not affect $V(q^*, d)$ for other values of q^*.

Under this modification, the left and right hand sides of 11 are continuous in q^* for $q^* \in [0, 1]$. It follows that the set of q^* that satisfy the inequality in 11 is a compact set. Call this set A.

Now A is not an actual feasible set that we need. We have to discard the assumption that $E(q|I_-) = 0$ at $q^* = 0$. The only thing that can potentially change, from discarding this assumption, is $q^* = 0$ to be added to the set A. If $0 \notin A$ then $0 \cup A$ would be compact because we know A is compact and also one point set is compact. If $0 \in A$ then $0 \cup A = A$ that is compact. Hence, the actual constrained set must be compact. Then, by the Bolzano-Weierstrass theorem there exists q^{**} that solves the problem defined by 10 and 11.

□

A.4 Theoretical Foundation for the Worst Punishment

In this part: 1. We modify the game; 2. argue that the modified game is empirically relevant and; 3. discuss how, under this modified game, the platform would choose to announce ITS only at the beginning of period 0 and would choose the worst punishment if it is ever detected to have deviated from the announced ITS.

Suppose that the platform, at the beginning of each period, can announce a plan of continuation play. In this modification of the game, the public history is amended with the platforms' decision whether or not to announce the plan in each period and the announced plan. A plan announced at the beginning of t prescribes the platform's, creators' and investors' behavioral strategies for each realization of public history from t onward. This modification is closely related to Safronov and Strulovici (2014) and, can be interpreted as the platform having the renegotiation power.

The platform and only it having the ability to announce a plan of continuation play at each date is justified as follows. First, even if in practice we do not observe the platform announcing the entire continuation play, it could have done so if this would be beneficial for it. Hence, the platform not announcing such plans should mean that it cannot benefit by doing so and hence it cannot be in the equilibrium that is worse for it than having explicitly announced a plan. Second, since creators and investors are short lived on the platform and there is a large population of them, they cannot coordinate to compete with the platform by rejecting the platform's plans and suggesting their own.

In this modified game, the platform's behavioral strategy in each period in addition to the mixing over signals includes mixing over the continuation plans. We restrict the plan announcement decisions, plans and ITSs to depend only on the quality of the last project that was verified by the public and last announced plan.

Note that the value to the platform (expected discounted sum of revenues) at the beginning of period 0, must be maximized across all the equilibria in this modified game because such a plan would be chosen by the platform at the beginning of period 0.

First, since the platform is maximizing its value at the beginning of period 0 by announcing a plan, it is clear that it should announce the worst equilibrium punishment for itself if it takes off the equilibrium actions.

Second, we argue that we can without loss of generality focus on equilibria in which the platform makes the plan announcement only at the beginning of period 0 and any further announcement is punished by the permanent babbling equilibrium. To see this, suppose the platform announces a plan at date 0, other plan at date t after some history and maybe yet another plan after some history at $t' > t$. Since those plans do not depend on previous projects' qualities observed by the platform (note that in this modified game we are assuming that the plan announcement decisions, plans and ITSs can depend only on the quality of the last project that was verified by the public and last announced plan), they cannot signal platform's private information to the entrepreneurs or investors. Consider plan announced at t. It prescribes certain ITS from t onward. We can prescribe exactly same ITS after that history at t according to the plan in period 0.

So, we end up with the model in the main text i.e. ITS is announced only at the beginning of period 0 and any deviation by the platform is punished by the permanent babbling equilibrium.

A.5 Proof of Identification for Parameters in θ_1

First, recall the distribution of investors as implied by the model is Negative Binomial with the probability mass function,

$$g(k'|F_b(E(q|I))) =$$

$$\binom{k'+\beta_s-1}{k'}\left(\frac{\alpha_s}{\alpha_s+F_b(E(q|I))}\right)^{\beta}\left(\frac{F_b(E(q|I))}{\alpha_s+F_b(E(q|I))}\right)^{k'}$$

The mean of that distribution conditional on $\underline{I}_- \equiv \{\underline{m}, \underline{l}, 0, q^{**}\}$ is,

$$\frac{\beta_0}{\alpha_0}F_b(E(q|\underline{I}_-))$$

Let $h(\underline{I}_-)$ be the mean from the data as the sample size approaches infinity. Then we must have,

$$h(\underline{I}_-) = \frac{\beta_0}{\alpha_0}F_b(E(q|\underline{I}_-)) \tag{17}$$

Similarly we have,

$$h(\underline{I}_+) = \frac{\beta_1}{\alpha_1}F_b(E(q|\underline{I}_+)) \tag{18}$$

We also have similar identities for the variances,

$$h'(\underline{I}_-) = \frac{\beta_0 F_b(E(q|\underline{I}_-))(\alpha_0 + F_b(E(q|\underline{I}_-))}{\alpha_0^2} \tag{19}$$

$$h'(\underline{I}_+) = \frac{\beta_1 F_b(E(q|\underline{I}_+)(\alpha_1 + F_b(E(q|\underline{I}_+)))}{\alpha_1^2} \tag{20}$$

We can rewrite the identities, 17, 18, 19 and 20, as follows,

$$\beta_0 = \frac{h(\underline{I}_-)^2}{h'(\underline{I}_-) - h(\underline{I}_-)} \tag{21}$$

$$\beta_1 = \frac{h(\underline{I}_+)^2}{h'(\underline{I}_+) - h(\underline{I}_+)} \tag{22}$$

$$\alpha_0 = \frac{F_b(E(q|\underline{I}_-))h(\underline{I}_-)}{h'(\underline{I}_-) - h(\underline{I}_-)} \tag{23}$$

$$\alpha_1 = \frac{F_b(E(q|\underline{I}_+))h(\underline{I}+)}{h'(\underline{I}_+) - h(\underline{I}_+)} \tag{24}$$

From 21 and 22 we have identified β as those expressions depend only on the data. If we knew the right hand sides of 23 and 24 we would also identify α. However, right hand sides of 23 and 24 depend on q^{**} and β_b.

