Herding in Equity Crowdfunding[*]

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Abstract

We build a model of equity crowdfunding that incorporates the two major funding models: All-or-Nothing (AoN) and Keep-It-All (KIA). Both informed and uninformed investors arrive sequentially and rationally choose whether and how much to invest. The KIA solution turns out to be a reduced version of AoN without signaling. We test predictions using data from a leading European equity crowdfunding platform and find support. Results are consistent with rational information aggregation. However, negative information cascades may still appear. The AoN crowdfunding mechanism might therefore fail to finance a non-negligible percentage of positive NPV projects.

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1 Introduction

Start-up founders have historically raised equity either informally from friends and family, or through bi-party agreements with angel investors or Venture Capitalists specialized in early stage funding. In recent years, an increasing fraction of start-ups have started to raise funds by selling equity through equity crowdfunding campaigns run on dedicated on-line platforms using a lightly regulated standardized equity offering scheme. In the three first quarters of 2019, the UK had 1,241 SME equity deals, of which 561 (45%) were private equity (PE)/venture capital (VC), and 291 (23%) were equity crowdfunding (British Business Bank, 2020).[1]

The fundraising process consists of first, publishing an equity offering on an equity crowdfunding platform to make it visible to a large number of potential investors. Then, a large number of dispersed investors may visit the platform and purchase, or not, the shares offered. Finally, a campaign is closed if the capital raising goal is reached. If investors can observe the amount invested by others, one can view equity crowdfunding campaigns as a mechanisms to aggregate dispersed private information about the fundamental value of the issuer's equities. This view is challenged by the idea that the crowd tends to behave as a herd and may be induced to invest irrationally simply by seeing others invest (Shiller, 2015). It is possible, then, that the proceeds from the sale of shares might not reflect the aggregate opinion of many investors, but merely the opinion of those who invested first.

An important distinguishing feature of some equity crowdfunding platforms is the so called All-or-Nothing clause (henceforth AoN). It stipulates that if the campaign proceeds do not exceed a pre-specified threshold (the "campaign goal") by a deadline, the start-up will not issue its shares and investors will be returned the cash they have pledged. An alternative design is the so called Keep-It-All clause (henceforth KIA). Here, investors' pledges are immediately accepted no matter the size of overall proceeds raised. In other words, whereas in KIA investors' behavior only affects the size of issuer's proceeds, in AoN investors' behavior will also determine whether the start-up will be at all financed.

Understanding whether the outcome of AoN and KIA crowdfunding campaign reflects aggregate fundamental information or just result from herd behavior is crucial. We ask whether these campaigns can gather the wisdom of the crowd to finance start-ups with positive net

[1] The UK has had the world's most rapid growth in equity crowdfunding campaigns. UK had a regulatory framework for equity crowdfunding in place end of 2011, whereas the US regulatory framework was put into place in April 2016.

present value and not to finance those with negative net present value. To address this question we model the behavior of rational investors participating in an AoN and a KIA crowdfunding campaign. And we compare the predictions of our model to actual investor behavior on a UK-based leading equity crowdfunding platform.

Our model features a crowdfunding campaign that aims to raise an exogenous goal. The project can be profitable or not. Investors (henceforth, backers) arrival to the crowdfunding campaign is random. Upon arrival, a backer chooses whether and how much to pledge. Backers are risk averse, privately informed about the project's profitability and differ in their wealth. Past pledges are publicly observable, but backers' arrivals are not. The absence of pledges in a given period could therefore result from the fact that no backer visited the campaign, or from the fact that the backer who visited the campaign chose not to pledge. In the model (and in practice), a campaign initially follows the AoN clause. If the goal is reached before the deadline, the campaign enters an over-funding phase, and takes the KIA format.

We start with the equilibrium of a KIA campaign: The equilibrium pledge of a backer arriving in a KIA campaign is increasing in her wealth, and in her belief that the project is profitable. This belief depends on her private signal but also on previous pledges: Periods without pledges provide partially negative information about the project quality, whereas a large sized pledge provide partially positive information.

Turning to the AoN stage: Here a backer is uncertain whether her pledge will actually be claimed or not. For this reason, she must also take into consideration future backers' pledges, and how these are influenced by her own pledge. We show that a campaign for a positive NPV project is more likely to succeed than a campaign for a negative NPV project, the more so, the larger the distance to the goal, i.e., the amount of funds still necessary to reach the goal. As a result, in equilibrium backers' willingness to pledge increases with the distance to the goal. However, a large distance to the goal might also be due to the fact that past backers have not pledged, and this is in itself negative information about the project's profitability. That is, keeping fixed the distance to the goal, backers' willingness to pledge increases with the time remaining to the deadline.

We then test these key features of our model: The first group of predictions concerns the effect of the most recent pledges on the size and likelihood of a pledge. The size of a pledge and the probability that a pledge will be made should be positively correlated with the size of the most recent pledges and negatively correlated with the time since the most recent pledge.

The second group of predictions, related to the AoN clause, concerns the effect of a campaign's state on backers' behavior, specifically the distance to the goal, and the remaining time in the campaign. For this analysis we construct the ratio between the distance to the goal and the remaining time until the campaign deadline, which we call the "required pledge ratio." For campaigns with a high required pledge ratio, the model predicts little chance of succeeding, as these are campaigns that have collected a low number of pledges after running for a long period. Intermediate values of this ratio are associated with a strong start. Past pledges provide positive information on project profitability, and as the goal is still far away, the correlation between reaching the campaign goal and the project profitability is high. It is in this situation that backers pledge the most. Finally, a low required pledge ratio is associated with campaigns close to completion. Here the willingness to pledge should be intermediate.

The third group of predictions concerns efficiency: A good start generates momentum and is associated with a greater probability that the campaign will reach the goal. In equilibrium, whereas most profitable projects run successful campaigns, a large proportion of campaigns for profitable projects fail because they do not have a good start. To a lesser extent, some of the bad projects succeed thanks to a particularly lucky start. This asymmetry is due to the fact that although all backers' pledges are observable, the arrival of backers who do not pledge is not.

We test these model predictions using a rich data set on 69,699 pledges in 710 AoN equity campaigns launched on Seedrs (www.seedrs.com) during the period 2012-2016. We have detailed information about the size of each pledge, its exact time, and backers' identities. We can also construct the public information available to backers on each campaign's page on Seedrs at every point in time, which include all backers' pledges, the cumulative amount invested, the number of backers, and the number of days left in the campaign as well as project-specific information. Because approximately half the pledges are made anonymously to other backers, we possess information about those backers' identity and past pledge behavior that is not available to other backers, which turns out to be useful for identification purposes.

A challenge for the identification strategy is that cross-sectional differences between campaigns are difficult to measure. This is important because investors choose which campaigns to invest in, which will likely depend on the projects' characteristics (observed and unobserved), leading to selection problems in cross-campaign analysis. However, because we have the exact timing of every pledge made in every campaign, we can focus the analysis on within-campaign dynamics, controlling for all time-invariant unobserved heterogeneity across campaigns.

Our main model predictions are corroborated by data. In particular, we find that the size and the probability of a pledge are both positively correlated with the size of the most recent pledges and negatively correlated with the time since the most recent pledge. A worry about using the sequence of pledges is that there might be time-varying shocks that generate a correlation across pledges. We propose an instrument based on the investor's wealth that is plausibly uncorrelated with these time-varying shocks and does not directly affect the information set because it is not disclosed to backers.

Illustrating our main empirical findings, we observe that in our preferred specification a doubling (a 100% increase) in the value of the most recent pledge is associated with an increase of 10.6 percent in the subsequent amount pledged. For an average pledge size of £1,202, the 10.6 percent increase translates into £127 in additional investment. In the alternative IV specification, the total marginal effect is instead close to 15.4 percent, which translates into £185 in additional investment. The causal effects are not statistically significantly different from the effects estimated by ordinary least squares (OLS), suggesting that our model of rational information aggregation can represent all the correlated effects between adjacent pledges that are observed.

Finally, Seedrs and other crowdfunding platforms differ in the presentation of data, which offers a unique opportunity for informing regulators and platform designers. Seedrs is one of the few platforms that displays individual pledges. As their arrival appears to represent a key piece of information for future investors, it is likely that other crowdfunding platforms could offer a greater investor benefit from listing individual pledges. Overall, our tests show that equity crowdfunding backers seem to make inferences on project quality from previous pledges consistent with a model of rational behavior. The findings are at odds with the pure herding model.

The rest of the article is organized as follows. Section 2 places our article in the literature. In Section 3 we present a theoretical model and define the solution concept. In section 4 we illustrate the construction of a Markov equilibrium. Section 5 contains a qualitative description of the Markov equilibrium and its empirical implications. Section 6 provides a description of the data used in the analysis. In Section 7 we describe our empirical strategy. Section 8 presents the result of our empirical analysis. Finally, Section 9 concludes. The proofs of all propositions, lemmas, and corollaries are presented in Appendix A.

2 Related literature

Our article is related to a couple of strands in the literature: empirically it is related to experiments on social influence and field data analyses of crowdfunding campaigns. The theory relates to theories on crowdfunding campaigns and more general theoretical work on dynamic social learning.

Bursztyn et al. (2014) is an experimental study which investigates the effect on private and observable investment decisions by peers. The authors disentangle investment herding based on social learning and social utility and find that both are at play. Closely related are three randomized controlled experiments in crowdfunding in which a treatment campaign receives an early donation, and the control campaign does not (Koning and Model, 2014; Van De Rijt et al., 2014; Zaggl and Block, 2019). Koning and Model (2014) and Zaggl and Block (2019) both find that campaigns to which they made a small initial contribution (e.g. $5) had significantly lower chances of meeting their funding goal. Our model rationalizes these results by suggesting that campaigns that have a poor initial start run the risk of ending up in a negative information cascade.

Many articles look at field data analysis of crowdfunding campaigns. As the number of such articles is very large, we focus on those that are the most related to ours. In an early publication, Zhang and Liu (2012) use data on a peer-to-peer lending web site, *prosper.com*, correlating daily lending amounts to the cumulative amount of funding, and its interaction with observable project attributes, while controlling for project-fixed effects. The study led many to correlate cumulative prior funding with the size or probability of a pledge, generally finding positive correlations, and arguing that these correlations indicate herding (e.g., Colombo et al. (2015); Hornuf and Schwienbacher (2018); Vismara (2018)).

Our article also contributes to the growing theoretical literature on crowdfunding. For reviews, see Schwienbacher (2019) and Belleflamme et al. (2015). Within a private value framework, Belleflamme et al. (2014); Ellman and Hurkens (2019); Chemla and Tinn (2019) and Strausz (2017) analyze the use of rewards-based crowdfunding to probe uncertain demand. For example, Chemla and Tinn (2019) contrast the optimal design of the AoN with the KIA model. In all these articles, backers move simultaneously and therefore do not influence one another's investment decisions.

To the best of our knowledge, Alaei et al. (2016) is the first article to explore the effect of the AoN clause on sequential investments. As in our setting, the backers' arrival is stochastic, and the AoN clause implies that backers are uncertain as to whether the campaign goal will be reached. Deb et al. (2019) extend Alaei et al. (2016)'s setting by introducing one donor who can choose when and how much to donate. Both articles analyze rewards-based crowdfunding, an alternative format to equity crowdfunding. [2] In both models, all backers have perfect knowledge about the intrinsic value of the project, so there is no collective learning about fundamentals, and success or failure of the campaign provides no information about the project's intrinsic quality. Still, because backers prefer not to pledge in a campaign that will fail, they need some form of coordination. A coordination mechanism is given by the past number of pledges, the time remaining, and, in Deb et al. (2019), by a single donation. In Deb et al. (2019) model, donations serve as a strong coordination mechanism for reaching the funding goal, but lacks any collective learning about the quality of the project from these donations. Pure donations are apparently empirically important in rewards-based campaigns. For example, they represent about 28% of the funding on Kickstarter (Deb et al., 2019). They are also increasingly frequent at the end of a campaign and therefore often key to reaching the funding goal. Donations then drop to almost zero, even though rewards-based campaigns may well accept additional contributions. In contrast, in our model of AoN equity crowdfunding there is a signaling role of pledges which is quite important. And in contrast to the Kickstarter data, the campaigns we study on the platform Seedrs apparently do not experience nearly as much end-of-campaign pledge activity and also differ in that pledges for equity often continue to arrive at a steady pace after the goal is achieved (Vulkan et al., 2016). We conclude that the specific mechanism designs apparently cause very different campaigns dynamics and we encourage more work on exploring these dynamics.

Using settings that are similar to ours , Chakraborty and Swinney (2021), Liu (2020), and Cong and Xiao (2021) examine projects with either good or of bad quality, and backers with asymmetric information.

Chakraborty and Swinney (2021) focus on the entrepreneur's choice of campaign setting (funding goal and share price). Because they assume that backers do not learn from other backers' pledges, their model does not permit herding. In Liu (2020) there are only two periods, and in equilibrium only backers with positive-enough information make pledges in the first

[2]Compared to equity crowdfunding, which exclusively accepts investment in shares, rewards-based campaigns enables participants to purchase a reward (a product to be developed, a T-shirt stating "I supported ... ," or another reward) or to donate an amount while not obtaining any shares in return.

period. Thus, having enough pledges in the first period triggers pledges by other backers in the second period. Cong and Xiao (2021) is the closest to our work, as it has $T \geq 2$ periods, backers learn from the pledges of past backers, and backers take into account the effect of their pledges on future pledges. All these articles, like ours, show that campaigns are more likely to succeed if they have a good start. However, in all these articles, the quantities traded are assumed to be fixed, that is, backers can choose whether to pledge but not how much to pledge. Variable quantities are a key element of our model, as they enable us to explore the effect of the size of individual pledges on future pledges.

Our work is also related to the theoretical literature on rational herding (Banerjee, 1992; Welch, 1992; Bikhchandani et al., 1992; Smith and Sørensen, 2000; Herrera and Hörner, 2013) and rational herding in financial markets (Avery and Zemsky, 1998; Decamps and Lovo, 2006; Drehmann et al., 2005). None of these models contain the AoN mechanism, which seems to be a unique and theoretically interesting feature in crowdfunding campaigns.

3 A model of the wisdom of crowds in equity crowdfunding

Setup

Firm. A firm seeks to raise an amount Y to finance a risky project. The project's quality can be 'good' or 'bad'. Each dollar invested in the project generates ρ dollars, where $\rho = \alpha > 1$ for a good project, and $\rho = 0$ for a bad project. The firm is not informed about ρ. We denote the ex-ante probability that the project is good as π_0. Henceforth, an agent's 'belief' refers to the probability that she attaches to $\rho = \alpha$. Given the belief $\pi \in [0, 1]$, we define the expected return on the project as $\pi\alpha - 1$.

Crowdfunding campaign. The firm tries to raise funds from backers using a crowdfunding platform. The crowdfunding campaign starts at $t = 0$ and closes at $t = T$. Time is discrete, i.e., $t \in \mathcal{T} := \{0, 1, \ldots, T\}$. The fundraising goal Y is announced at $t = 0$. In every period t, with probability $\lambda \in (0, 1)$, a new backer visits the campaign, and with probability $1 - \lambda > 0$, no backer arrives. Upon arrival, the backer chooses whether to pledge an amount $x_t = 1$, to pledge an amount $x_t = 2$, or not to pledge at all. Thus the set of actions available to a backer is $\mathcal{X} := \{0, 1, 2\}$. Let y_t be the cumulative amount of pledges *at the beginning* of period t, i.e., $y_t = x_1 + x_2 + \cdots + x_{t-1}$. If, at $t = T$, the cumulative amount y_T is at least Y, the campaign is successful, and committed funds are invested. In this case, a backer who pledged $x > 0$ during the campaign receives a cash flow of $(\rho - 1)x$. If $y_T < Y$, the campaign fails, and pledges are returned to all backers. This feature is the so-called *All-or-Nothing clause* and differentiates crowdfunding campaigns from a classical situation of sequential investing, in which investors know for certain that the amount they pledge will be invested in the project. In what follows, we use the following wording and notations: *the goal* refers to the amount Y, *period* t refers to the calendar date; to any t and y_t correspond a *time* $\tau := T - t$ that remains until the deadline and a *distance to the goal* $z_\tau := Y - y_t$, respectively. Thus the campaign *succeeds* if and only if, at time $\tau = 0$, the distance to the goal is $z_0 \leq 0$.