Consider some $I' \equiv \{m', l', s, q^{**}\}$ with $(m', l') \neq (\underline{m}, \underline{l})$. We can write down similar identities as above for the mean and variance of the number of investors conditional on I'_- and the mean of the number of investors for I'_+. We get,

$$h(I'_-) = \frac{\beta_0}{\alpha_0} F_b(E(q|I'_-)) \tag{25}$$

$$h(I'_+) = \frac{\beta_1}{\alpha_1} F_b(E(q|I'_+)) \tag{26}$$

$$h'(I'_-) = \frac{\beta_0(\alpha_0 + F_b(E(q|I'_-))}{\alpha_0^2} \tag{27}$$

Using 21,22,23 and 24 into 25,26 and 27 and the fact that $F_b(E(q|I)) = e^{-\beta_b/E(q|I)}$ we arrive at the following,

$$\beta_b = ln\left(\frac{h(I'_-)}{h(\underline{I}_-)}\right) \frac{E(q|\underline{I}_-)E(q|I'_-)}{E(q|I'_-) - E(q|\underline{I}_-)} \tag{28}$$

$$\left(ln\left(\frac{h(I'_-)}{h(\underline{I}_-)}\right)\right)^{-1} \frac{h(I'_+)}{h(\underline{I}_+)} = \frac{E(q|\underline{I}_-)E(q|I'_-)}{E(q|I'_-) - E(q|\underline{I}_-)} \frac{E(q|I'_+) - E(q|\underline{I}_+)}{E(q|\underline{I}_+)E(q|I'_+)} \tag{29}$$

$$\left(ln\left(\frac{h(I'_-)}{h(\underline{I}_-)}\right)\right)^{-1} \frac{h(I'_-)h'(I'_-)}{(h(I'_-) + h'(\underline{I}_-) - h(\underline{I}_-))h(\underline{I}_-)^2} = \frac{E(q|\underline{I}_-)}{E(q|I'_-) - E(q|\underline{I}_-)} \tag{30}$$

In 28, the right hand side depends only on q^{**} and $\gamma(m', l')$. The left hand sides of the equations 29 and 30 are functions of only data and the right hand sides depend only on q^{**} and $\gamma(m', l')$. If we verify that only a unique $(q^{**}, \gamma(m', l'))$ can solve 29 and 30 then this will imply that $(\alpha, \beta, \beta_b, q^{**}, \gamma(m', l'))$ is identified. We verify this numerically.

From Figure 4 one can see that the level curves of the right hand sides of the equations 29 and 30 intersect only once. Even though Figure 4 is constructed for $q^{**} \in [0.3, 1]$ and $\gamma(m', l') \in [0, 10]$, we have verified that level curves intersect only once for other ranges of the parameters, as well.

From θ_1, it remains to identify $\{\gamma(m, l)\}_{(m,l) \in M \times L \setminus \{(\underline{m}, \underline{l}), (m', l')\}}$. This can be done by considering the mean number of investors for each $(m, l) \in M \times L \setminus \{(\underline{m}, \underline{l}), (m', l')\}$. The only unknown parameter in the mean number of investors for a project with observable characteristics (m, l) is now $\gamma(m, l)$. In addition, it is easily verified that the mean is monotonic in $\gamma(m, l)$. Hence, $\{\gamma(m, l)\}_{(m,l) \in M \times L \setminus \{(\underline{m}, \underline{l}), (m', l')\}}$ is identified.

A.6 Derivation of the Variance-Covariance Matrix of θ

Here we sketch the derivation of the asymptotic distribution of $\hat{\theta}$. The three stage maximum likelihood estimator satisfies,

$$\sum_{i=1}^{n} \frac{\partial L_{1i}(\hat{\theta}_1)}{\partial \theta_1} = 0 \tag{31}$$

$$\sum_{i=1}^{n} \frac{\partial L_{2i}(\hat{\theta}_1, \hat{\theta}_2)}{\partial \theta_2} = 0 \tag{32}$$

$$\sum_{i=1}^{n} \frac{\partial L_{3i}(\hat{\theta}_1, \hat{\theta}_2, \hat{\theta}_3)}{\partial \theta_3} = 0 \tag{33}$$

Under standard regularity conditions, $\hat{\theta}$ is consistent (see Murohy & Topel 1985). Using mean-value theorem we can expand 31, 32 and 33 about θ, yielding,

$$-\frac{1}{n^{1/2}} \sum_{i=1}^{n} \frac{\partial L_{1i}(\theta_1)}{\partial \theta_1} = \frac{1}{n} \sum_{i=1}^{n} \frac{\partial^2 L_{1i}(\bar{\theta}_1)}{\partial \theta_1 \partial \theta_1'} n^{1/2}(\hat{\theta}_1 - \theta_1) \tag{34}$$

$$-\frac{1}{n^{1/2}}\sum_{i=1}^{n}\frac{\partial L_{2i}(\theta_1,\theta_2)}{\partial\theta_2}=\frac{1}{n}\sum_{i=1}^{n}\frac{\partial^2 L_{2i}(\bar\theta_1,\bar\theta_2)}{\partial\theta_2\partial\theta_1'}n^{1/2}(\hat\theta_1-\theta_1)+$$
$$\frac{1}{n}\sum_{i=1}^{n}\frac{\partial^2 L_{2i}(\bar\theta_1,\bar\theta_2)}{\partial\theta_2\partial\theta_2'}n^{1/2}(\hat\theta_2-\theta_2) \tag{35}$$

$$-\frac{1}{n^{1/2}}\sum_{i=1}^{n}\frac{\partial L_{3i}(\theta_1,\theta_2,\theta_3)}{\partial\theta_3}=\frac{1}{n}\sum_{i=1}^{n}\frac{\partial^2 L_{3i}(\bar\theta_1,\bar\theta_2,\bar\theta_3)}{\partial\theta_3\partial\theta_1'}n^{1/2}(\hat\theta_1-\theta_1)+$$
$$\frac{1}{n}\sum_{i=1}^{n}\frac{\partial^2 L_{3i}(\bar\theta_1,\bar\theta_2,\bar\theta_3)}{\partial\theta_3\partial\theta_2'}n^{1/2}(\hat\theta_2-\theta_2)+\frac{1}{n}\sum_{i=1}^{n}\frac{\partial^2 L_{3i}(\bar\theta_1,\bar\theta_2,\bar\theta_3)}{\partial\theta_3\partial\theta_3'}n^{1/2}(\hat\theta_3-\theta_3) \tag{36}$$

In 34, 35 and 36 bars above variables denote their values between true value and estimate. Using the law of large numbers, the fact that $\bar\theta \xrightarrow{p} \theta$ and properties of Fisher Information we have,

$$\frac{1}{n}\sum_{i=1}^{n}\frac{\partial^2 L_{1i}(\bar\theta_1)}{\partial\theta_1\partial\theta_1'}\xrightarrow{p}-E\frac{\partial L_1(\theta_1)}{\partial\theta_1}\left(\frac{\partial L_1(\theta_1)}{\partial\theta_1}\right)'\equiv R_1(\theta_1)$$

$$\frac{1}{n}\sum_{i=1}^{n}\frac{\partial^2 L_{2i}(\bar\theta_1,\bar\theta_2)}{\partial\theta_2\partial\theta_1'}\xrightarrow{p}-E\frac{\partial L_2(\theta_1,\theta_2)}{\partial\theta_2}\left(\frac{\partial L_2(\theta_1,\theta_2)}{\partial\theta_1}\right)'\equiv R_2(\theta)'$$

$$\frac{1}{n}\sum_{i=1}^{n}\frac{\partial^2 L_{2i}(\bar\theta_1,\bar\theta_2)}{\partial\theta_2\partial\theta_2'}\xrightarrow{p}-E\frac{\partial L_2(\theta_1,\theta_2)}{\partial\theta_2}\left(\frac{\partial L_2(\theta_1,\theta_2)}{\partial\theta_2}\right)'\equiv R_2(\theta_2)$$

$$\frac{1}{n}\sum_{i=1}^{n}\frac{\partial^2 L_{3i}(\bar\theta_1,\bar\theta_2,\bar\theta_3)}{\partial\theta_3\partial\theta_1'}\xrightarrow{p}-E\frac{\partial L_3(\theta_1,\theta_2,\bar\theta_3)}{\partial\theta_3}\left(\frac{\partial L_3(\theta_1,\theta_2,\bar\theta_3)}{\partial\theta_1}\right)'\equiv R_3(\theta)'$$

$$\frac{1}{n}\sum_{i=1}^{n}\frac{\partial^2 L_{3i}(\bar\theta_1,\bar\theta_2,\bar\theta_3)}{\partial\theta_3\partial\theta_2'}\xrightarrow{p}-E\frac{\partial L_3(\theta_1,\theta_2,\bar\theta_3)}{\partial\theta_3}\left(\frac{\partial L_3(\theta_1,\theta_2,\bar\theta_3)}{\partial\theta_2}\right)'\equiv R_4(\theta)'$$

$$\frac{1}{n}\sum_{i=1}^{n}\frac{\partial^2 L_{3i}(\bar\theta_1,\bar\theta_2,\bar\theta_3)}{\partial\theta_3\partial\theta_3'}\xrightarrow{p}-E\frac{\partial L_3(\theta_1,\theta_2,\bar\theta_3)}{\partial\theta_3}\left(\frac{\partial L_3(\theta_1,\theta_2,\bar\theta_3)}{\partial\theta_3}\right)'\equiv R_3(\theta_3)$$

Then, from equation 34 we have the following asymptotic equivalence:

$$n^{1/2}(\hat\theta_1-\theta_1)=-R_1(\theta_1)^{-1}\frac{1}{n^{1/2}}\sum_{i=1}^{n}\frac{\partial L_{1i}(\theta_1)}{\partial\theta_1} \tag{37}$$

Substituting 37 into 35 we have the following asymptotic equivalence:

$$n^{1/2}(\hat{\theta}_2-\theta_2) = -R_2(\theta_2)^{-1}\frac{1}{n^{1/2}}\sum_{i=1}^{n}\frac{\partial L_{2i}(\theta_1,\theta_2)}{\partial\theta_2}+$$
$$R_2(\theta_2)^{-1}R_2(\theta)'R_1(\theta_1)^{-1}\frac{1}{n^{1/2}}\sum_{i=1}^{n}\frac{\partial L_{1i}(\theta_1)}{\partial\theta_1} \qquad (38)$$