Public history. Backers' pledges are publicly observable, but their arrival is not. Thus, a public history at time t, denoted $h_t = \{y_1, y_2, \ldots, y_t\}$, is the history of the evolution of the cumulative amount. That is, in every period t, strictly positive pledges are publicly observable and anonymous, but in the absence of pledges, the public cannot tell whether no backer arrived in t or a backer arrived but chose not to pledge. We set $h_0 = \emptyset$, and use H_t to denote the set of all possible public histories of length t, and use $H := \cup_{t \leq T} H_t$ to denote the set of all possible public histories. For any given $x \in \mathcal{X}$, we use $h_t + x := \{h_t, y_t + x\}$, to denote the history h_t completed by a pledge of size x in period t, if $x > 0$, whereas $h_t + 0$ occurs either because no backer arrived in period t or because the period t backer chose not to pledge.

Backers. Backers are risk averse with log utility and differ in their wealth w and private signal θ about project quality ρ. Formally, the type of backer is the pair $(\theta, w) \in \Theta \times \mathcal{W}$, where $\Theta := \{H, M, L\}$, and $\mathcal{W} = \{w_1, w_2\}$ with $1 < w_1 < 2 < w_2$. We make the following assumptions about the distribution of backers' types. First, the types of backers are not correlated with their arrival time. Second, backers' wealth are i.i.d. and not correlated with the project's quality or with the backers' private signals. For simplicity we assume that the probability that period t backer's wealth equals w_1 is $1/2$. Third, after conditioning on project quality ρ, backers' private signals are i.i.d.,

$$Pr(\theta_t = H|\rho = \alpha) = \quad q_{\alpha H} > q_{0H} \quad = Pr(\theta_t = H|\rho = 0), \tag{1}$$

$$Pr(\theta_t = M|\rho = \alpha) = \quad q_{\alpha M} = q_{0M} \quad = Pr(\theta_t = M|\rho = 0), \tag{2}$$

$$Pr(\theta_t = L|\rho = \alpha) = \quad 0 < q_{0L} \quad = Pr(\theta_t = L|\rho = 0). \tag{3}$$

Signals can be interpreted as follows. A signal $\theta = H$ is a partially informative positive private signal about the project quality ρ. Signal $\theta = M$ is not informative about ρ. Signal L is a private fully informative signal, disclosing that $\rho = 0$.[3] Thus, conditional on the project quality ρ, the probability that, at a generic date t, a backer of type (θ, w) visits the campaign equals

$$Q_\rho(\theta, w) := \lambda \frac{q_{\rho\theta}}{2}. \tag{4}$$

Strategies. In general, a backer's strategy consists of a mapping from a public history and the backer's type into a pledge decision. Formally, a strategy is a mapping $\sigma : H \times W \times \Theta \to \Delta\mathcal{X}$, in which we use $\Delta\mathcal{X}$ to define the set of all probability distributions in the set $\mathcal{X}$.

Public belief and private belief. To any given strategy, σ corresponds a set $H_\sigma \subseteq H$ of possible histories. At a Bayesian equilibrium, the posterior public belief that results from any history $h_t \in H_\sigma$ must be consistent with σ, whereas in a off-equilibrium path history $h_t \notin H_\sigma$, the posterior belief can be fixed arbitrarily, such that it does not induce the off-path action to be taken. We use $P_\sigma : H \to [0, 1]$ to denote the mapping from public histories to the posterior public belief, given the strategy σ. We say that P is *non-decreasing* if, for any given history h_t and $x' > x$, one has $P_\sigma(h_t + x') \geq P_\sigma(h_t + x)$, that is, larger pledges lead to weakly higher public belief. We use π_t to denote the public belief at date t, that is,

$$\pi_t := P_\sigma(h_t) = Pr(\rho = \alpha|h_t, \sigma).$$

We use $\Pi(\theta, \pi_t)$ to denote the belief for a backer that arrives at date t with private signal θ when the public belief is π_t. Then we have:

[3] We chose a perfectly informative negative signal to lighten the exposition; however, qualitatively, none of the model's main predictions change if L is a partial negative signal.

$$
\begin{aligned}
\Pi(H,\pi_t) &= \frac{\pi_t q_{\alpha H}}{\pi_t q_{\alpha H} + (1-\pi_t) q_{0H}} \geq \pi_t. \\
\Pi(M,\pi_t) &= \pi_t. \qquad (5) \\
\Pi(L,\pi_t) &= 0.
\end{aligned}
$$

where the inequality is strict for any $\pi_t \in (0,1)$.

Probability that the campaign succeeds. We denote with $S_{\rho_\sigma}(h_t)$ the endogenous probability that the campaign will eventually succeed, calculated at the beginning of period t after public history h_t is observed and conditional on the project having quality ρ, backers following strategy σ, and the public belief evolving according to P_σ.

Best response. Consider a backer of type (θ, w) who arrives in period t. Suppose that all other backers use strategy σ, the current public belief is π_t, and campaign success probabilities is $S_{\alpha\sigma}(.)$, for a good quality project, and $S_{0\sigma}(.)$, for a bad quality project. Then the backer's best response is

$$
\begin{aligned}
BR_\sigma(h_t,\theta,w) = \arg\max_{x\in\Delta\mathcal{X}} \quad & \Pi(\theta,\pi_t) S_{\alpha\sigma}(h_t+x)(ln(w+(\alpha-1)x) - ln(w)) \qquad (6) \\
+ \quad & (1-\Pi(\theta,\pi_t)) S_{0\sigma}(h_t+x)(ln(w-x) - ln(w)).
\end{aligned}
$$

The objective function can be interpreted as follows. Given the backer's private signal θ and the past history h_t that results from past backers' use of strategy σ, the backer attach probability $\Pi(\theta,\pi_t)$ to the event $\rho = \alpha$, and probability $1 - \Pi(\theta,\pi_t)$ to the event $\rho = 0$. If the backer pledges x, then a good project campaign succeeds with probability $S_{\alpha\sigma}(h_t + x)$. This results in an increase in utility of $ln((\alpha-1)x + w) - ln(w)$. A bad project campaign succeeds with probability $S_{0\sigma}(h_t + x)$, and in this case the backer's utility changes by $ln(-x+w) - ln(w)$. If the campaign does not succeed, all pledges are returned, and there are no gains or losses.

Definition 1. *A Bayesian Nash equilibrium is a strategy $\sigma : H \times \Theta \times W \to \Delta\mathcal{X}$ and a system of public beliefs $P_\sigma : H \to [0,1]$, such that: (i) At any time t, $\pi_t = P_\sigma(h_t)$; (ii) a backer of type (θ, w) arriving at time t pledges an amount $\sigma(h_t,\theta,w) \in BR_\sigma(h_t,\theta,w)$ satisfying (6), with $\Pi(\theta,\pi_t)$ given by (5).*

To simplify the notation, we drop the subscript σ in P_σ, S_{ρ_σ}.

Model assumptions, the institutional context

We briefly discuss how our model assumptions fit the specific institutional context of Seedrs equity crowdfunding campaigns for the period for which data were collected.[4] A campaign has 60 days to raise funds on the platform. If it does not reach the campaign goal within 60 days, all pledges are null and void. Entrepreneurs may accept pledges beyond the funding goal.[5] Backers can pledge any amount above £10. All these features are reflected in our model, with the stylistic simplification that pledges are to be in the set $\{0, 1, 2\}$, as this is sufficient to illustrate the main economic trade-offs. Further, in our model the pledge history is public information, which implies that backers do not need to actively monitor the campaign h_t. We think this assumption is reasonable because we focus on Markov equilibria. In this equilibrium a time τ backer's pledge depends on the public belief π_τ, no matter what the specific pledge history h_τ lead to such a belief.

Preliminaries

Because this is a finite game, a Bayesian Nash equilibrium exists, but there may be multiple equilibria. The multiplicity of equilibria has two sources, and both are due to the AoN clause. First, if a backer expects the campaign to fail with certainty, pledges of any size $x \in \mathcal{X}$ become optimal as they all lead to the same payoff 0. We address this by limiting attention to equilibria where the following condition is met:

Condition 1: *A backer does not pledge if she is certain that the campaign will fail.*

This condition can be justified by opportunity costs, however small.

The second source of multiplicity of equilibria is the signaling structure created by the AoN clause. When choosing whether and how much to pledge, each backer takes into account two elements. The first element is the probability that the project is of good or bad quality. This probability is the belief $\Pi(\theta, \pi_t)$ that the backer forms based on her own private signal and the public information that she deduced from past pledges. The second element is how future backers will react to this pledge. This matters because future backers' reactions will affect the

[4] Seedrs continues to change the website, and current views will be different.

[5] If entrepreneurs accept funding beyond the target, the equity increases relative to the overfunded amount, so share prices are unchanged.

probabilities $S_\alpha(\cdot)$ and $S_0(\cdot)$ that the goal will eventually be reached and hence that the backer's pledge will actually be invested. In fact, future backers will try to guess the time t backer's private signal from the amount pledged at t. This affects their beliefs about the quality of the project and hence their pledges. The resulting game boils down to a multi-period sequential signaling game in which, upon arrival, each backer simultaneously plays roles as a sender and a receiver.

Multiplicity of equilibria implies that we need to base our empirical analysis on properties that are common to all equilibria. We detail these properties here.

Proposition 1. *1. A backer's pledge is non-decreasing in her wealth.*

2. *If, at date t, the equilibrium probabilities $S_\alpha(\cdot)$ and $S_0(\cdot)$ that the campaign succeeds are non-decreasing in the size of time t backer's pledge, then time t backer's pledge is weakly increasing in her belief that $\rho = \alpha$.*

3. *If, at date t, there is no pledge, then, at date $t+1$, the public belief $\pi_{t+1} \leq \pi_t$.*

Proposition 1 states that a backer's wealth and the backer's belief that the project is good are key in determining whether and how much a backer pledges: An increase in a backer's wealth increases the size of her pledge (property 1.). $S_\rho(\cdot)$ determines whether a more or less aggressive pledge is associated with an increase in the backer's belief that $\rho = \alpha$. When larger pledges increase the equilibrium probability that the campaign will succeed, then backers' pledges are weakly increasing in their belief. In this case, large past pledges signal positive private information, this increases the public belief and hence the probability that future backers will pledge, as well as the amount that they pledge. Point 3 of Proposition 1 suggests that the absence of pledges has the opposite effect, as long as backers' pledges increases with their belief. This is summarized in the following corollary.

Corollary 1. *1. If, in equilibrium, backers' pledges are non-decreasing in their belief that $\rho = \alpha$, then*

   (a) A backer's pledge size is weakly increasing in the size of the most recent pledges and decreasing in the time since the most recent pledge.

   (b) The probability of observing a pledge is weakly increasing in the size of the most recent pledges and decreasing in the time since the most recent pledge.

(c) *For any h_t, the campaign is weakly more likely to succeed if the project is good than if the project is bad.*

2. *Under Condition 1, all backers abstain from pledging as soon as $z_\tau > \tau/2$ or $\pi_\tau < \pi^A(\tau)$, where, for any given $n \in \mathbb{N}$, $\pi^A(n)$ is the level of π_t such that*

$$\frac{\pi_t q_{\alpha H}^n}{\pi_t q_{\alpha H}^n + (1-\pi_t) q_{0H}^n} = \frac{1}{\alpha}.$$

Property 1 of Proposition 1, together with properties 1.a-1.c of Corollary 1, are key elements in our empirical strategy. Property 2 of Corollary 1 identifies situations in which, because of an excessively pessimistic belief about project quality, and too little pledging at the beginning of a campaign, backers have no strict incentive to pledge, and the campaign is doomed to fail.

Note that the size of a backer's equilibrium pledge does not depend exclusively on her belief and wealth. As we illustrate in Sections 3-4, two other factors enter the picture: the time that remains in the campaign and the amount of funds still necessary to reach the goal. Below we define a Markov equilibrium in which all these dimensions are taken into account. In Section 4 we describe how this equilibrium can be constructed by backward induction. In Section 5 we provide a qualitative description of the Markov equilibrium that we constructed and its empirical implications.

Markov equilibria: definition

Definition 2. *A strategy is* Markov *if a backer's pledge only depends on her arrival time τ, the distance to the goal z_τ, the public belief π_τ, and the backer's type (θ, w).*

The strategy $\sigma(\tau, z, \pi, \theta, w)$ describes the pledge that a backer of type (θ, w) makes if she arrives at time τ, when the distance to the goal is z, and the public belief is π. For a given pledge size $x \in \mathcal{X}$, we use

$$\sigma(\tau, z, \pi, \theta, w)[x]$$

to denote the probability that such a backer makes a pledge of x.

Definition 3. *An equilibrium is* Markov *if it is in Markov strategies.*

In a Markov equilibrium, two histories $h_{T-\tau}$ and $h'_{T-\tau}$ that lead to the same π_τ, and z_τ induces the same mapping from the type of time τ backer to her pledge.

We use

$$P(\tau, z, \pi, x)$$

to denote the next-period public belief, given that, at time τ, the public belief is $\pi_\tau = \pi$, the distance to the goal is $z_t = z$, and the cumulative pledge amount increased by x. In equilibrim this belief needs to be consistent with the strategy used by the backer at time τ. Applying Bayes's rule, for $x > 0$ one has,

$$P(\tau, z, \pi, x) = \frac{\overbrace{\pi \sum_{\theta,w} \overbrace{Q_\alpha(\theta, w)}^{Pr \text{ type } \theta,w \text{ arrives, given} \rho=\alpha} \sigma(\tau, z, \pi, \theta, w)[x]}^{Pr \text{ pledge } x \text{ given } \rho=\alpha}}{\sum_{\theta,w} \underbrace{(\pi Q_\alpha(\theta, w) + (1-\pi) Q_0(\theta, w))}_{Pr \text{ type } \theta,w \text{ arrives}} \underbrace{\sigma(\tau, z, \pi, \theta, w)[x]}_{Pr \text{ type } \theta,w \text{ pledges } x}}. \tag{7}$$

For $x = 0$, one has

$$P(\tau, z, \pi, 0) = \frac{\pi \left(1 - \lambda + \sum_{\theta,w} Q_\alpha(\theta, w) \sigma(\tau, z, \pi, \theta, w)[0]\right)}{1 - \lambda + \sum_{\theta,w} (\pi Q_\alpha(\theta, w) + (1-\pi) Q_0(\theta, w)) \sigma(\tau, z, \pi, \theta, w)[0]}. \tag{8}$$

Note that the equilibrium probability that $x = 0$ is at least $1 - \lambda > 0$, hence the r.h.s. of (8) is always well defined. By contrast, we cannot exclude that some $x > 0$ are off the equilibrium path, that is, given (τ, z, π), no backer pledges x in equilibrium, i.e., $\sigma(\tau, z, \pi, \theta, w)[x] = 0$ for all $(\theta, w) \in \Theta \times \mathcal{W}$. For off-path x, the r.h.s. of (7) is not defined, and, although it can be set arbitrarily, this must be done in a way that is consistent with σ.[6]

We use

$$S_\rho(\tau, z_\tau, \pi_\tau)$$

to denote the equilibrium probability that the campaign will succeed calculated at the beginning of time τ, given the project quality ρ, the distance to the goal z_τ, and the public belief π_τ. If a time τ a backer pledges $x \in \mathcal{X}$, then, in the next period, $z_{\tau-1} = z_\tau - x$, and the public belief is $\pi_{\tau-1} = P(\tau, z_\tau, \pi_\tau, x)$. Thus, for a given $\rho \in \{0, \alpha\}$, if the time τ pledge is x, the probability that the campaign will succeed equals

$$S_\rho(\tau - 1, z_\tau - x, P(\tau, z_\tau, \pi_\tau, x)). \tag{9}$$

[6]If σ is such that, in campaign state (τ, z, π), no backer pledges x, the off-path belief $P(\tau, z, \pi, x)$ should not induce any backer to pledge x when the campaign state is (τ, z, π).

Consider a time τ backer of type (θ, w). In equilibrium, one must have

$$\begin{aligned}\sigma(\tau, z_\tau, \pi_\tau, \theta, w) \in \arg\max_{x \in \Delta\mathcal{X}} \quad & \Pi(\pi_\tau, \theta) S_\alpha(\tau - 1, z_\tau - x, P(\tau, z_\tau, \pi_\tau, x))(\ln(w + (\alpha - 1)x) - \ln(w)) \\ + \quad & (1 - \Pi(\pi_\tau, \theta)) S_0(\tau - 1, z_\tau - x, P(\tau, z_\tau, \pi_\tau, x))(ln(w - x) - ln(w)).\end{aligned} \tag{10}$$

Clearly, the solution to (10) only depends on the Markovian state variables τ, π_τ, and z_τ and backer type (θ, w), thus leading to a Markovian strategy.