Substituting 37 and 38 into 36 we have the following asymptotic equivalence:

$$n^{1/2}(\hat{\theta}_3-\theta_3) = -R_3(\theta_3)^{-1}\frac{1}{n^{1/2}}\sum_{i=1}^{n}\frac{\partial L_{3i}(\theta_1,\theta_2,\theta_3)}{\partial\theta_3}+$$
$$R_3(\theta_3)^{-1}R_3(\theta)'R_1(\theta_1)^{-1}\frac{1}{n^{1/2}}\sum_{i=1}^{n}\frac{\partial L_{1i}(\theta_1)}{\partial\theta_1}+$$
$$R_3(\theta_3)^{-1}R_4(\theta)'R_2(\theta_2)^{-1}R_2(\theta)'R_1(\theta_1)^{-1}\frac{1}{n^{1/2}}\sum_{i=1}^{n}\frac{\partial L_{1i}(\theta_1)}{\partial\theta_1}- \qquad (39)$$
$$R_3(\theta_3)^{-1}R_4(\theta)'R_2(\theta_2)^{-1}\frac{1}{n^{1/2}}\sum_{i=1}^{n}\frac{\partial L_{2i}(\theta_1,\theta_2)}{\partial\theta_2}$$

The only random vectors that the right hand sides of 37,38 and 39 involve are,

$$\frac{1}{n^{1/2}}\sum_{i=1}^{n}\frac{\partial L_{1i}(\theta_1)}{\partial\theta_1}$$

$$\frac{1}{n^{1/2}}\sum_{i=1}^{n}\frac{\partial L_{2i}(\theta_1,\theta_2)}{\partial\theta_2}$$

$$\frac{1}{n^{1/2}}\sum_{i=1}^{n}\frac{\partial L_{3i}(\theta_1,\theta_2,\theta_3)}{\partial\theta_3}$$

By the central limit theorem, as n approaches infinity, the distribution of those vectors converges to joint normal. This implies that $n^{1/2}(\hat{\theta}-\theta)$ is asymptotically normally distributed with the mean 0 and some variance-covariance matrix, that we denote Σ. To find Σ, we calculate variance-covariance of the right hand sides of 37, 38 and 39. Let us introduce some additional notation,

$$R_5(\theta) \equiv \frac{\partial L_1(\theta_1)}{\partial\theta_1}\left(\frac{\partial L_{2i}(\theta_1,\theta_2)}{\partial\theta_2}\right)'$$

$$R_6(\theta) \equiv \frac{\partial L_1(\theta_1)}{\partial\theta_1}\left(\frac{\partial L_3(\theta_1,\theta_2,\theta_3)}{\partial\theta_3}\right)'$$

$$R_7(\theta) \equiv \frac{\partial L_2(\theta_1, \theta_2)}{\partial \theta_2} \left(\frac{\partial L_3(\theta_1, \theta_2, \theta_3)}{\partial \theta_3} \right)'$$

Let $\Sigma_{\theta_i,\theta_j}$ denote variance-covariance of (θ_i, θ_j) for $i = 1, 2, 3$ and $j = 1, 2, 3$. We have the following:

$$\Sigma_{\theta_1,\theta_1} = R_1(\theta_1)^{-1}$$

$$\Sigma_{\theta_2,\theta_2} = R_2(\theta_2)^{-1} +$$
$$R_2(\theta_2)^{-1}[R_2(\theta)' R_1(\theta_1)^{-1} R_2(\theta) - R_5(\theta)' R_1(\theta_1)^{-1} R_2(\theta) - R_2(\theta)' R_1(\theta_1)^{-1} R_5(\theta)] R_2(\theta_2)^{-1}$$

$$\Sigma_{\theta_1,\theta_2} = R_1(\theta_1)^{-1}[R_5(\theta) - R_2(\theta)] R_2(\theta_2)^{-1}$$

$$\Sigma_{\theta_3,\theta_3} = R_3(\theta_3)^{-1} + R_3(\theta_3)^{-1} R_3(\theta)' R_1(\theta_1)^{-1} R_3(\theta) R_3(\theta_3)^{-1} +$$
$$R_3(\theta_3)^{-1} R_4(\theta)' R_2(\theta_2)^{-1} R_2(\theta)' R_1(\theta_1)^{-1} R_2(\theta) R_2(\theta_2)^{-1} R_4(\theta) R_3(\theta_3)^{-1} -$$
$$R_3(\theta_3)^{-1}[R_4(\theta)' R_2(\theta_2)^{-1} R_4(\theta) + R_6(\theta)' R_1(\theta_1)^{-1} R_3(\theta)] R_3(\theta_3)^{-1} -$$
$$R_3(\theta_3)^{-1} R_6(\theta)' R_1(\theta_1)^{-1} R_2(\theta) R_2(\theta_2)^{-1} R_4(\theta) R_3(\theta_3)^{-1} +$$
$$R_3(\theta_3)^{-1}[R_7(\theta)' R_2(\theta_2)^{-1} R_4(\theta) - R_3(\theta)' R_1(\theta_1)^{-1} R_6(\theta)] R_3(\theta_3)^{-1} +$$
$$R_3(\theta_3)^{-1} R_3(\theta)' R_1(\theta_1)^{-1} R_2(\theta) R_2(\theta_2)^{-1} R_4(\theta) R_3(\theta_3)^{-1} -$$
$$R_3(\theta_3)^{-1} R_3(\theta)' R_1(\theta_1)^{-1} R_5(\theta) R_2(\theta_2)^{-1} R_4(\theta) R_3(\theta_3)^{-1} -$$
$$R_3(\theta_3)^{-1} R_4(\theta)' R_2(\theta_2)^{-1} R_2(\theta)' R_1(\theta_1)^{-1} R_6(\theta) R_3(\theta_3)^{-1} +$$
$$R_3(\theta_3)^{-1} R_4(\theta)' R_2(\theta_2)^{-1} R_2(\theta)' R_1(\theta_1)^{-1} R_3(\theta) R_3(\theta_3)^{-1} -$$
$$R_3(\theta_3)^{-1} R_4(\theta)' R_2(\theta_2)^{-1} R_2(\theta)' R_1(\theta_1)^{-1} R_5(\theta) R_2(\theta_2)^{-1} R_4(\theta) R_3(\theta_3)^{-1} +$$
$$R_3(\theta_3)^{-1}[R_4(\theta)' R_2(\theta_2)^{-1} R_7(\theta) - R_4(\theta)' R_2(\theta_2)^{-1} R_5(\theta)' R_1(\theta_1)^{-1} R_3(\theta)] R_3(\theta_3)^{-1} -$$
$$R_3(\theta_3)^{-1} R_4(\theta)' R_2(\theta_2)^{-1} R_5(\theta)' R_1(\theta_1)^{-1} R_2(\theta) R_2(\theta_2)^{-1} R_4(\theta) R_3(\theta_3)^{-1}$$

$$\Sigma_{\theta_1,\theta_3} = R_1(\theta_1)^{-1}[R_6(\theta) - R_3(\theta) + (R_5(\theta) - R_2(\theta))R_2(\theta_2)^{-1}R_4(\theta)]R_3(\theta_3)^{-1}$$

$$\begin{aligned}
\Sigma_{\theta_2,\theta_3} &= R_2(\theta_2)^{-1}[R_7(\theta) - R_5(\theta)'R_1(\theta_1)^{-1}R_3(\theta)]R_3(\theta_3)^{-1}+ \\
&R_2(\theta_2)^{-1}[R_4(\theta) - R_5(\theta)'R_1(\theta_1)^{-1}R_2(\theta)R_2(\theta_2)^{-1}R_4(\theta)]R_3(\theta_3)^{-1}+ \\
&R_2(\theta_2)^{-1}R_2(\theta)'R_1(\theta_1)^{-1}[R_3(\theta) - R_6(\theta)]R_3(\theta_3)^{-1}+ \\
&R_2(\theta_2)^{-1}R_2(\theta)'R_1(\theta_1)^{-1}[R_2(\theta) - R_5(\theta)]R_2(\theta_2)^{-1}R_4(\theta)R_3(\theta_3)^{-1}
\end{aligned}$$

A.7 Calculating $V(q^*, d)$

The state space for $V(q^*, d)$ is the set of all natural numbers. We take $750/\pi$ as the upper bound on the state space when finding the fixed point of $V(q^*, d)$. For a given probability of verifying project quality, π, the probability of detecting at least one deviation becomes numerically zero whenever $d \approx 750/\pi$. Hence, for all states above $750/\pi$ we know that the platform will be detected for sure in the following period and hence we can pin down the value for such states. Pinning down the value for very high states enables us to, alternatively, solve the problem using backward induction on the states starting from the state $750/\pi$. However, the value function iteration is more time efficient as it allows us to avoid loops. For the results presented in the current version of the paper, for each π we consider at most $100,000$ equally spaced points in the state space.

B Tables and Figures

Table 1: Data Summary

Variable	Mean	Std. Dev.	25%	50%	75%	Min	Max
Goal	19,931	13,497	10,000	15,000	28,334	5,000	50,000
Length (days)	34.85	10.57	30	30	39.3	1	64
Badged	0.09	0.29	1	1	1	0	1
Pledged	14,508	32,321	50	1,799	17,028	0	667,311
Investors	101.89	161.42	2	20	136	0	800
Funded	0.38	0.48	1	1	1	0	1

Table 2: Regression Results

Dependent Variable:	# of Investors	Amount Pledged
Intercept	-145.123***	-9492.555**
	(23.788)	(3858.387)
Goal	0.002**	0.45***
	(0.001)	(0.129)
Length	11.447***	208.979
	(1.149)	(187.482)
$Goal^2$	-3.282e-08***	-1.404e-06
	(1.18e-08)	(1.9e-06)
$Length^2$	-0.137***	-2.220
	(0.014)	(2.254)
$Goal \times Length$	-7.476e-06	-0.001
	(1.48e-05)	(0.002)
Badged	46.163	-2818.919
	(30.724)	(4967.345)
$Badged \times Goal$	0.003***	0.793***
	(0.001)	(0.084)
$Badged \times Length$	1.085	-39.915
	(0.825)	(133.438)
# of Investors		111.167***
		(2.199)
R^2	0.102	0.419

Notes: ***, ** and * stand for the significance at the 1, 5 and 10 percent level, respectively.

Table 3: Estimate of θ_1

$\hat{q}^{**}$	$\hat{\gamma}(lo, hi)$	$\hat{\gamma}(hi, lo)$	$\hat{\gamma}(hi, hi)$	$\hat{\beta}_b$	$\hat{\alpha}_0$	$\hat{\alpha}_1$	$\hat{\beta}_0$	$\hat{\beta}_1$
0.3003	0.0025	0.9713	1.003e-5	1.624	5.778e-8	4.653e-4	0.3305	1.509
(0.094)	(0.1198)	(0.0936)	(3.695e-6)	(0.1659)	(1.943e-7)	(1.5e-4)	(0.0072)	(0.1045)

Table 4: Estimate of θ_2

$\hat{a}_1$	$\hat{a}_2$	$\hat{a}_3$	$\hat{a}_4$	$\hat{a}_5$	$\hat{a}_6$
3.096e-5	0.0275	-1.533	-1.668e-5	-1.476e-6	-9.545e-6
(1.449e-6)	(0.0015)	(0.0964)	(1.750e-5)	(2.588e-5)	(3.259e-5)

Table 5: Estimate of θ_3

$\hat{f}(lo,lo)$	$\hat{f}(lo,hi)$	$\hat{f}(hi,lo)$	$\hat{f}(hi,hi)$	$\hat{\beta}_{cr}$
3.435e-5	2.754e-5	1.594e-5	1.400e-5	1.431e-15
(8.344e-6)	(7.657e-6)	(3.829e-6)	(3.734e-6)	

Table 6: Model Fit: # of Investors

	Mean		Std. Dev.	
	Data	Model	Data	Model
$(lo, lo, 0)$	65.80	65.04	125.60	113.42
$(lo, lo, 1)$	194.30	226.09	158.14	184.66
$(lo, hi, 0)$	116.81	114.72	168.47	199.83
$(lo, hi, 1)$	232.89	266.76	196.01	217.77
$(hi, lo, 0)$	64.28	66.17	136.37	115.38
$(hi, lo, 1)$	281.06	227.22	201.07	185.58
$(hi, hi, 0)$	111.06	114.83	171.52	200.01
$(hi, hi, 1)$	324.64	266.87	199.88	217.86

Notes: The table presents the model fit of the first two moments of the distribution of the number of investors for all combinations of (m, l, s).