Let us see how the function $S_\rho(\tau, \cdot)$ can be obtained recursively from $S_\rho(\tau - 1, \cdot)$, using $\sigma(\tau, \cdot)$ and $P(\tau, \cdot)$. First, note that, at the campaign deadline, $\tau = 0$, regardless of the project's quality ρ, the campaign succeeds if and only if the goal has been reached, i.e., $z_0 \leq 0$. Thus

$$S_\alpha(0, z, \pi) = S_0(0, z, \pi) = \begin{cases} 1 \text{ if } z \leq 0 \\ 0 \text{ if } z > 0 \end{cases} \tag{11}$$

Now, given $S_\rho(\tau - 1, \cdot)$, the function $S_\rho(\tau, z, \pi)$ is obtained taking into account the expectation over all possible $S_\rho(\tau - 1, \cdot)$ that could result from a time τ pledge:

$$\begin{aligned} S_\rho(\tau, z, \pi) &= E[S_\rho(\tau - 1, \cdot) | z_\tau = z, \pi_\tau = \pi] \\ &= \underbrace{(1 - \lambda)}_{\text{Pr. no arrival at } \tau} \overbrace{S_\rho(\tau - 1, z, P(\tau, z, \pi, 0))}^{\text{Pr. campaign succeeds, given no pledge at } \tau \text{ and } \rho} \\ &+ \sum_{x \in \mathcal{X}} \underbrace{\sum_{\theta, w} Q_\rho(\theta, w) \sigma(\tau, z, \pi, \theta, w)[x]}_{Pr(x_\tau = x | \rho)} \underbrace{S_\rho(\tau - 1, z - x, P(\tau, z, \pi, x))}_{\text{Pr. campaign succeeds, given pledge } x \text{ at } \tau \text{ and } \rho} . \end{aligned} \tag{12}$$

In other words, at time τ: with probability $1 - \lambda$, no backer arrives. Thus, at the beginning of the next period, $\tau - 1$, one has $z_{\tau-1} = z_\tau$, and $\pi_{\tau-1} = P(\tau, z, \pi, 0)$, leading to a probability of success $S_\rho(\tau - 1, z, P(\tau, z, \pi, 0))$. With probability $Q_\rho(\theta, w)$, a backer arrives and is of type (θ, w). The probability that the backer will pledge x is $\sigma(\tau, z, \pi, \theta, w)[x]$, leading to $z_{\tau-1} = z_\tau - x$, and $\pi_{\tau-1} = P(\tau, z, \pi, x)$, and thus to the probability of success $S_\rho(\tau - 1, z - x, P(\tau, z, \pi, x))$.

In the next session , we describe how to construct a Markovian equilibrium using backward induction, and applying properties (7)-(12).

4 Markov equilibrium construction by backward induction

Note first that at any give date τ, there are two situations in which a backer knows the campaign outcome. The first situation is the case where the backer is certain that the campaign will fail, i.e., $S_0(.) = S_\rho(.) = 0$. This corresponds to result 2 of Corollary 1 and happens in two scenarios: either there is not enough time to collect enough pledges to reach the goal, or the public belief is so pessimistic that even after conditioning on each of the next τ backers having signal H, the project's expected NPV would remain negative. In both cases Condition 1 implies that there will be no pledge.

In the second situation, such as in a KIA campaign, the backer is certain that her pledge will been invested in the project. For an AoN campaign $S_0(.) = S_\rho(.) = 1$ either because the goal has already be reached, or for a backer who triggers campaign success. The next section analyzes backers' equilibrium behavior when $S_0(.) = S_\rho(.) = 1$.

KIA campaigns / Overfunding phase

Consider a backer who is certain her pledge will be invested. This is always the case for a KIA campaign. Whereas for an AoN campaign, this occurs when $z_\tau \leq 1$. We refer to this situation of an AoN campaign as the *overfunding phase.*[7] In all these situations, $S_0(\cdot) = S_\alpha(\cdot) = 1$, so that, given a level π of public belief, a type (θ, w) backer's maximization problem (10) boils down to choosing the pledge $x \in \mathcal{X}$ that maximizes the following function

$$V(x, \theta, w, \pi_\tau) := \Pi(\theta, \pi_\tau)(\ln(w + (\alpha - 1)x) - \ln(w)) + (1 - \Pi(\theta, \pi_\tau))(\ln(w - x) - \ln(w)). \quad (13)$$

The resulting strategy is weakly increasing in: the public belief π_t; in the backer's wealth; and in the backer's information.

Given a condition C, let $1_{\{C\}}$ denote the indicator function that takes value 1 if C is satisfied, and 0 if C is not satisfied. Then we have:

Proposition 2. (KIA/Overfunding) *If $z_\tau \leq 1$, then, in equilibrium, for any backer type (θ, w), there are public belief thresholds $0 \leq \underline{\pi}^{OF}(\theta, w) \leq \overline{\pi}^{OF}(\theta, w) \leq 1$, such that the backer*

[7] The same is true if the AoN campaign remains open to pledges after the goal has been reached.

pledge is

$$\begin{cases} \sigma^{OF}(\pi,\theta,w)[0] = 1_{\{\pi_\tau \leq \underline{\pi}^{OF}(\theta,w)\}} \\ \sigma^{OF}(\pi,\theta,w)[1] = 1_{\{\underline{\pi}^{OF}(\theta,w) < \pi_\tau \leq \overline{\pi}^{OF}(\theta,w)\}} \\ \sigma^{OF}(\pi,\theta,w)[2] = 1_{\{\pi_\tau \geq \overline{\pi}^{OF}(\theta,w)\}} \end{cases} \tag{14}$$

Thresholds $\underline{\pi}(.)$ and $\overline{\pi}(.)$ are decreasing in w and in the signal. That is, for the same private signal, a wealthy backer pledges weakly more than a less wealthy one. For the same wealth, backers with signal H pledge more than backer with signal M. Backers who received signal L do not pledge.

Note that, in in the overfunding phase, the backer's equilibrium strategy depends on the backer's type (θ, w), and the public belief π, but it does not depend on τ or on $z_\tau \leq 1$. Figure 1 depicts the pledge strategy in the KIA/overfunding phase as a function of the public belief for the four types of backers who pledge with a positive probability, i.e., all backers whose private signal is not L.

Insert Figure 1 about here

Last period play

In the last period of the campaign, there are only three possible scenarios. First, the campaign goal is not larger then 1, and either the campaign goal has already been reached, or it can be reached by the last pledge. Second, the distance to the goal is exactly 2, and the goal is reached only if the last backer pledges 2. Third, the distance to the goal is larger then 2, and the campaign fails with certainty. In each scenario the last backer faces no uncertainty whether the campaign will fail or succeed after she has made her pledge. We can therefore use the KIA campaign analysis to describe the equilibrium behavior in the last period of an AoN campaign.

Proposition 3. (Final period) *In the last period of the AoN campaign:*

For $z_1 \leq 1$, a backer follows the KIA/overfunding phase strategy $\sigma^{OF}(.)$.

For $z_1 = 2$, a backer pledges $x_1 = 2$, if $V(2, \pi, \theta, w) \geq 0$, and pledges 0 otherwise.

For $z_1 > 2$, a backer does not pledge.

Given the equilibrium pledge strategy in the last period, one can obtain $S_\rho(1, z, \pi)$, i.e., the equilibrium success probability at the beginning of the last period as a function of the project's quality ρ, the public belief π, and the distance to the goal z. To this purpose, it is sufficient to replace $S_\rho(0, \cdot)$, given in (11), and $\sigma(1, \cdot)$ resulting from Proposition 3 into equation (12). Figure 2 depicts the resulting $S_\rho(1, \cdot)$ as a function of the public belief π for a good quality and a bad quality project. Panel a) depicts the success probabilities for $z = 1$, and panel b) for $z = 2$. When $z > 2$ the distance to the goal is too large implying $S_\rho(1, z, \cdot) = 0$.

Insert Figure 2 about here

A few remarks about these functions. First, in each panel, for a low enough public belief, the campaign fails. Not even a positively informed wealthy backer will pledge. An increase in the public belief weakly increases campaign success probability, but this probability cannot reach one, as there is always a strictly positive probability that no backer arrives in the last period. Second, a campaign for a good quality project (dashed line) is weakly more likely to succeeds than a campaign for a bad quality project (solid line). Yet, the threshold for the public belief below which a campaign fails with certainty does not depend on project quality. Third, when comparing the two panels, one can see that when the public belief is low, the success probability is weakly larger for $z = 2$ than for $z = 1$. This is because for the same level of π, a larger distance to the goal increases the correlation between campaign success and project quality and hence backer willingness to pledge. Fourth, for π large enough, all backers who have not received a signal L pledge, and the only uncertainty is whether enough backers arrive to cover the distance to the goal. In this case a campaign that is closer to the goal is more likely to succeed.

Equilibrium construction for $\tau > 1$

Note that, in the overfunding phase and in the last period, since a backer perfectly knows whether the campaign succeeds or fails after her pledge, she does not care about the effect of her pledge on future backers' belief, and for this reason the equilibrium is unique. By contrast for $\tau > 1$ and $z_\tau > 1$, a backer affects the campaign success probability by reducing the distance to the goal but also by affecting future backers' beliefs. Hence, her optimal strategy also depends on the mapping $P(\tau,\cdot)$ from her action into the public belief $\pi_{\tau-1}$. This implies that for $\tau > 1$ the game admits multiple equilibria. That is, different pairs $\{\sigma, P\}$ can form an equilibrium.[8] Because we have already characterized $S_\rho(1,\cdot)$, the whole equilibrium can be obtained by induction for any $\tau > 1$. The idea is to start from known $S_\rho(\tau-1,\cdot)$, compute the equilibrium pledge strategy $\sigma(\tau,\cdot)$ and public belief updating rule $P(\tau,\cdot)$, and from these obtain $S_\rho(\tau,\cdot)$.

We will use the following algorithm. Consider time $\tau > 1$ and suppose that the equilibrium success probability functions $S_\alpha(\tau-1,\cdot)$ and $S_0(\tau-1,\cdot)$ are known. Start with with following rather arbitrary belief updating function $P^0(\tau,\cdot)$:[9]

$$\begin{aligned}
P^0(\tau,z,\pi,0) &= \frac{\pi}{2} \\
P^0(\tau,z,\pi,1) &= \frac{\pi+\Pi(H,\pi)}{2} \\
P^0(\tau,z,\pi,2) &= \Pi(H,\pi)
\end{aligned}$$

We then replace this belief updating rule and $S_\rho(\tau-1,z,\pi)$ in the maximization problem (10) for time τ backer, to find

$$\begin{aligned}
\sigma^0(\tau,z_\tau,\pi_\tau,\theta,w) \in \arg\max_{x\in\Delta\mathcal{X}} \quad & \Pi(\pi_\tau,\theta)S_\alpha(\tau-1,z_\tau-x,P^0(\tau,z_\tau,\pi_\tau,x))(\ln(w+(\alpha-1)x)-\ln(w)) \\
& \qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad (15) \\
+ \quad & (1-\Pi(\pi_\tau,\theta))S_0(\tau-1,z_\tau-x,P^0(\tau,z_\tau,\pi_\tau,x))(ln(w-x)-ln(w)).
\end{aligned}$$

The strategy $\sigma^0(\tau,\cdot)$ obtained in this way, however, needs not be consistent with the updating rule $P^0(\tau,\cdot)$. In particular, $P^0(\tau,\cdot)$ needs not satisfy the public belief updating rules (7) and(8), for $\sigma=\sigma^0(\cdot)$. We therefore implement an in iterative process to find $P(\tau,\cdot)$ and $\sigma(\tau,\cdot)$ that are mutually consistent. Namely, we first use $\sigma^0(\tau,.)$ in belief updating formulas (7) and (8) to find a new belief updating rule $P^1(\tau,.)$, on the path, whereas for off-path actions, we set $P^1(\tau,\cdot) = P^0(\tau,\cdot)$. In this way we obtain a new maximization problem (10) by using $S_\rho(\tau-1,z,\pi)$ and $P^1(\tau,.)$. The solution to this problem gives us $\sigma^1(\tau,.)$, from which we can deduce $P^2(\tau,.)$ using (7)-(8). We iterate the process to find $\{\sigma^2(\tau,\cdot),P^3(\tau,\cdot)\},\ldots,\{\sigma^i(\tau,\cdot),P^{i+1}(\tau,\cdot)\},\ldots$. We stop

[8]For example, take any given $\tau^* \geq 2$ and $z^* > 2$. One can choose (σ, P) to have an equilibrium in which if, at $\tau=\tau^*$, one has $z_\tau \geq z^*$, then the campaign fails regardless of the public belief π_τ.

[9]$P^0(\tau,\cdot)$ interprets no pledge, $x_\tau = 0$, as the result of no arrival or of the arrival of a backer with signal L, with equal probability; a pledge $x_\tau = 1$ as coming from an uninformed backer or from a positively informed backer, with equal probability; and a pledge $x_\tau = 2$ as coming from a positively informed backer.

the iteration when $P^i(\tau,\cdot) = P^{i-1}(\tau,\cdot)$ as we have identified a pledge strategy $\sigma(\tau,\cdot) = \sigma^i(\tau,\cdot)$ and public belief updating rule $P(\tau,\cdot) = P^i(\tau,\cdot)$ that are mutually consistent and form an equilibrium. That is, $\sigma(\tau,\cdot)$ solves maximization problem (10), given the updating rule $P(\tau\cdot)$, and $P(\tau\cdot)$ satisfies updating formulas (7) and ((8) given the strategy $\sigma(\tau,\cdot)$. [10]

We can now use expression (12) to compute $S(\tau,\cdot)$ starting from $S(\tau-1,\cdot)$, $\sigma(\tau,\cdot)$ and $P(\tau,\cdot)$. We use this algorithm to numerically compute the equilibrium in a campaign lasting $T = 30$ periods and with a goal of $Y = 20$. The other exogenous parameters are : $\alpha = 3$, $\lambda = 0.8$, $q_{\alpha H} = 0.6$, $q_{\alpha M} = 0.4$, $q_{\alpha L} = 0$, $q_{0H} = 0.2$, $q_{0M} = 0.4$, $q_{0L} = 0.4$, $w_1 = 1.55$, and $w_2 = 2.55$. Details are given in Appendix A.

5 Qualitative description of the equilibrium and empirical implications

Success probability and campaign state variables

Let us now consider how the probability of success for the campaign $S_\rho(\tau,z,\pi)$ depends on the project's quality ρ and the campaign Markov state (τ,z,π). We have seen that pledges tend to be increasing in the public belief, thus a high π in general is associated with a higher probability of campaign success. Also, as long as the campaign is not in an abstention cascade, the probability of campaign success increases with the time that remains until the deadline, as more backers are expected to visit the campaign site and possibly pledge. The monotonicity of S_ρ in π and τ applies to both good quality and bad quality projects and is illustrated in Panels (a) and (b) of Figure 3. How the distance to the goal z affects the probability of success depends on the level of the public belief and the magnitude of z. When z is large enough compared to τ, the bigger it is, the lower the probability of success. This is because the larger is the ratio z/τ, the greater the likelihood that an insufficient number of backers will visit the campaign site by the deadline. For a small z, the effect of an increase in z depends on the level of the public belief. If π_τ is high enough to induce large pledges, the same mechanism applies, and S_ρ decreases with z (see Panel (c) of Figure 3, where $\pi_\tau = 0.8$). When both z and the public belief are relatively small, success only requires a pledge by one or two backers. This implies that the information content of the campaign outcome is small, and, given the low π_t, backers prefer

[10] If, for some values of (z,π), and after iteration $i = 20$ the process does not converge, the equilibrium must be in mixed strategies. We then identify the (π,z,θ) for which σ does not converge and approximate the equilibrium strategy by mixing $\sigma^i(\tau,\pi,z,\theta) = \sigma^{19}(\tau,\pi,z,\theta)0.5 + \sigma^{20}(\tau,\pi,z,\theta)0.5$.

to abstain, rather than directly trigger success. Larger z implies that campaign success occurs only if enough backers pledge. As the correlation between campaign success and the quality of the project increases, backers' willingness to pledge increases and hence so does the probability of success. The effect of z on S_ρ for low values of public belief ($\pi_\tau = 0.2$) is illustrated in Panel (d) of Figure 3.

Insert Figure 3 about here

Pledging strategy

In equilibrium, a backer's pledge is non-decreasing in his wealth and in his private signal. To understand the effect of campaign-state variables (τ, z, π), let us see how they affect the ratio $\frac{S_\alpha(\cdot)}{S_0(\cdot)}$, as this is a key element driving backers' behavior. We have shown that a campaign for a good project is weakly more likely to succeed than a campaign for a bad project, that is, $\frac{S_\alpha(\cdot)}{S_0(\cdot)} \geq 1$. The greater the ratio $\frac{S_\alpha(\cdot)}{S_0(\cdot)}$, the stronger is the correlation between a campaign's successful outcome and the good quality of a project. Thus, a greater $\frac{S_\alpha(\cdot)}{S_0(\cdot)}$ induces backers to pledge more.