Table 7: Model Fit: Pledges

	Mean	
	Data	Model
$(lo, lo, 0)$	6,701	7,560
$(lo, lo, 1)$	31,229	23,848
$(lo, hi, 0)$	12,450	12,368
$(lo, hi, 1)$	29,267	26,761
$(hi, lo, 0)$	12,048	11,352
$(hi, lo, 1)$	61,437	62,474
$(hi, hi, 0)$	21,143	22,286
$(hi, hi, 1)$	69,187	82,101

Table 8: Model Fit: Probability of Posting a Project (per second)

	Mean	
	Data	Model
(lo, lo)	3.435e-5	3.435e-5
(lo, hi)	2.754e-5	2.754e-5
(hi, lo)	1.594e-5	1.594e-5
(hi, hi)	1.40e-5	1.40e-5

Table 9: Welfare Effects of Commitment

	$\Delta Percent$
Platform	7.4
Investor	0.5
Creator	4.0

Table 10: Best ITS for the Investors

	$\Delta Percent$
Platform	1.6
Investor	0.7
Creator	-5.5

Notes: The percentage changes are from the factual ITS.

Table 11: Best ITS for the Creators

	$\Delta Percent$
Platform	6.9
Investor	0.4
Creator	4.5

Notes: The percentage changes are from the factual ITS.

Figure 2: Distribution of the Number of Investors

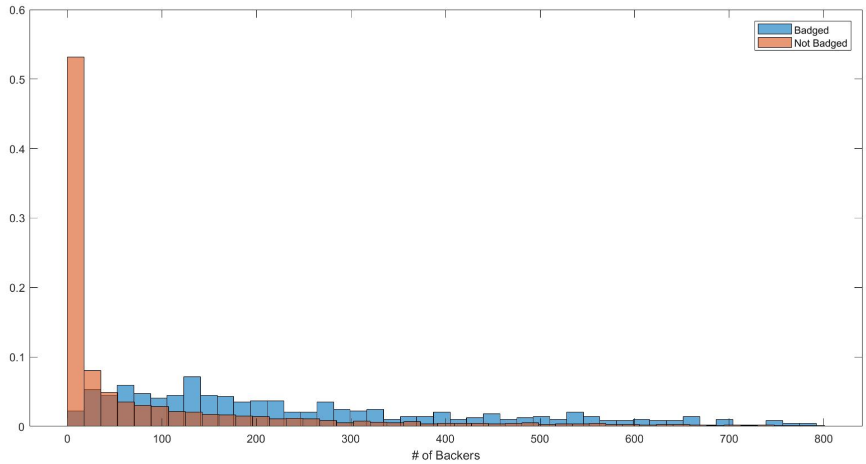

Figure 3: Distribution of the Amount Pledged

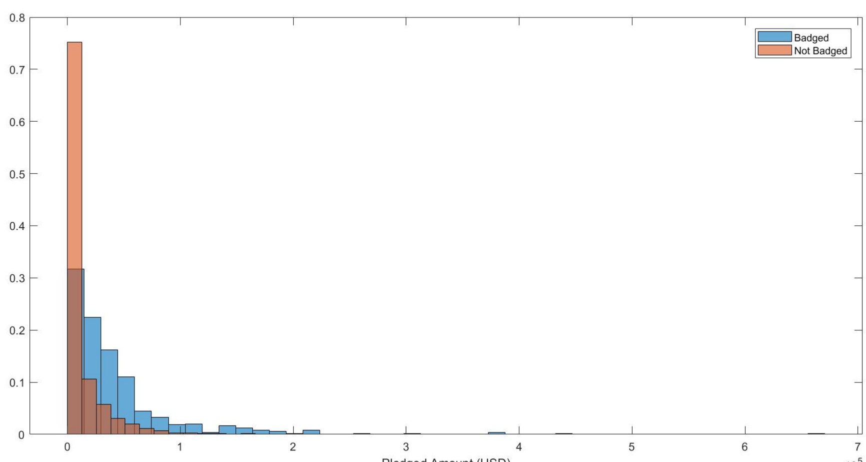

Figure 4: Level Curves for the Right Hand Sides of the Equations 29 and 30

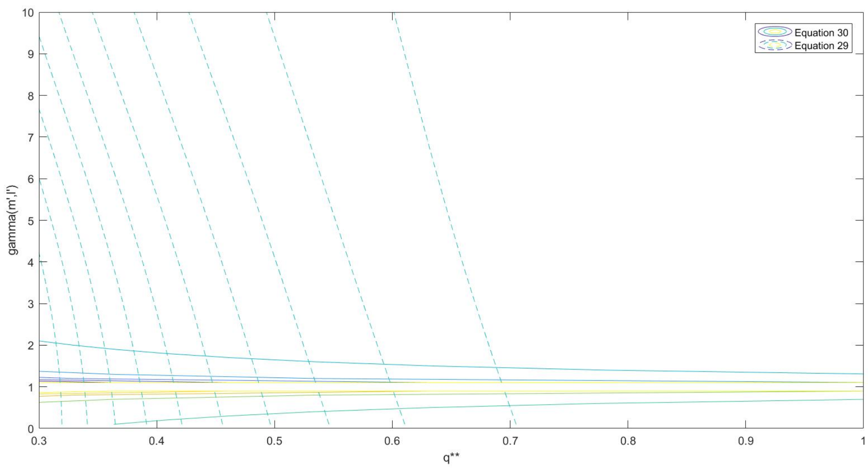

Figure 5: Distribution of the Goal

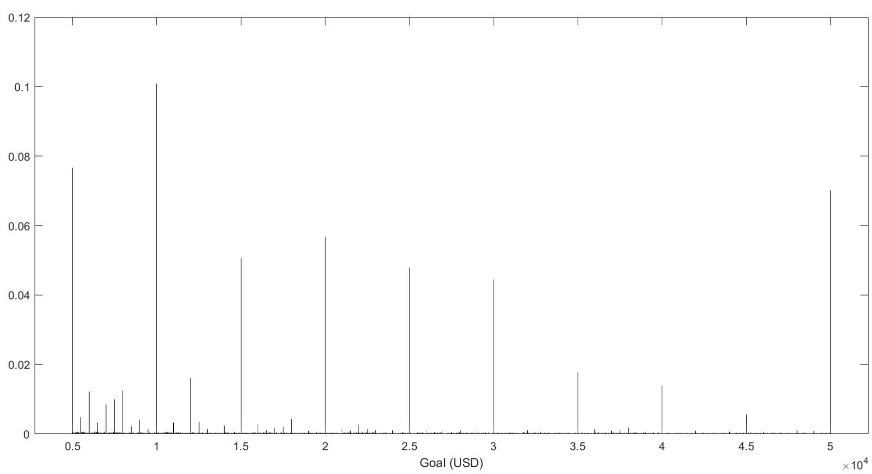