Let us define the *required pledge ratio* as the ratio z/τ, i.e., the minimum amount that needs to be invested on average in each remaining period for the campaign to succeed.

When the required pledge ratio z/τ is large, the probability of campaign failure is also large, just because not enough backers will have time to visit the campaign site.[11] Because this probability does not depend on ρ, *ceteris paribus*, a high z/τ is associated with a low ratio $\frac{S_\alpha(\cdot)}{S_0(\cdot)}$ and hence few pledges. That is, a high required pledge ratio is associated with campaigns that do not take off.

Take a τ substantially larger than z such that the risk of campaign failure *because* due to an insufficient number of backers visiting the campaign site is small. Then, the larger is z, the greater is the number of backers with signal H who need to visit the campaign site for the goal to be reached. The probability that a large number of backers arrives is greater if $\rho = \alpha$ than if $\rho = 0$, and the more so when z is larger. Thus, for intermediate values of z/τ, the ratio $\frac{S_\alpha(\cdot)}{S_0(\cdot)}$

[11]For example, the campaign certainly fails at $z/\tau > 2$.

is large, implying that backers' willingness to pledge is high. At the beginning of a campaign, as long as the campaign goal is not too ambitious, the required pledge ratio is moderate.

The opposite reasoning applies when the required pledge ratio is low, for example, when only a few pledges remain for the goal to be reached. However, the probability that pledges exceed a small z is similar for good and bad projects, implying that $\frac{S_\alpha(\cdot)}{S_0(\cdot)}$ is relatively small. This, then, actually dampens backers' willingness to pledge.

When the required pledge ratio is fixed, the ratio $\frac{S_\alpha(\cdot)}{S_0(\cdot)}$ is an inverse-U shape of the public belief. That is, for a π close enough to 0, no backer pledges, and hence $S_\alpha(\cdot) = S_0(\cdot) = 0$. For a π close enough to 1, all backers are persuaded that the project has high quality, their private signals have a small effect on their pledge, and the probability of success depends mostly on backers' arrival, which is independent of ρ, implying that $\frac{S_\alpha(\cdot)}{S_0(\cdot)} \simeq 1$. By contrast, for a π around 0.5, the sensitivity of pledges to their private signal is at a maximum, thus maximizing the ratio $\frac{S_\alpha(\cdot)}{S_0(\cdot)}$.

Model empirical implications

With these considerations in mind, the model generates testable predictions that we can apply to the data. We focus on predictions that are common to all Markov equilibria, in which backers' pledges are non-decreasing in their belief that the project is good and for which we can develop a clear identification strategy, given the data constraints.

Empirical predictions that we test:

1. *A backer's pledge size is weakly increasing in the size of the most recent pledges.*

2. *A backer's pledge size is decreasing in the time since the most recent pledge.*

3. *The probability of observing a pledge is weakly increasing in the size of the most recent pledges and decreasing in the time since the most recent pledge.*

4. *The pledge size and the probability of a pledge both take an inverse-U shaped pattern as a function of the ratio z_τ/τ and are nil when this ratio is large enough.*

How wise can the crowd be?

We have seen that a campaign is more likely to succeed if the project is good than if the project is bad. But how efficient is the AoN crowdfunding mechanism in financing good-quality projects and rejecting poor-quality projects? This can be measured by the equilibrium probability of success at the beginning of the campaign, $S_\alpha(T, Y, \pi_0)$ and $S_0(T, Y, \pi_0)$. The closer $S_\alpha(T, Y, \pi_0)$ and $1 - S_0(T, Y, \pi_0)$ are to 1, the more efficient is the selection resulting from the aggregate behavior of backers. Another measure of project-quality selection efficiency is the proportion of the financed projects that are good projects, that is, the ratio $\frac{S_\alpha(T,Y,\pi_0)}{S_\alpha(T,Y,\pi_0)+S_0(T,Y,\pi_0)}$. Our numerical calculations of the equilibrium values of $S_\rho(.)$ suggest that quality-selection efficiency depends in a non-trivial way on the level of the goal Y. This is illustrated in Table 1. The larger is Y, the smaller is $S_0(T, Y, \pi_0)$. The table shows that the equilibrium is extremely effective at rejecting unprofitable projects, the more so when Y is larger. Equity crowdfunding campaigns' ability to finance profitable projects is non-monotonic in Y. When the goal Y is small, a few pledges can enable the success of the campaign. However, because the success of the campaign depends on the pledges of only a few backers, the campaign outcome has little information content about the project's quality, i.e., the ratio $\frac{S_\alpha(T,Y,\pi_0)}{S_0(T,Y,\pi_0)}$ is close to 1. Thus, the risk that pledges will eventually be invested in poor-quality projects is not negligible, and this induces risk-averse backers to hesitate about pledging. The overall effect is a relatively low level of $S_\alpha(T, Y, \pi_0)$. The ratio $\frac{S_\alpha(T,Y,\pi_0)}{S_0(T,Y,\pi_0)}$ quickly increases for higher levels of the goal Y. This increased correlation between campaign success and project quality induces more backers to pledge or make larger pledges. This initially increases $S_\alpha(T, Y, \pi_0)$ with Y. However, when the goal Y is too ambitious, the probability that an insufficient number of backers will visit the campaign site by the deadline grows, which reduces the probability of achieving the goal even for a good-quality project.[12]

It is interesting to compare these probabilities across two polar cases. First, the full information case in which all backers who arrive have their signal disclosed and success occurs only if the expected return on the project is positive, conditional on all backers' signals. Because signal L is perfectly informative of a bad project, this can be approximated by the following rule: finance the project if and only if no backer receives signal L.

Using the same parameter values as those that we used to build Table 1, the resulting probability of financing a good project is almost 1, whereas the probability of financing a bad project is close to zero. The opposite case is a situation in which the project is financed if and only if the first backer's signal is H. This represents an extreme form of naïve herding.

[12]Empirical research, indeed, shows an overwhelming negative correlation between Y and the probability of achieving the goal. For one example, see Vulkan et al. (2016). We did not find any other articles that examine the conditional non-linearities in the relationship proposed here.

A good-quality project is financed with the probability $\lambda q_{\alpha H} = 0.48$ whereas a bad project is financed with the probability $\lambda q_{\alpha L} = 0.16$.

Insert Table 1 about here

To qualitatively describe how the dynamics of pledges differ depending on campaign success and whether the project is of good or bad quality, we used our Markov equilibrium strategy to numerically simulate pledges in 50,000 campaigns. This simulation is illustrated in Figure 4. A few remarks are noteworthy: First, the average pledge size tend to decrease over the life of the campaign. Second, campaigns that succeed tend to have a substantially better start than campaigns that fail. Third, after the goal has been reached, campaigns for bad projects lose momentum much more quickly than campaigns for good projects.

Insert Figure 4 about here

6 Data, variables, and descriptives

The data come from the equity crowdfunding platform Seedrs. Information was made available to us directly by Seedrs and comprises the full universe of campaigns from October 2012 until March 2016. Filtering the data yielded 710 campaigns, 22,615 unique backers, and 69,699 pledges.[13] For each project, we have information about the date that the campaign started raising funds, the declared funding goal, the pre-money valuation of the company, and the timing and value of each pledge received while the campaign was in progress. Each pledge is also matched to a specific investor, associated with some descriptive investor data, so that we can analyze the behavior of both individual campaigns and individual backers. Variable definitions are displayed in Table 2.

Insert Table 2 about here

[13] Seedrs allows investors to withdraw pledges before a campaign closes. We dropped all pledges made and later withdrawn, which are close to 12,373. All estimations shown in the article are replicated to include the withdrawn pledges, and the results remain qualitatively unchanged.

We provide descriptive statistics at the campaign level in Table 3.[14] Out of the 710 campaigns, 243 (34.2%) were successful in meeting the funding goal. The average campaign goal was £174,215, but the amounts sought by individual projects varied widely, from £2,500 to more than £1,600,000. These funding goals correspond to average equity offered (in pre-money valuation terms) of 12 percent. The funding goals and pre-money valuations of the campaigns on Seedrs present a sharp contrast to those of other non-equity crowdfunding schemes. For example, in a study of more than 48,500 rewards-based projects, Mollick (2014) shows that the average funding goal on *Kickstarter* is less than $10,000, much lower than is observed in our sample. The main analysis is performed with campaign fixed effects, effectively controlling for all cross-campaign variations in characteristics such as the pre-money valuation.

Insert Table 3 about here

Although hidden from other investors, we have information on potential investors' self-selection into one of three groups: 'authorized', 'sophisticated', and 'high-net-worth' (see Table 2 for definitions). These options are required for regulatory purposes. Most backers in a campaign (79%) are 'authorized', and the rest are either 'sophisticated' (7%) backers or 'high-net-worth' (14%) backers. Approximately 23 percent of the investors on Seedrs are recurrent, meaning that they have made pledges in more than one campaign, and such investors represent on average 73 percent of the pledges to a campaign.

The average pledge is £1,202. It is much smaller for authorized backers (£931) than for high-net-worth backers (£3,696), while sophisticated backers pledge on average £1,894. Recurrent investors pledge £897 on average, which is three times less than for one-time investors.

Some suggestive patterns appear in the descriptive statistics. First, early performance appears to be a major predictor of the likelihood that a campaign will reach the funding goal. Successful campaigns raise, on average, close to 75 percent of the goal in the first week. Failed campaigns, however, never really get started. Halfway through the time period until the deadline, these projects raise only about 15 percent of the total sought. Campaigns that fail to raise the desired capital tend to do so by a large margin, whereas most successful campaigns overfund, on average by 110 percent of the target. A few large pledges also appear to have a

[14] Vulkan et al. (2016) analyze cross-campaign data from the same platform. In this article, we report updated figures for a longer data series.

major role in driving the success of a campaign. The largest pledge in an average campaign represents a full 15 percent of the goal, and for the average successful campaign, it accounts for about 31 percent of the total investment sought.

7 Empirical strategy

We have detailed information on the timing of investment decisions, and we can also reconstruct the information available to all backers on the platform at the moment of every investment. We use these features of the data to analyze whether investors act as predicted by our model.

We start by providing scatter plots of the relation between the size of a pledge and the size and timing of the most recent pledge. The first two empirical predictions in Section 3 state that the pledge size should be *increasing* in the size of the most recent pledges, but *decreasing* in the time since the most recent pledge. Figure 5 shows suggestive evidence to support this prediction.[15] We find a positive correlation between the amounts pledged by the current and the most recent backers in a campaign, with a slope of the linear fit of the variables (in logs) estimated at around 0.32. Also consistent with the model is the negative correlation between the time since the most recent pledge and the amount pledged, in which the slope of the linear fit (in logs) is estimated at around -0.07.

Insert Figure 5 about here

The model states that some information content is found in the most recent pledges, not just the most recent. The current backer cannot fully deduce the public belief from the size of the most recent pledge because that pledge also depends on the backer's wealth. Therefore, to obtain an idea about the public belief, a potential backer needs to observe several recent pledges. Figure 6 shows support for this prediction. The construction of the figure is similar to that of Panel (a) of Figure 5, but each panel corresponds to a different lagged 'distance' between the pledges. For example, Panel (a) replicates the results when we look at correlations between adjacent pledges, Panel (b) looks at the correlation between the nth and $n-2$ pledges in a campaign, while Panels (c) and (d) display correlations between the nth to the fifth-lagged

[15] To construct the figure, we first organize all pledges in a campaign into bins of 5 log points according to the size of (Panel (a)), and time since (Panel (b)), the most recent pledge. We then calculate the average amount pledged in each bin. The figure reports the scatter plot and the correlation between the median point of the bin and the respective averages.

pledge. The slope of the linear fit of the variables (in logs) declines monotonically, going from 0.32 between the current and most recent pledge, to 0.16 between the nth and the $n-5$ pledge, suggesting that the most informative pledge about the public belief is the most recent and that the prior four pledges matter but have decreasing importance.

Insert Figure 6 about here

Baseline econometric model

We now formalize the identification strategy.[16] Let all backers who make pledges to a campaign c be ordered according to the arrival time of the pledge. Let $I_{n,c}$ be the amount pledged by the nth backer after the start of the campaign c. Let $T_{(n,n-1),c}$ be the time (in hours) between the $n-1$ and the nth pledges made to the campaign c. We first estimate a distributed lag model of the form:

$$\log I_{n,c} = \sum\nolimits_{k=1}^{5} \beta_k \log I_{n-k,c} + \beta_6 \log T_{(n,n-1),c} + \alpha W_{n,c} + \gamma Z_{n,c} + \eta_c + \epsilon_{n,c}, \tag{16}$$

where our interest is in the estimates of the beta coefficients accompanying the values of the investment lags $(\beta_1, ..., \beta_5)$ and the time since the most recent pledge (β_6). If correctly identified, these estimates can be interpreted as the effect of the size of the most recent pledges on a backer's pledge or the effect of the time elapsed since the most recent pledge on a backer's pledge.

We need to address three main identification challenges: (i) selection of investors in campaigns; (ii) the dependence of the pledge size on the state of the campaign and backers' characteristics; and (iii) non-random bunching of pledges or correlated backer types in campaigns. We deal with these issues in part with the inclusion of campaign fixed effects (η_c) and a broad set of controls included in the vectors $Z_{n,c}$ and $W_{n,c}$, which we discuss in detail in Appendix B. These variables characterize the state of each campaign at any point in time in a flexible way and account for the heterogeneity in backers' characteristics. However, even with the controls included in the model, the predicted pledge dynamics could still be rationalized by unobserved correlated signals or coordination among investors. To disentangle these alternative

[16] In this section, we provide a succinct description of the identification strategy. For a comprehensive discussion, see Appendix B.

mechanisms from the one proposed in the model, we complement the empirical strategy with two alternative instrumental variable (IV) approaches.

Instrumentation strategy (A). In an ideal scenario, we would change the amount pledged by a random set of investors and analyze whether subsequent pledges respond to these changes. We cannot experimentally vary the amounts pledged, but we have indicators for investor liquidity and level of wealth, which the model predicts will affect the pledge size in a manner that is consistent with the exclusion restriction. The AoN clause says that if a campaign fails, the amounts pledged are returned to the backers. The money that is returned can then be used by recurrent investors for pledges in future campaigns, in which the extra liquidity can be thought of as unexpected (i.e., a windfall). The unexpected liquidity should increase the size of future optimal investments via a wealth effect (Property 1 of Proposition 1), satisfying the relevance condition. In the absence of a high degree of coordination and communication among investors, a scenario we discuss in Appendix B, the fact that a backer receives a windfall from the failure of a previous campaign is not known to other backers, so there is no other plausible reason for it to affect their pledges, thus satisfying the exclusion restriction. The instrument is then defined as the inverse hyperbolic sine (IHS) transformation [17] of the total amount returned to a backer in the last failed campaign in which she invested, conditional on the failure of that campaign before campaign c started.

Instrumentation strategy (B). One pitfall with our preferred (money returned) IV is that the instrument can only affect a small fraction of pledges (8.6 percent). We use a second set of instruments for $\log I_{n-k,c}$ to validate the results. Intuitively, we use information on previous pledging behavior and investor profiles that we observe in the data but that subsequent backers do not observe. All backers making a pledge for a project appears on the campaign's page, but they can choose whether to have their names and profiles be made public or remain anonymous. For backers who choose to be anonymous, only the amount pledged is displayed, therefore no information on the anonymous backer can be inferred in any way by a subsequent backer. Although the past investment history of backers with anonymous profiles is not public, we have access to it in our data set. We use this information to construct variables that contain relevant information to predict the wealth of an anonymous investor and hence the size of a pledge,

[17] The IHS transformation can be interpreted in the same way as the standard logarithmic transformation, but it has the property of being defined at zero. This is important because a large number of investors have invested only once on the platform or have not pledged to a failed campaign before.

but that is not observed by subsequent backers, so it cannot directly influence their pledging behavior.

We use two pieces of information as instruments for each prior pledge ($\log I_{n-k,c}$):[18] (1) the total number of pledges made by the investor $(n-k)$ in all previous campaigns before campaign c started interacted with the anonymous indicator; and (2) the largest single amount pledged by the backer $(n-k)$ in previous campaigns interacted with the anonymous indicator. Recurrent backers tend to make smaller pledges than single-campaign backers, so the first instrument is expected to have a negative correlation with pledge size. However, backers who have previously made large pledges are potentially wealthier (Property 1 of Proposition 1), so the second instrument is expected to have a positive correlation with pledge size.

Econometric model in discrete time

The design of the platform is such that information is updated on an hourly basis. It is then possible that backers who arrive within the same hour might not be able to know the exact timing or size of recent contributions, nor could they distinguish in time between multiple contributions made within the same hour. On average, the time between adjacent pledges is 11.2 hours, so we do not expect this to be a major limitation, nevertheless we estimate an alternative specification of the model that accounts for these features.

For the alternative specification, we expand our data set so that the total duration of a campaign is divided into one-hour bins, indexed by $t \in \{0, ..., T_c\}$. We now define $I_{t,c}$ as the total amount invested in campaign c at the hourly bin t, in which the value is zero if no investments were made or the sum of all positive investments within the respective hour. The model takes the form:

$$(\text{IHS})I_{t,c} = \sum\nolimits_{k=1}^{5} \beta_k (\text{IHS})I_{t-k,c} + \beta_6 \log H_{t,c} + \gamma Z_{t-1,c} + \eta_c + \epsilon_{t,c}, \tag{17}$$

where $H_{t,c}$ is the number of hours since the last bin in which a positive pledge was made to campaign c. Given the large number of observations for which the amount invested in the hourly bin is zero, the amount pledged is transformed using the IHS transformation. The vector $Z_{t,c}$ includes the same variables as the main specification, but each variable is now defined as the

[18] By using two instruments for each pledge, the model is overidentified, so we can report standard Hansen test statistics for overidentifying restrictions.

maximum value of $Z_{n,c}$ over the last hourly bin $(t-1, c)$.

The interest remains in the same set of parameters $(\beta_1, ..., \beta_5, \beta_6)$, but the interpretation of them differs slightly. They are now interpreted as the effect of an increase in the amount invested in most recent hourly bins or the effect of the time elapsed since a positive pledge on a campaign's hourly contributions. The identification strategy remains the same, but the windfall instrument for investment lags is now defined as the sum of money returned to investors who pledged in the respective lagged hourly bin, where the value is zero if there were no investments or if no backer in that bin had money returned from previous failed campaigns. The alternative instruments are defined in an equivalent way, but we use averages over the respective hourly bins, instead of adding the value of the instruments.

8 Empirical results

Predictions 1 and 2. The results of estimating Equations 16 and 17 are shown in Tables 4 and 5 respectively. We present estimates for six specifications, with and without the instruments and varying the sets of controls included. The F-statistic on the excluded instrument for each first stage is shown at the bottom of the table. In all cases, the value of the statistic is above 18, which indicates that the instrument has sufficient power.hen it applies, we also report the result from Hansen's overidentification test at the bottom of the table. We cannot reject the null hypothesis that the instruments are valid at standard levels of significance.

Examining Prediction 1 of the model, we find that backers who immediately follow pledges with a larger value, on average, invest higher amounts in the campaigns. Also consistent with the model, we find that this relation is stronger when the pledges are 'closer' to each other. To get a sense of the magnitude, consider first the results from our preferred specification using instrumentation strategy (A) (Column IV-A) in Table 4. The estimates imply that doubling (100% increase) the value of the most recent pledge is associated with a rise of 10.6 percent in the subsequent amount pledged. For example, if the most recent backer pledged not the average amount (£1,202) but twice that number (£2,404), it would translate into £127 of extra investment for the subsequent backer. This can be a non-trivial amount for an individual investor, but, taken in isolation, the extra £127 only represent 0.07 percent of the average investment sought across campaigns, so it will not be enough by itself to change the fate of a campaign. The magnitude of the effect also dissipates rapidly: for the backer corresponding to the second-most-recent pledge, the size of the estimated coefficient declines to 9.0 percent for a similar change, but it is no longer statistically significant at standard levels. The point estimates tend to be stable across specifications, even in a comparison of IV and OLS estimates or alternative IVs.

Insert Table 4 about here

The discrete-time version of the model paints a similar picture (see Table 5). In our preferred specification (Column IV-A), doubling (100% increase) the total amount invested in the previous hour is associated with a rise of 16.7 percent in a campaign's total contribution over the next hour. The average hourly contribution in a campaign is £106, which is low, reflecting that the average frequency of investment per hour is 0.08, so the 16.7 percent increase translates into £17.7 of extra investment in the hour. We again find that the magnitude of the effects monotonically decreases as we consider the response to total contributions in more remote hourly bins. For example, for the fifth hourly bin lag, the estimated effect is about a third of that of the first lag. We again find very stable estimates across specifications.

Insert Table 5 about here

Examining Prediction 2, we find that the time since the most recent pledge is negatively correlated with the size of a pledge, which is consistent with the model's prediction. In our preferred specification in Table 4, doubling (100% increase) the time since the last pledge is associated with a fall in the pledge size of 7.3 percent. For example, if the number of hours between two pledges increases by half a day (doubling of the average), a pledge of average size is predicted to decline by close to £88. In this case, however, estimates are less precise, and the effect is only marginally significant. The corresponding estimated effect in the preferred specification of the discrete-time version of the model is almost exactly the same, with a point estimate of -0.079, so a doubling of the time since any activity occurred in an hourly bin results in total hourly contributions that are about £8.4 lower. In this case, the estimates are more stable across specifications, and they are all statistically significant at standard levels.

Both descriptive and econometric evidence thus suggests that backers respond to the size of the most recent pledges and to the time since the arrival of the most recent pledge in a way that is consistent with Predictions 1 and 2 of our model of rational information aggregation.

Prediction 3. The third empirical prediction states that the probability of observing any positive pledges during a time interval is weakly increasing in the size of the most recent pledges and decreasing in the time since the most recent pledge. This prediction is closely related to the previous two, but the emphasis is on the extensive, rather than intensive, margin of investment. To test whether the prediction is consistent with the data, we use the discrete-time version of the econometric model but change the dependent variable, called $DI_{t,c}$, which is a dichotomous indicator of activity in campaign c at the hourly bin t. The linear probability model takes the form:

$$DI_{t,c} = \sum_{k=1}^{5} \beta_k (\text{IHS}) I_{t-k,c} + \beta_6 \log H_{t,c} + \gamma Z_{t-1,c} + \eta_c + \epsilon_{t,c}. \quad (18)$$

Results presented in Table 6 show evidence that the data are consistent with the prediction. In our preferred specification, the likelihood of observing a pledge at any given hour increases by 2.2 percentage points after a doubling in the amount pledged during the previous hour. Because the unconditional chance of observing a pledge is around 6.2 percent, the magnitude of the effect is considerable: nearly a 35.4 percent increase in the probability of observing a pledge. The effect decreases monotonically when hourly contributions farther back in time are considered. In the alternative IV model (column IV-B), we marginally reject the null hypothesis that the instruments are valid, so the estimates should be interpreted with this caveat in mind.

Increasing the number of hours since any activity occurred in the campaign has a negative effect on the probability of observing pledges in an hourly bin. In the preferred specification, doubling the number of hours without positive pledges lowers this probability by 0.7 percent. This can also be seen clearly in Figure 7, in which we plot the unconditional share of hourly bins with positive pledges as a function of the hours since the most recent activity in a bin, an estimate of the hazard function. There is a clear negative correlation between the length of time without positive pledges and the likelihood of observing a pledge.

Insert Table 6 about here

Insert Figure 7 about here

Prediction 4. The last empirical prediction states that backers will not pledge if the amount that remains until the goal is reached, relative to the time left in the campaign (z_τ/τ), is large enough. The campaign is then in a precarious situation. The fundraising goal is far from achieved, and relatively little time remains to do so, leading to pessimistic beliefs about the quality of a project. The qualitative description of backers' equilibrium strategy goes even further (see Section 5), suggesting that the dependence of pledge sizes on z_τ/τ is (asymmetrically) *inverse-U-shaped*. This is partly explained by the effect of the odds-ratio of campaign success $\frac{S_\alpha(\tau,z,\pi)}{S_0(\tau,z,\pi)}$ on equilibrium pledges. When z_τ/τ is small, the campaign is close to the goal, but every pledge can be decisive in achieving success in the campaign, so investors are relatively cautious. For intermediate levels of z_τ/τ, it is generally the case that the campaign still has some time to go, so arriving backers might be more aggressive because they count on the campaign's success only if the project is good (i.e. if enough arriving backers have positive signals, which is more likely for a good project). Finally, when z_τ/τ is large, the campaign is doomed to fail, so there is little reason to invest.

Figure 8 shows that the data are consistent with the aforementioned *inverse-U-shaped* pattern. For the upper percentiles of $z_\tau/\tau Y$, the probability of observing a positive pledge is the lowest, consistent with backers abstaining from support for campaigns that appear to be doomed. Both the average amounts pledged and the probability of observing a pledge are the highest at intermediate (but low) percentiles of $z_\tau/\tau Y$, declining again for the lowest values of $z_\tau/\tau Y$.

Insert Figure 8 about here

Early campaign dynamics, probability of success. The model generates additional empirical predictions that we cannot formally test, but for which we can provide some suggestive evidence. We consider two. The first predictions is that, when the public belief that a project is good is extreme, either very high or very low, the information content of recent pledges becomes less important. Variation in pledge sizes in this scenario mostly reflect variation in wealth and private signals, which we assume are independent across backers.

We do not observe the public belief, but we can use some features of the crowdfunding platform to try and approximate it under specific circumstances. Before a campaign goes live on the platform, Seedrs allows entrepreneurs to have a *private phase* in which the campaign landing page is accessible only to those who were privately invited.[19] Most, but not all, campaigns on Seedrs use this feature. The data include information on the amounts raised during a campaign's private phase, which we use as a proxy for the ex-ante probability that the project is good (π_0). The expectation is that backers in campaigns in which a relatively large share of the goal was raised before it went live —which presumably have a large initial public belief —on average are less responsive to previous backers' pledges.

Table 7 reports estimates of Equation 16 using our preferred money-returned instrument for three samples: (1) all campaigns, (2) campaigns that reached 35% or less of their goal in the private phase, and (3) campaigns that reached more than 35% of their campaign goal in the private phase. The 35% threshold corresponds to the 80th percentile of the cross-campaign distribution of amounts raised in the private phase.[20] For campaigns that generated a strong initial public signal, the coefficient on the most recent pledge is almost half of that of campaigns that did not perform as well in the private phase. The same is true for the responsiveness to time without pledges, which is only significant in campaigns with weaker private phases. Although not direct proof, these results are consistent with the theoretical prediction.

Insert Table 7 about here

The second prediction is that the dynamics of successful and failing campaigns are different from the outset. Because there are more (less) backers with good signals if the project is of good quality, in equilibrium, the campaign is more likely to succeed if the project is of good quality than if it is of poor quality. Moreover, a bad project is unlikely to get any traction and will be doomed from an early stage of the campaign.

We start with some descriptive information of what typically happens at the outset of successful and unsuccessful campaigns. Figure 9 shows the average and median (across campaigns) number of backers (Panel(a) and (b)), and the average and median (across campaigns) cumulative amount invested (Panel(c) and (d)), for each day that a campaign is active in its public phase. We report two series: one for successful campaigns and one for unsuccessful

[19] Having a private phase is a common strategy on most crowdfunding platforms, including Indiegogo and Kickstarter. It is often associated with significant traditional fundraising efforts, such as private meetings with potential investors, as well as larger arranged fundraising events.

[20] Other possible cut-offs for defining good and bad private phases generated qualitatively similar results.

campaigns. The figure shows clear differences between successful and unsuccessful campaigns. On average, campaigns that end up raising the funding goal can attract both more backers and more capital during the first days. Moreover, as predicted by the theory, failed campaigns never get much traction and, at least on average, are unable to rebound later, after having had a bad start.

Insert Figure 9 about here

We now formalize the graphical evidence in a regression framework, and we make use of the fact that, as described before, most campaigns contain, first, a hidden private phase and, then, a public phase. For the public phase that immediately follows, the outcome of the private phase provides a public signal about private-phase backers' opinion of the project's quality on the first day of the public phase. Table 8 reports the average marginal effect of a change in a set of measures of campaign support in the private phase on the probability of a campaign's ultimate success. In particular, we are interested in changes in the probability of success with the (log of) total cumulative investment in the private phase of a campaign. The table reports coefficients and estimated margins from two probit specifications: the first without any additional controls; and second controlling for predetermined characteristics of the campaign (pre-money valuation, campaign goal, number of entrepreneurs, and access to tax incentives for investors).[21] The models also contain year * month of start campaign fixed effects.

Insert Table 8 about here

The econometric results are in line with the prediction that early campaign support is strongly correlated with the probability of campaign success. For example, an increase of one standard deviation in the log cumulative investment covered during the private phase is associated with a probability of success that is 24 percentage points larger in the model with the full set of controls. Interestingly, the number of backers has a much lower impact on the probability of success than the sum of the amounts pledged by them. Note also that the funding

[21]The standardized effect is calculated by multiplying each variable's standard deviation by the respective average marginal effect. Of course, this is only an approximation because the effects are non-linear by assumption, so they should be understood with that caveat in mind.

goal is also strongly and negatively correlated with the chance of a campaign's success. This is consistent with our model prediction in Table 1 that $S_\rho(T, Y, \pi_0)$ decreases for a large enough Y.

The fact that we can only use campaign-level variation to explore the determinants of the probability of campaign success implies that we cannot control for campaign-specific characteristics. This is a limitation that impedes causal interpretation of these specific results. The evidence reported in Table 8 must be assessed with caution.

9 Discussion and conclusions

In this article, we provide a detailed study using micro-level data on investment by the crowd on a major equity crowdfunding platform. Equity crowdfunding is an important and rapidly growing economic phenomenon. It has already had a significant impact on early-stage funding in the UK and is likely to become an important avenue for entrepreneurial finance in the US in years to come as regulations about its provision were recently introduced.

Herding is likely common in all types of crowdfunding. It is what we expect in a situation with so much uncertainty. When the crowd herds, entrepreneurial projects that should have been funded might not be funded, and vice versa. However, through the process of information aggregation, the crowd can provide information about the value of entrepreneurial projects in the absence of much other information. We develop a micro-founded model that captures what we believe is the main rational information aggregation process on one investment platform. The model can predict much of the dynamics of campaign funding based on the random arrival of investors with different private information about the projects. The model specifies the value of the information aggregated from the public without resorting to costly signaling efforts. Importantly, the model is matched to the design of a specific crowdfunding site that displays the arrival and size of each individual pledge by the hour to a potential investor. Not all crowdfunding platforms provide this detailed level of information. For example, Crowdcube, the other major equity crowdfunding platform, and Kickstarter and Indiegogo, the two major rewards-based platforms, decline to report each individual pledge.

We show that the amount pledged and the probability of a pledge in a campaign are robustly affected by the size of the most recent pledges. This is because a large pledge signals to the public that the backer making the pledge might know something about the project that others might not. This, in turn, might cause subsequent investors to alter their investment strategies, even though they do not actually observe the information on the investor making the pledges. The model also predicts that the time elapsed since the most recent pledge has a negative effect on the amount and probability of a pledge. This is because the absence of pledges indicates that investors in the campaign are not arriving with sufficiently good private signals. Our IV estimates are similar in size to the OLS estimates, and the standard errors of our key point estimates generated from the two methods overlap, suggesting that aggregation of rational information captures all the pledge-on-pledge correlation in the data.

We estimate that doubling a pledge causes the next pledge to increase by 10.6 percent. Taking a typical pledge size of approximately £1,200, that is £127 of extra investment. Given that the average investment sought is approximately £170,000, it seems that this effect in isolation would not make a big difference to campaign success.

Consistent with other studies about early campaign dynamics in crowdfunding, and based on a few experimental articles in which small pledges were randomly made at the very beginning of a campaign, we show that the probability of a campaign's success depends largely on the support it receives at the early stage of fundraising. The model rationalizes why low or absent early pledges have a negative effect on the initial public belief about the project. Lack of support for a campaign indicates that only a few arriving investors have positive signals. Having a bad start makes potential backers more pessimistic about whether the project is of good quality, so they either pledge lower amounts or decide not to invest at all. In this context, an abstention information cascade could occur at the outset, and failed campaigns end up missing the mark by a large margin. Having a good start, by contrast, makes signals from pledges made later have less informational value. The empirical results are consistent with the crowd's ability to aggregate information rationally, at least for campaigns that do not have a very bad start.