Figure 6: Distribution of the Project Length

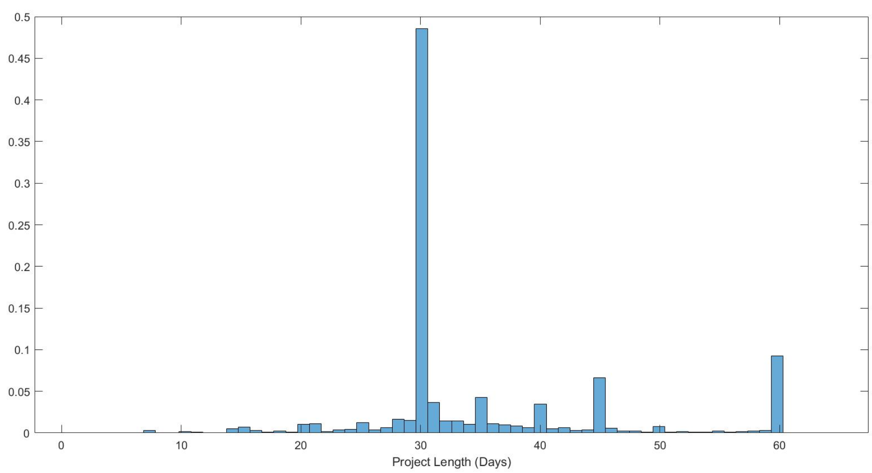

Figure 7: Model Fit of the Distr. of # of Investors

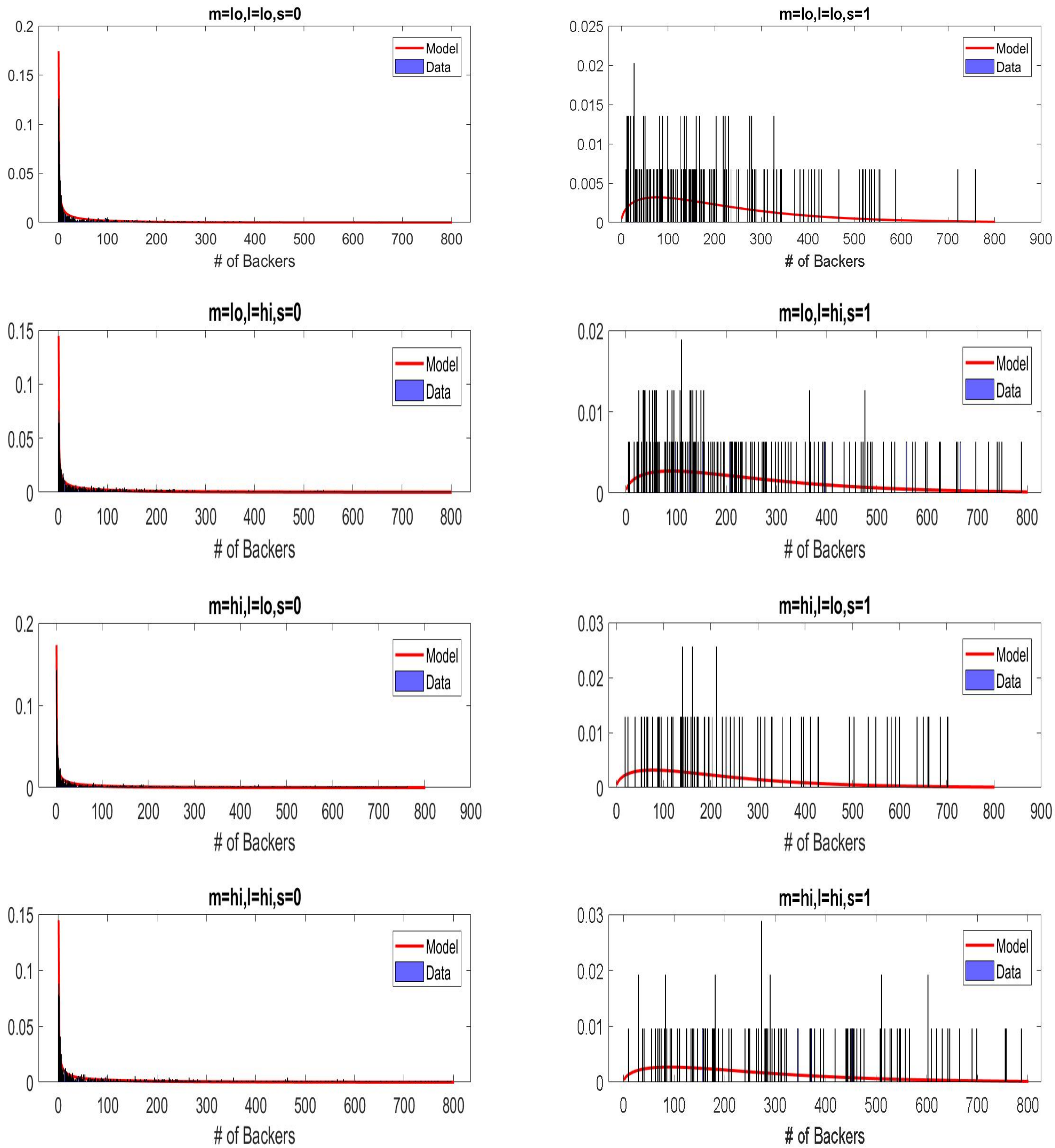

Figure 8: Model Fit of the Mean Pledges Against # of Investors

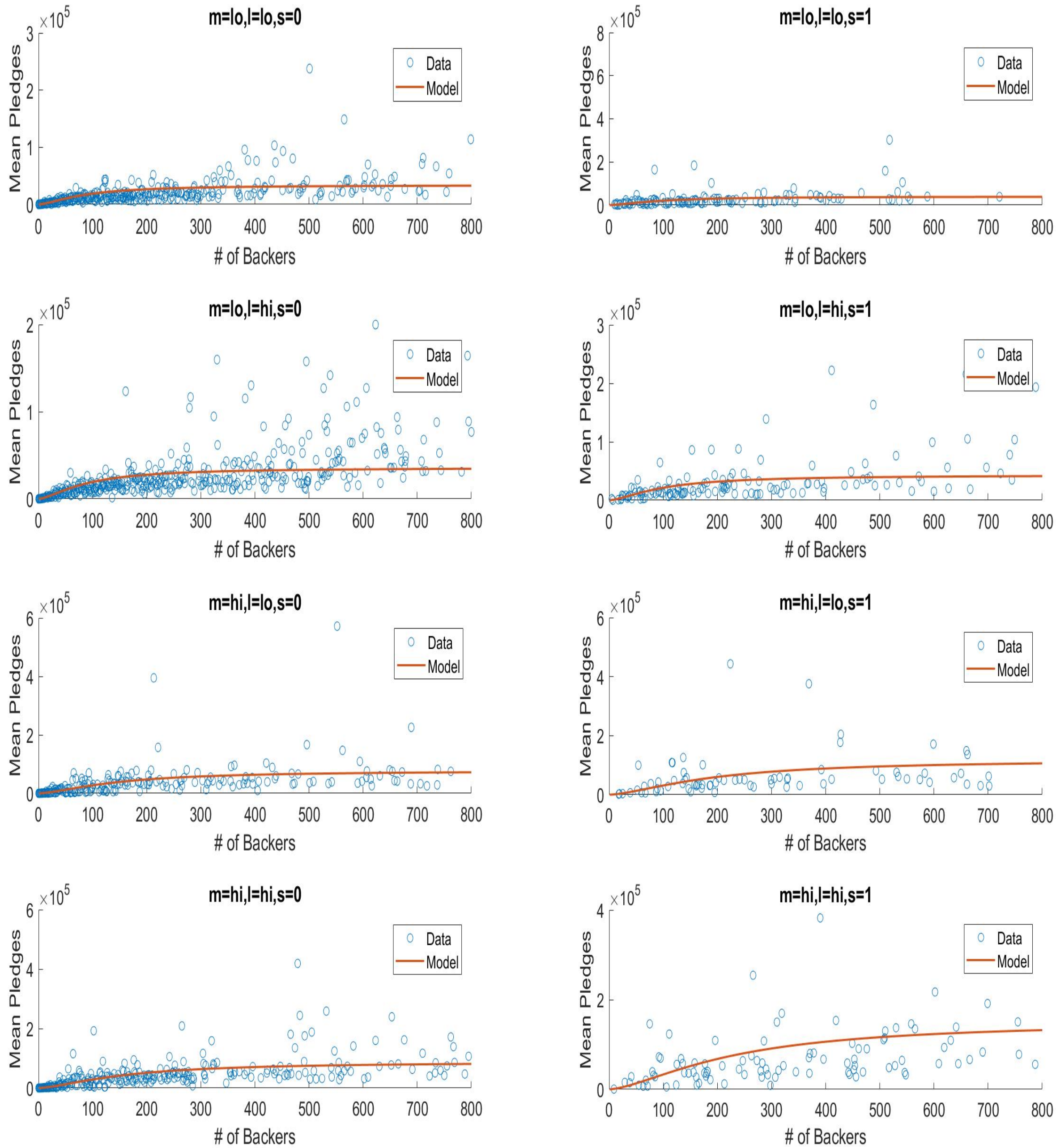

Figure 9: Investor, Creator and Platform Welfare