The theoretical model has specific implications for understanding the dynamics of equity crowdfunding campaigns under the AoN fundraising structure. One implication of the model is that pledges are also affected by the ratio of the amount of money that still needs to be raised to reach the goal relative to the time left in the campaign. This ratio has a general asymmetric *inverse-U-shaped* effect on pledges. This relationship is due to the effect of the odds-ratio of campaign success on equilibrium pledges, which changes in a non-trivial way in a dynamic game because of the AoN clause. For example, the model suggests that investors are relatively cautious about investing in campaigns that are close to the goal. But the size of pledges to a campaign that is close to the deadline increase when the goal is not too far away.

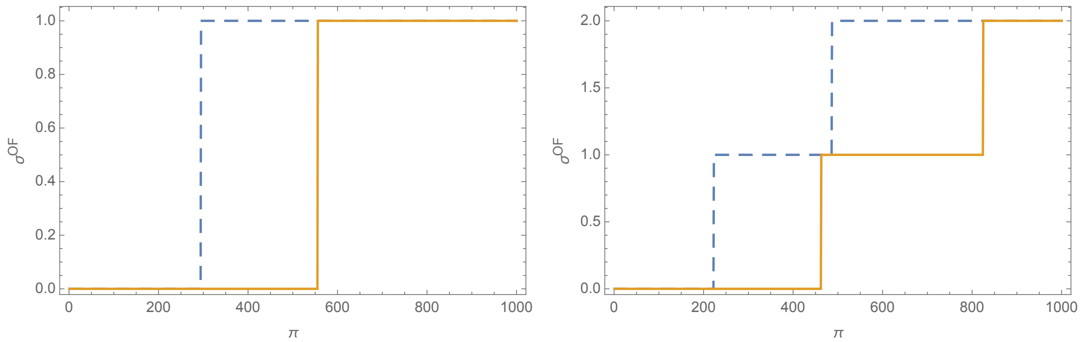
We can now rationalize some differences observed across rewards-based and Seedrs campaigns. Although increases in the frequency of pledges at the end of campaigns is often observed in rewards-based crowdfunding campaigns, this pattern is much less pronounced at Seedrs. We think that this is because, in rewards-based crowdfunding campaigns, backers' valuation of the pre-sold (or pre-rewarded) object is largely independent across backers (private values). In these campaigns, late-arriving backers might be willing to pledge when they have a high private valuation of the product. This incentive is much lower in an equity crowdfunding campaign: late-arriving backers who see that the campaign goal is still relatively far from being met deduce that the common value of the equity is low and, hence, have much less incentive to pledge. This discussion suggests that rewards-based and equity crowdfunding campaigns require different models for describing their respective funding dynamics.

Our results are useful for entrepreneurs who consider whether and how to run an equity crowdfunding or a rewards-based campaign, designers of equity crowdfunding platforms, and regulators. Seedrs is a somewhat unique platform in that it provides information about each individual pledge. We show that this helps investors form rational beliefs about project value based on the aggregation of rational information. Other equity crowdfunding platforms could consider voluntarily adopting the practice of reporting each individual pledge, and regulators could consider recommending it.

Tables and Figures

Figure 1: Overfunding phase equilibrium pledging strategies

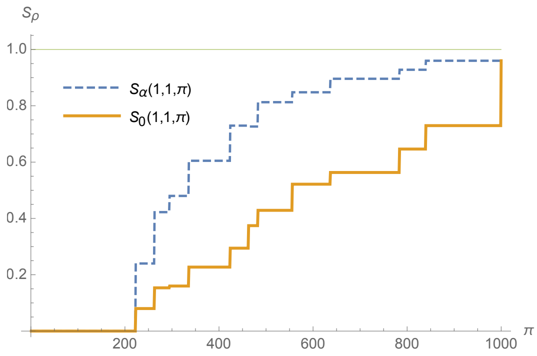
(a) Low wealth backers (b) High wealth backers



Notes: The figure depict backers equilibrium strategies in the over-funding phase as a function of the public belief (in 1000%), backer's signal and wealth. Backer signals are H (Dahsed line), M (solid line). Backers with signa L do not pledge. Panel (a): Strategies for backers with wealth $w = 1$. Panel (b) Strategies for backers with wealth $w = 2$

Figure 2: Success probability $S_\rho(1, z, \pi)$ as a function of π (in %) for $\rho \in \{\alpha, 0\}$ and $z \in \{1, 2\}$

(a)



(b)

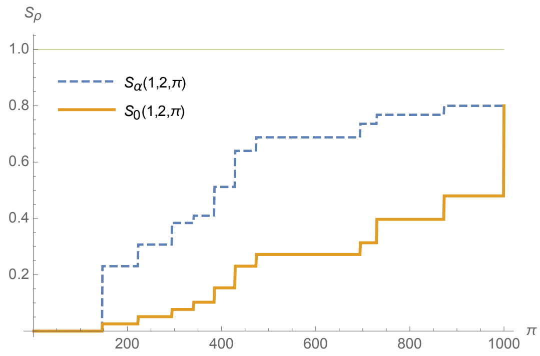


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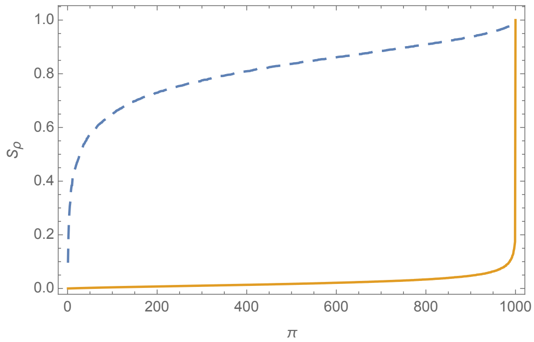
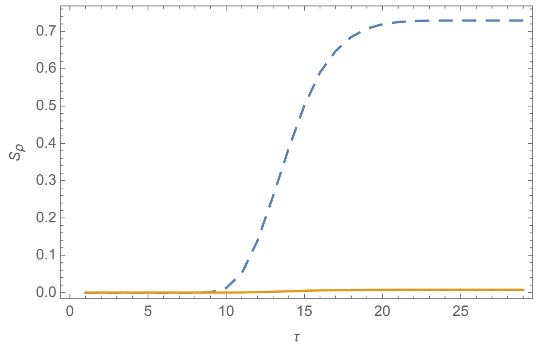
Figure 3: Campaign success probabilities

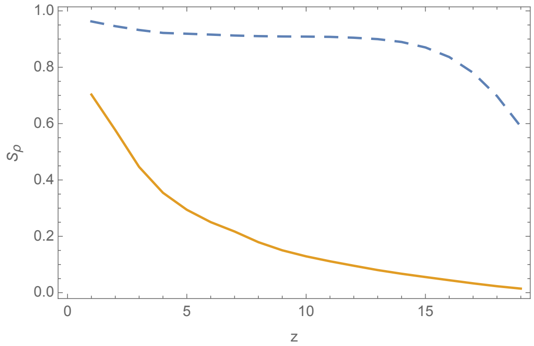
(a) Success probabilities as function of public belief



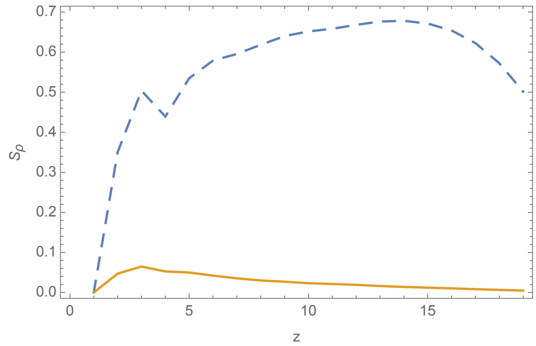
(b) Success probabilities as function of remaining time



(c) Success probabilities as function of z for $\pi_\tau = 0.8$

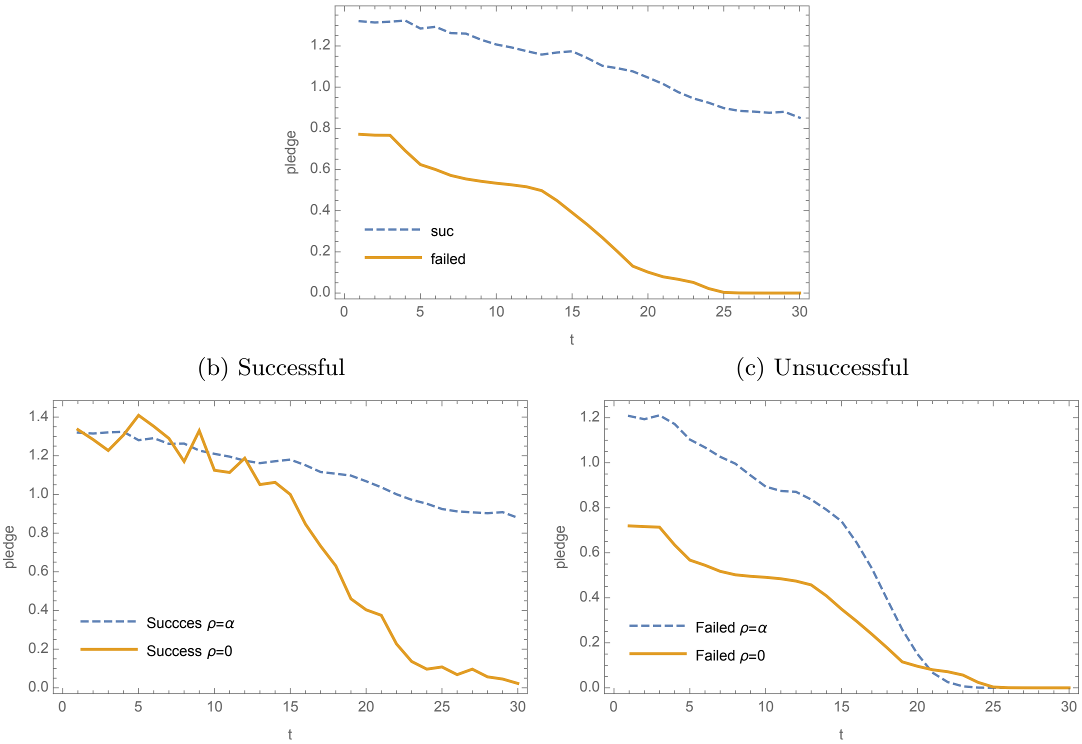


(d) Success probabilities as function of z for $\pi_\tau = 0.2$



Dashed lines represent represent success probability for good quality project campaigns. Solid lines represent success probability for bad quality project campaigns. : Panel (a) illustrates how at the beginning of the campaign, i.e. for $\tau = T$ and $z = Y$, success probabilities S_ρ are affected by the public belief π_0. Panel (b) illustrates how success probabilities S_ρ are affected by the remaining time τ, given $\pi_\tau = 0.2$ an $z = Y$. Panel (c) illustrates how success probabilities S_ρ are affected by the distance to the goal for $\tau = 15$, given $\pi_\tau = 0.8$. Panel (d) illustrates how success probabilities S_ρ are affected by the distance to the goal for $\tau = 15$, given $\pi_\tau = 0.2$. Success probabilities $S_\rho(\tau, Y, \pi_0)$ are computed for the following values of the exogenous parameters: $\alpha = 3$, $T = 30$, $Y = 20$, $\lambda = 0.8$, $q_{\alpha H} = 0.6$, $q_{\alpha M} = 0.4$, $q_{\alpha L} = 0$, $q_{0H} = 0.2$, $q_{0M} = 0.4$, $q_{0L} = 0.4$, $w_1 = 1.55$, and $w_2 = 2.55$.

Figure 4: Average pledges in simulated campaigns



(a) Average pledge

(b) Successful

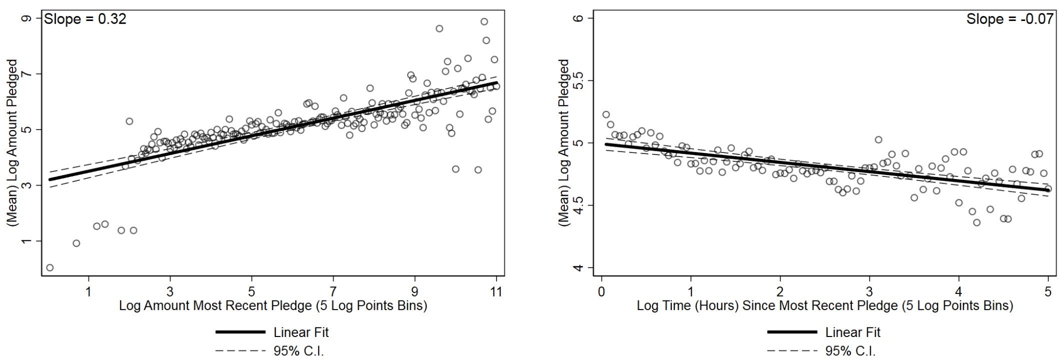
(c) Unsuccessful

Notes: Average pledge as a function of time for a simulation of 50000 campaigns using the equilibrium strategies obtained for the parameters: $\alpha = 3$, $T = 30$, $Y = 20$, $\lambda = 0.8$, $q_{\alpha H} = 0.6$, $q_{\alpha M} = 0.4$, $q_{\alpha L} = 0$, $q_{0H} = 0.2$, $q_{0M} = 0.4$, $q_{0L} = 0.4$, $w_1 = 1.55$, and $w_2 = 2.55$. Panel (a) plots the average pledges for campaign that reached the goal (blue line) and those who did not (orange line). Panel (b) and (c) report the same variables but separate campaigns for good project (panel (b) from campaign for bad projects (panel (c)

Figure 5: Correlations Between the Amount Pledged by an Investor and the Timing and Size of the Most Recent Pledge

(a) Size of Most Recent Pledge

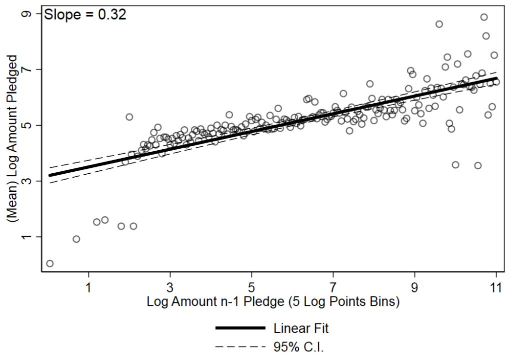
(b) Time Since Most Recent Pledge



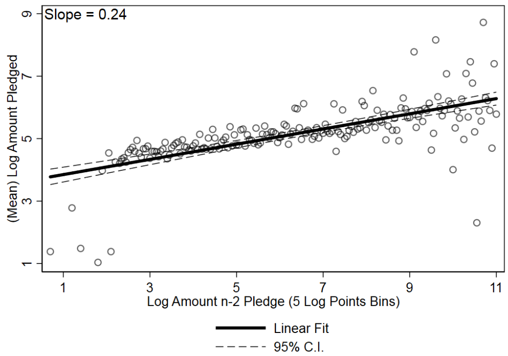
Notes: All pledges are organized in bins of size 5 log points according to the size of the most recent pledge (Panel (a)), and the time elapsed (in hours) since the most recent pledge (Panel (b)). Each panel shows the relation between the median value of the respective bin and the average amount invested by the adjacent backers.

Figure 6: Correlations Between the Amounts Pledged by Adjacent Backers in a Campaign

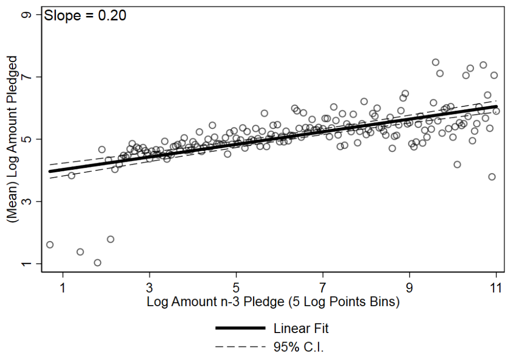
(a) $(n, n-1)$



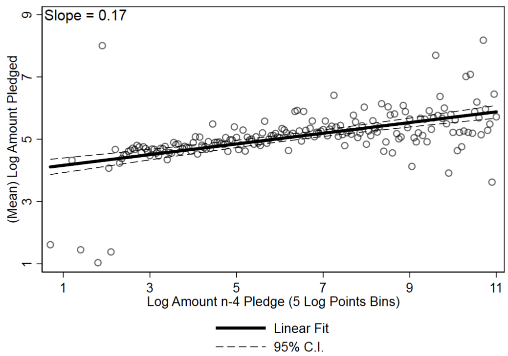
(b) $(n, n-2)$



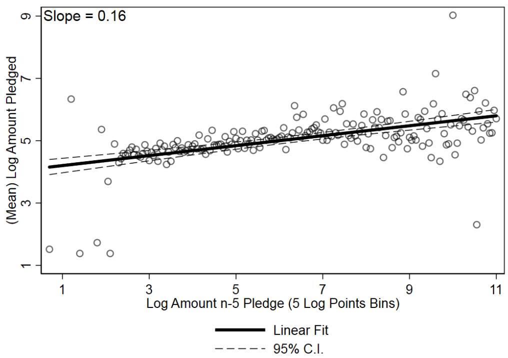
(c) $(n, n-3)$



(d) $(n, n-4)$

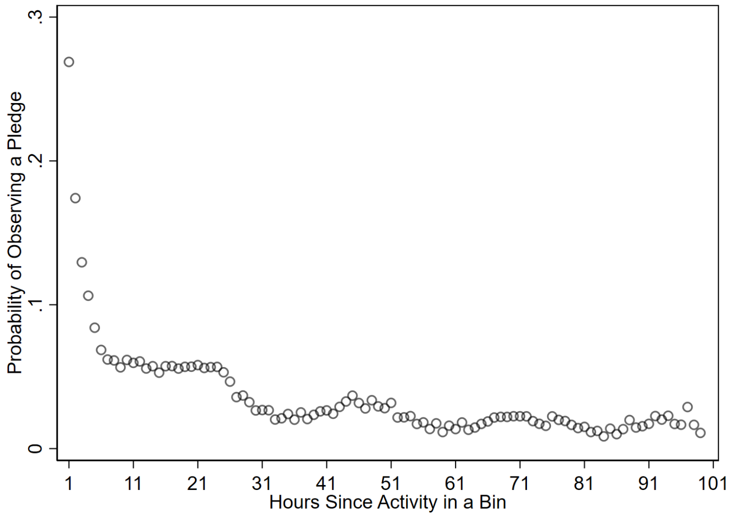


(e) $(n, n-5)$



Notes: All pledges are organized in bins of size 5 log points according to the size of the previous $n-k$ pledge, where $k \in \{1, 2, 3, 4, 5\}$. For example, "n" refers to the nth pledge made since the start of a campaign, and "n-k" refers to the kth pledge before the nth pledge in the campaign. Each panel shows the relation between the median value of the respective bin and the average amount invested by the backers.

Figure 7: Probability of Observing a Pledge at Any Given Hour as a Function of Time Since Most Recent Activity in an Hourly Bin

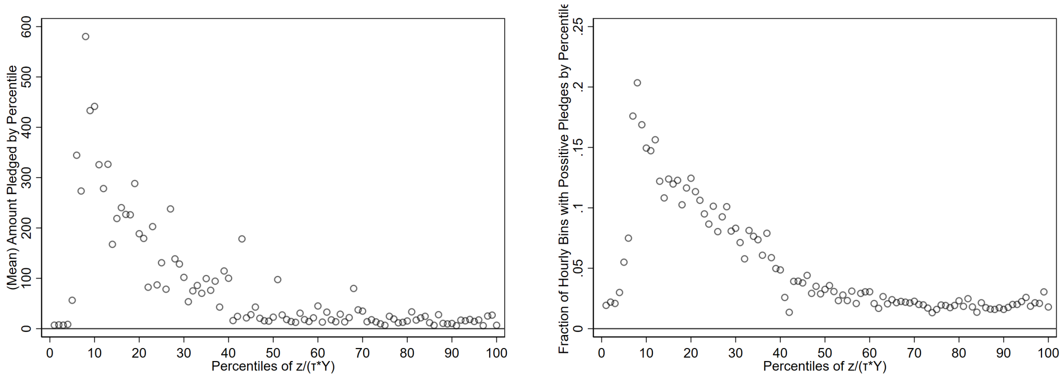


Notes: The total time that a campaign is running is divided into bins of length one hour. For each bin we create two variables: a dummy equal to one if there was at least one positive pledge, and zero otherwise; and a variable equal to the number of hours since the most recent pledge. The figure reports the average of the dummy variable for each time interval.

Figure 8: Average Amount Pledged, and the Probability of Observing a Pledge, as a Function of Percentiles of the $z_\tau/\tau Y$ Ratio

(a) (Mean) Amount Pledged

(b) Share of Positive Pledges

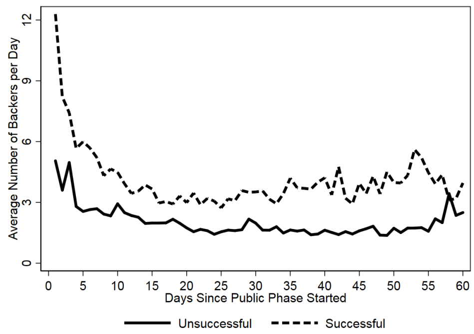


Notes: The total time that a campaign is running is divided into bins of length one hour. For each hourly bin, we calculate the ratio between the share of the goal still necessary for the campaign to be successful (z_τ/Y) and the remaining time to the campaign deadline (τ). We then classify hourly bins by percentiles of $z_\tau/\tau Y$. Finally, we calculate the i. average amount pledged across bins within each percentile –including bins with no amounts pledged–, and ii. the share of bins with positive pledges within each percentile. The figure plots the relation between the resulting variables and the respective percentiles.

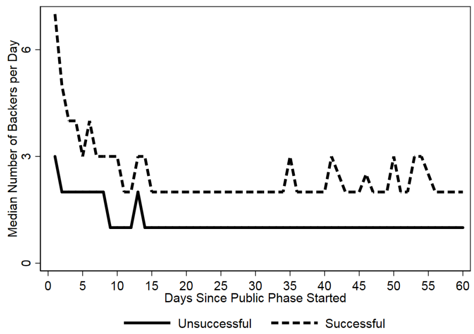
Figure 9: Number of Backers and Cumulative Investments to the Campaigns Across Time During the Public Phase: Successful and Unsuccessful Campaigns

Average and Median Number of Backers per Day

(a) Mean

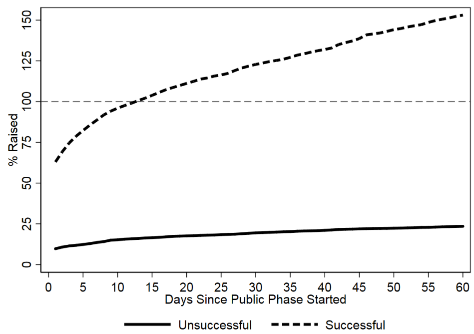


(b) Median

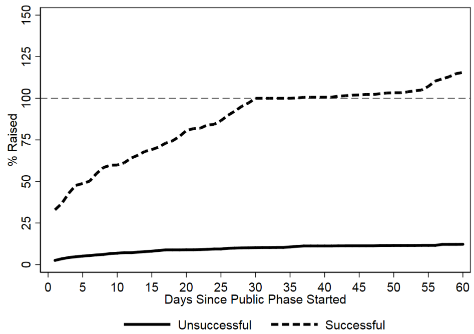


Number of Days to Reach a Given Percentage of the Investment Target

(c) Mean



(d) Median



Notes: Panel (a) and (b) depict the average and median number of backers making pledges to a campaign each day during the public phase, conditional on whether they end up being successful or not. Panels (c) and (d) depict the average and median number of days that a campaign needs to reach a given percentage of the overall desired investment during the public phase, conditional on whether they end up being successful or not.

Table 1: Campaign success probability for different levels of the goal Y

Y	$S_0(T,Y,\pi_0)$	$S_\alpha(T,Y,\pi_0)$	$\frac{S_\alpha(T,Y,\pi_0)}{S_0(T,Y,\pi_0)}$	$\frac{S_\alpha(T,Y,\pi_0)}{S_\alpha(T,Y,\pi_0)+S_0(T,Y,\pi_0)}$
2	0	0	-	-
5	0.055	0.47	8.5	0.89
10	0.028	0.64	23.2	0.96
15	0.015	0.69	46.7	0.98
20	0.007	0.72	93.5	99
25	0.003	0.736	190	99.5
30	0.002	0.741	384	99.9
40	< 0.001	0.26	3165	¿99.99

Notes: Success probabilities $S_\rho(T,Y,\pi_0)$ are computed for the following values of the exogenous parameters: $\alpha = 3$, $\pi_0 = 0.2$, $T = 30$, $\lambda = 0.8$, $q_{\alpha H} = 0.6$, $q_{\alpha M} = 0.4$, $q_{\alpha L} = 0$, $q_{0H} = 0.2$, $q_{0M} = 0.4$, $q_{0L} = 0.4$, $w_1 = 1.55$, and $w_2 = 2.55$.

Table 2: Variable Descriptions

Variable	Definition
Successful campaign	=1 if the campaign goal was met, zero otherwise. SEEDRS is an "all or nothing" platform in which projects have up to 60 days to raise investment, so companies only receive funding if they reach the declared investment goal within the time limit.
Pre-money valuation	Self-reported pre-money valuation of the project.
Equity offered	Percentage of equity that the campaign managers are offering.
Campaign goal	Declared desired investment by the campaign promoters.
% Raised	Total amount raised by the campaign divided by the campaign goal. SEEDRS allows campaign promoters to accept more capital than what they had originally asked for, so they can "overfund" the projects once the target is reached. In cases in which there is overfunding, the variable takes a value that is greater than 100.
# Entrepreneur	Number of entrepreneurs in charge of the project.
# Backers	Number of different investors that have made pledges to the campaign.
# Pledges	Number of different pledges made to the campaign.
% Anonymous pledges	Investors can choose to share their SEEDRS' profile with other members of the platform. Each profile includes information about the investor location, the amount they have invested in different projects within the platform, campaigns in which they are promoters, and, occasionally, social media contacts or short biographic descriptions. Each pledge made is recorded in the campaign's page in order of magnitude, and investors are asked if they want their profiles to be seen next to the value of the investment. The variable is then constructed as the ratio between investments that are not public, that is, investments in which the backer profile is not available to the public, and total investments made in a given campaign.
Hotness indicator	Seedrs has an automatic algorithm to rank how much interest a campaign is generating at any given point in time. The algorithm measures four factors across the last three days: (i) amount invested; (ii) number of investors; (iii) investment traction; and (iv) days since the start of the campaign. The index takes values between [0,100], and is constructed using a weighted average of the four factors.
Intraday increase hotness indicator	=1 if hotness indicator increased during the day; =0 otherwise.
Authorized, High net worth and Sophisticated	Seedrs uses a classification scheme in which all individuals that subscribe to the platform have to self- select into one of three groups: high net worth, sophisticated, or authorized. High-net-worth corresponds to individuals who had annual incomes of at least £100,000 and/or held net assets to of at least £250,000 in the preceding financial year, as defined in regulations made pursuant to the UK Financial Services and Markets Act 2000. A sophisticated investor is an individual who has been an angel investor for at least the last six months, or for at least the last two years has made at least one investment in an unlisted company, has worked in private equity or corporate finance and/or has been a director of a company with an annual turnover of at least £1 million, as defined in regulations made pursuant to the UK Financial Services and Markets Act 2000. The rest of authorized individuals are those that do not fit in the previous categories, and need to fill out a questionnaire and score all questions correct in order to qualifyas investors.
Recurrent investor	=1 if investor has made pledges in more than one campaign; =0 otherwise.
Mean/median Pledge	Average/median value in pounds of the pledges made to the campaign.
Max pledge	Maximum single pledge made in each campaign.
Max pledge / goal	Maximum single pledge made divided by campaign goal.
% Covered	The share of the campaign goal that was raised during a given period of time.

Table 3: Summary Statistics

	All	Successful (34.2%)	Unsuccessful	Difference
Campaigns				
Pre-money valuation (£)	1,845,466	2,793,642	1,352,090	1,441,552***
	(5,028,624)	(7,834,238)	(2,426,414)	
Equity offered	11.95	8.82	13.57	-4.75***
	(7.66)	(6.43)	(7.75)	
Campaign goal (£)	174,215	176,629	172,959	3,670
	(327,598)	(252,718)	(360,711)	
% Raised	76.40	179.06	22.98	156.07***
	(195.39)	(306.91)	(28.57)	
# Entrepreneurs	3.28	3.74	3.04	0.70***
	(1.97)	(2.07)	(1.87)	
# Backers	83.44	169.47	38.68	130.78***
	(126.38)	(174.62)	(50.99)	
# Pledges	96.48	199.03	43.12	155.91***
	(146.15)	(200.67)	(56.99)	
% Anonymous pledges	51.40	54.22	49.93	4.30***
	(18.60)	(9.50)	(21.76)	
# Days the campaign is active	54.70	58.19	52.89	5.30*
	(38.46)	(38.56)	(38.32)	
Type of Investor				
% Authorized	79.20	76.49	80.62	-4.12***
	(15.58)	(11.45)	(17.19)	
% High-net-worth	13.57	14.83	12.92	1.92*
	(12.72)	(10.30)	(13.77)	
% Sophisticated	7.22	8.68	6.47	2.21***
	(8.24)	(4.92)	(9.44)	
% Recurrent investors	72.64	79.16	69.25	9.91***
	(27.54)	(19.99)	(30.22)	
Investments				
Mean pledge (£)	1,202.46	1,745.97	919.64	826.33***
	(2,949.49)	(3,472.27)	(2,596.24)	
Median pledge (£)	354.32	571.29	241.42	329.87*
	(2,336.11)	(3,146.97)	(1,767.18)	
Max pledge (£)	38,201.94	81,341.40	15,754.64	65,586.76
	(158,251.56)	(259,065.82)	(42,113.87)	
Max pledge / goal	0.15	0.31	0.07	0.23
	(0.19)	(0.22)	(0.10)	
Timing				
% Covered in week 1	30.79	75.47	7.54	67.93***
	(165.42)	(276.97)	(14.45)	
% Covered in month 1	53.32	126.66	15.16	111.50***
	(187.78)	(306.94)	(21.33)	
Observations	710	243	467	

*** 1 percent ** 5 percent * 10 percent

Notes: Each cell is computed by taking the average across the campaigns. Standard deviation in parenthesis. The last column reports the difference of means between successful and unsuccessful campaigns for each variable, and the result from a mean comparison test at standard levels of statistical significance.

Table 4: The Effect of Prior Pledges and the Time Since the Most Recent Pledge

	Dependent Var: log amount pledged (£)					
	Model	Model Controls I	Model Controls II	Model Controls Full	IV-A	IV-B
Prior pledges						
Log amount pledged (n-1)	0.083***	0.076***	0.076***	0.074***	0.106**	0.115***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.053)	(0.020)
Log amount pledged (n-2)	0.032***	0.030***	0.030***	0.029***	0.090	0.039**
	(0.005)	(0.005)	(0.005)	(0.005)	(0.070)	(0.018)
Log amount pledged (n-3)	0.023***	0.023***	0.024***	0.023***	0.063	-0.003
	(0.005)	(0.005)	(0.004)	(0.004)	(0.060)	(0.018)
Log amount pledged (n-4)	0.015***	0.014***	0.015***	0.014***	-0.011	0.012
	(0.004)	(0.004)	(0.004)	(0.004)	(0.060)	(0.018)
Log amount pledged (n-5)	0.013**	0.014**	0.015***	0.014***	0.002	0.010
	(0.004)	(0.004)	(0.004)	(0.004)	(0.062)	(0.016)
Log time (hours) since most recent pledge	-0.035*	-0.013	-0.007	0.005	-0.073*	-0.088**
	(0.018)	(0.017)	(0.017)	(0.017)	(0.043)	(0.039)
Controls investor						
Dummy high-net-worth		1.204***	1.204***	1.200***	1.188***	1.190***
		(0.038)	(0.038)	(0.037)	(0.038)	(0.037)
Dummy sophisticated		0.454***	0.453***	0.451***	0.434***	0.439***
		(0.037)	(0.037)	(0.037)	(0.040)	(0.038)
Dummy recurrent investor		-0.647***	-0.639***	-0.635***	-0.621***	-0.621***
		(0.047)	(0.047)	(0.046)	(0.048)	(0.048)
Controls campaign						
Log total amount funded up to n-1			-0.071*	-0.069	-0.101	-0.069
			(0.042)	(0.042)	(0.072)	(0.047)
Log number of pledges up to n-1			0.058*	0.061*	0.145*	0.121**
			(0.034)	(0.036)	(0.075)	(0.044)
Share amount left n-1			0.070	0.137	0.389**	0.409**
			(0.117)	(0.117)	(0.132)	(0.137)
Share amount left n-1 × Days left			-0.002	-0.002	-0.005**	-0.005**
			(0.002)	(0.002)	(0.002)	(0.002)
Days left in the campaign			-0.003***	-0.003***	-0.003**	-0.003***
			(0.001)	(0.001)	(0.001)	(0.001)
=1 if goal already reached			-0.092**	-0.077**	-0.055*	-0.053*
			(0.032)	(0.031)	(0.030)	(0.032)
Standardized Campaign hotness at start of the day				0.045**	-0.002	-0.002
				(0.014)	(0.022)	(0.021)
Dummy campaign hotness intraday rise				0.180***	0.130***	0.131***
				(0.021)	(0.026)	(0.026)
Standardized average campaign hotness rest of campaigns				-0.004	0.008	0.009
				(0.011)	(0.012)	(0.013)
Standardized Google trend index				-0.018	-0.024	-0.027*
				(0.013)	(0.015)	(0.014)
Standardized FTSE 100 index				-0.002	0.013	0.013
				(0.025)	(0.025)	(0.026)
Observations	59,559	59,559	59,559	59,559	55,052	55,052
Average pledge (£)	1,232	1,232	1,232	1,232	1,228	1,228
SD pledge (£)	12,491	12,491	12,491	12,491	12,169	12,169
Average time (hours) since most recent pledge	11.2	11.2	11.2	11.2	11.4	11.4
S.D. time (hours) since most recent pledge	38.9	38.9	38.9	38.9	38.5	38.5
Kleibergen and Paap rk statistic					18.79	202.27
Hansen J statistic P-Val						0.37
Campaign FE	Yes	Yes	Yes	Yes	Yes	Yes

*** 1 percent ** 5 percent * 10 percent

Notes: Robust standard errors, clustered by campaign. Each lagged pledge in the IV setting (A) is instrumented using the inverse hyperbolic sine transformation (IHS) of the amount of money returned to the backer if the last campaign she supported failed. Each lagged pledge in the IV setting (B) has two instruments: (i) total number of pledges made by the investor in all campaigns interacted with the anonymous indicator; and (ii) the largest single amount pledged by the investor in previous campaigns interacted with the anonymous indicator. The time since the most recent pledge is instrumented in (A) and (B) with the (log) absolute value of the difference in hours between the hour in the day in which the previous pledge is made and 11am. See Section 7 for a detailed description.

Table 5: The Effect of Prior Pledges and the Time Since the Most Recent Pledge. Discrete Time Model Specification

	Dependent Var: (IHS) total amount pledged in hour bin in the Hourly Bin				
	Model	Model Controls I	Model Controls Full	IV-A	IV-B
Prior pledges					
(IHS) total amount pledged in hour bin t-1	0.127***	0.127***	0.121***	0.167***	0.099***
	(0.006)	(0.006)	(0.006)	(0.012)	(0.010)
(IHS) total amount pledged in hour bin t-2	0.100***	0.099***	0.093***	0.119***	0.101***
	(0.004)	(0.004)	(0.004)	(0.011)	(0.010)
(IHS) total amount pledged in hour bin t-3	0.075***	0.074***	0.067***	0.095***	0.073***
	(0.004)	(0.004)	(0.004)	(0.009)	(0.009)
(IHS) total amount pledged in hour bin t-4	0.063***	0.061***	0.055***	0.078***	0.057***
	(0.003)	(0.003)	(0.002)	(0.009)	(0.007)
(IHS) total amount pledged in hour bin t-5	0.051***	0.049***	0.042***	0.053***	0.032***
	(0.003)	(0.003)	(0.003)	(0.008)	(0.008)
Log Hours since most recent activity in bin	-0.016**	-0.027***	-0.033***	-0.079***	-0.025**
	(0.006)	(0.007)	(0.007)	(0.010)	(0.009)
Controls					
Log total amount funded up to bin t-1		0.038	0.027	0.015	0.029
		(0.025)	(0.022)	(0.021)	(0.021)
Log number of pledges up to t-1		-0.209**	-0.209**	-0.194**	-0.211**
		(0.083)	(0.067)	(0.065)	(0.067)
Share amount left up to t-1		-0.268***	-0.040	-0.063	-0.036
		(0.060)	(0.049)	(0.046)	(0.049)
Share amount left up to t-1 × Days left		0.003	0.001	0.001	0.001
		(0.002)	(0.002)	(0.002)	(0.002)
Days left in the campaign		-0.002**	-0.003***	-0.002**	-0.003***
		(0.001)	(0.001)	(0.001)	(0.001)
=1 if goal already reached		-0.188***	-0.145***	-0.124***	-0.146***
		(0.039)	(0.033)	(0.030)	(0.033)
Standardized Campaign hotness at start of the day			0.163***	0.142***	0.164***
			(0.011)	(0.010)	(0.011)
Dummy campaign hotness intraday rise			0.059***	0.050***	0.060***
			(0.006)	(0.006)	(0.006)
Standardized average campaign hotness rest of campaigns			-0.033***	-0.028***	-0.034***
			(0.004)	(0.004)	(0.005)
Standardized Google trend index			0.024***	0.020***	0.024***
			(0.006)	(0.005)	(0.006)
Standardized FTSE 100 index			0.011	0.011	0.011
			(0.013)	(0.012)	(0.013)
Observations	680,502	680,502	680,502	680,502	680,502
Frequency of Investments per hour	0.080	0.080	0.080	0.080	0.080
SD of Frequency of Investments per hour	0.599	0.599	0.599	0.599	0.599
Kleibergen and Paap rk statistic				166.125	326.764
Hansen J statistic P-Val					0.13
Campaign FE	Yes	Yes	Yes	Yes	Yes
Hour of Day FE	Yes	Yes	Yes	Yes	Yes

*** 1 percent ** 5 percent * 10 percent

Notes: Robust standard errors, clustered by campaign. The total time that a campaign is running is divided into bins of length one hour. The data set is then organized as a panel in which the time dimension corresponds to the hours passed since the start of the campaign. Total amount pledged corresponds to the sum all pledges made in the respective hourly bin. Given the large number of observations in which the amount invested in the time period is zero, the amount pledged is transformed using an inverse hyperbolic sine transformation. Each of the lags of the total amount pledged in the IV setting (A) is instrumented using the inverse hyperbolic sine transformation (IHS) of the sum amount of money returned to the backers as a result of a campaign failure. The total amount pledged in the IV setting (B) has two instruments: (i) the average number of pledges made by the anonymous investors in previous campaigns; and (ii) the average maximum pledges by the anonymous investors in previous campaigns. The time since the most recent pledge in IV setting (B) is instrumented with the (log) absolute value of the difference in hours between the hour in the day in which the last pledge is made and 11am. See Section 7 for a detailed description.

Table 6: Probability of Observing a Pledge at Any Given Hour and Amount Invested in Previous Hours and Time Since Last Pledge

	Dependent Var: Dummy Investment in the Hourly Bin				
	Model	Model Controls I	Model Controls Full	IV-A	IV-B
Prior pledges					
(IHS) total amount pledged in hour bin t-1	0.018***	0.018***	0.017***	0.022***	0.015***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
(IHS) total amount pledged in hour bin t-2	0.014***	0.014***	0.013***	0.016***	0.015***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.002)
(IHS) total amount pledged in hour bin t-3	0.011***	0.011***	0.010***	0.013***	0.011***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
(IHS) total amount pledged in hour bin t-4	0.009***	0.009***	0.008***	0.011***	0.009***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
(IHS) total amount pledged in hour bin t-5	0.008***	0.007***	0.006***	0.008***	0.005***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Log Hours since most recent activity in bin	-0.001*	-0.001	-0.002*	-0.007***	-0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Controls					
Log total amount funded up to bin t-1		0.009**	0.008**	0.006*	0.007**
		(0.004)	(0.004)	(0.004)	(0.004)
Log number of pledges up to t-1		-0.039**	-0.039**	-0.037**	-0.039**
		(0.014)	(0.012)	(0.012)	(0.012)
Share amount left up to t-1		-0.049***	-0.012	-0.015*	-0.012
		(0.010)	(0.008)	(0.008)	(0.008)
Share amount left up to t-1 × Days left		0.001	0.000	0.000	0.000
		(0.000)	(0.000)	(0.000)	(0.000)
Days left in the campaign		-0.000**	-0.000***	-0.000**	-0.000***
		(0.000)	(0.000)	(0.000)	(0.000)
=1 if goal already reached		-0.030***	-0.023***	-0.021***	-0.023***
		(0.006)	(0.005)	(0.005)	(0.005)
Standardized Campaign hotness at start of the day			0.026***	0.024***	0.026***
			(0.002)	(0.002)	(0.002)
Dummy campaign hotness intraday rise			0.008***	0.007***	0.008***
			(0.001)	(0.001)	(0.001)
Standardized average campaign hotness rest of campaigns			-0.006***	-0.005***	-0.005***
			(0.001)	(0.001)	(0.001)
Standardized Google trend index			0.004***	0.003***	0.004***
			(0.001)	(0.001)	(0.001)
Standardized FTSE 100 index			0.002	0.002	0.002
			(0.002)	(0.002)	(0.002)
Observations	680,502	680,502	680,502	680,502	680,502
Fraction of hourly bins with pledges	0.062	0.062	0.062	0.062	0.062
SD of fraction of hourly bins with pledges	0.242	0.242	0.242	0.242	0.242
Kleibergen and Paap rk statistic				166.125	326.764
Hansen J statistic P-Val					0.06
Campaign FE	Yes	Yes	Yes	Yes	Yes
Hour of Day FE	Yes	Yes	Yes	Yes	Yes

*** 1 percent ** 5 percent * 10 percent

Notes: Robust standard errors, clustered by campaign. The total time that a campaign is running is divided into bins of length one hour. The data set is then organized as a panel in which the time dimension corresponds to the hours passed since the start of the campaign. Total amount pledged corresponds to the sum all pledges made in the respective hourly bin. Given the large number of observations in which the amount invested in the time period is zero, the amount pledged is transformed using an inverse hyperbolic sine transformation. Each of the lags of the total amount pledged in the IV setting (A) is instrumented using the inverse hyperbolic sine transformation (IHS) of the sum amount of money returned to the backers as a result of a campaign failure. The total amount pledged in the IV setting (B) has two instruments: (i) the average number of pledges made by the anonymous investors in previous campaigns; and (ii) the average maximum pledges by the anonymous investors in previous campaigns. The time since the most recent pledge in IV setting (B) is instrumented with the (log) absolute value of the difference in hours between the hour in the day in which the last pledge is made and 11am. See Section 7 for a detailed description.

Table 7: The Effect of Prior Pledges and the Time Since the Most Recent Pledge. Conditional on Share of Desired Investment Raised in Private Phase

	Dependent Var: log amount pledged (£)		
	Model	Private Phase Share $\in (0, 35]$	Private Phase Share > 35
Prior pledges			
Log amount pledged (n-1)	0.106*	0.140***	0.074**
	(0.064)	(0.032)	(0.033)
Log amount pledged (n-2)	0.090	0.032	0.004
	(0.070)	(0.027)	(0.033)
Log amount pledged (n-3)	0.063	0.033	-0.060
	(0.060)	(0.024)	(0.055)
Log amount pledged (n-4)	-0.011	-0.013	0.020
	(0.060)	(0.023)	(0.040)
Log amount pledged (n-5)	0.002	0.031	0.009
	(0.062)	(0.022)	(0.027)
Log time (hours) since most recent pledge	-0.073*	-0.178***	0.092
	(0.043)	(0.049)	(0.094)
Observations	55,052	24,608	11,042
Average pledge (£)	1,228	1,215	1,205
SD pledge (£)	12,169	14,980	10,573
Average time (hours) since most recent pledge	11.4	12.9	7.2
S.D. time (hours) since most recent pledge	38.5	38.5	23.9
Kleibergen and Paap rk statistic	18.79	91.99	46.05
Campaign FE	Yes	Yes	Yes

*** 1 percent ** 5 percent * 10 percent

Notes: Robust standard errors, clustered by campaign. The first column replicates the results from our preferred IV specification (column IV-A) of Table 4. Column two (three) repeats the exercise for campaigns that raise less (more) than 35% of the desired goal during the private phase. The 35% cut-off is at the 80th percentiles of cross campaign distribution of amounts raised in the private phase. See Section 7 for a detailed description.

Table 8: Variables Associated with the Probability that a Campaign is Successful

	Average Marginal Effects after Probit	
	I	II
Private Phase		
Log covered in private phase	0.071***	0.108***
	(0.012)	(0.016)
Log number of backers in private phase	0.094***	0.061**
	(0.021)	(0.019)
Predetermined Campaign Controls		
Log pre-money valuation (£)		0.098**
		(0.033)
Log campaign goal (£)		-0.240***
		(0.030)
# Entrepreneurs		0.013
		(0.011)
% EIS tax relief		0.001
		(0.001)
% SEIS tax relief		0.001
		(0.001)
Observations	437	437
Year × month of start of campaign FE	Yes	Yes
Standardized Effect		
Log covered in private phase	0.16	0.24
Log number of backers in private phase	0.11	0.07
Log pre-money valuation		0.09
Log campaign goal		-0.26
# Entrepreneurs		0.03
% EIS tax relief		0.03
% SEIS tax relief		0.03

*** 1 percent ** 5 percent * 10 percent

Notes: Standard errors calculated using the delta-method. The standardized effect is calculated by multiplying each variable's standard deviation by the respective average marginal effect.

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Online Appendix

Appendix A

Proofs of propositions and lemmas in the main text

Proof. [Proof of Proposition 1]

1. Let us show that $\sigma(h_t, \theta, w_2) \geq \sigma(h_t, \theta, w_1)$. Note first that because $1 < w_1 < 2 < w_2$, a backer with wealth w_1 never pledges more than $x = 1$. Thus, it is sufficient to show that it is impossible to have $\sigma(\tau, z, \pi, \theta, w_1) = 1$ and $\sigma(\tau, z, \pi, \theta, w_2) = 0$. Note that $\sigma(\tau, z, \pi, \theta, w_1) = 1$ implies

$$\frac{\Pi(\pi,\theta)S_\alpha(h_t+1)}{(1-\Pi(\pi,\theta))S_0(h_t+1)} \geq \frac{\ln(w_1)-\ln(w_1-1)}{\ln(\alpha-1+w_1)-\ln(w_1)}$$

   because the r.h.s. is decreasing in w_1 one has

$$\frac{\Pi(\pi,\theta)S_\alpha(h_t+1)}{(1-\Pi(\pi,\theta))S_0(h_t+1)} > \frac{\ln(w_2)-\ln(w_2-1)}{\ln(\alpha-1+w_2)-\ln(w_2)}$$

   that implies

$$\Pi(\pi,\theta)S_\alpha(h_t+1)(\ln(\alpha-1+w_2)-\ln(w_2))+(1-\Pi(\pi,\theta))S_0(h_t+1)(\ln(w_2)-\ln(w_2-1)) > 0$$

   That is, a backer with wealth w_2 strictly prefers $x = 1$ to $x = 0$.

2. If for a given $h_t \in H$ success probability increases with a backer pledge, one has

$$x' > x \Rightarrow S_\rho(h_t+x') \geq S_\rho(h_t+x), \forall \rho \in \{0, \alpha\} \tag{19}$$

   Note that the objective function in (6) can be rewritten as

$$x \in \arg\max A(x)\Pi + B(x)$$

where we denoted

$$\begin{aligned}
\Pi &:= \Pi(\pi,\theta) \\
A(x) &:= S_\alpha(h_t+x)\underbrace{(\ln(w+(\alpha-1)x)-\ln(w))}_{>0}+S_0(h_t+x)\underbrace{(\ln(w)-\ln(w-x))}_{>0} \\
B(x) &:= S_\sigma(0,h_t+x)(\ln(w-x)-\ln(w)).
\end{aligned}$$

Note that (19) implies that the function $A(x)$ is non-decreasing. Now consider a backer arriving at time t with wealth w. Take two levels of belief $\Pi' > \Pi$ and let x' and x be the backer's optimal pledge if her belief is Π' and Π, respectively. Then one must have

$$\begin{aligned}
\Pi A(x)+B(x) &\geq \Pi A(x')+B(x') \\
\Pi' A(x')+B(x') &\geq \Pi' A(x)+B(x).
\end{aligned}$$

Summing up these two inequalities and rearranging them, we get $(\Pi'-\Pi)(A(x')-A(x)) \geq 0$. Thus, $\Pi' > \Pi$ and the monotonicity of $A(.)$ imply $x' \geq x$.

3. Note that because $q_{LG}=0$, one has $E[\rho|L]=0$. This implies that for a backer with signal L it is optimal not to pledge. Thus, any strictly positive pledge must come from either a backer with a positive signal H or a backer with a neutral signal M. As a consequence $P(h_t+x)|_{x>0} \geq \pi_t$. Because posterior Bayesian beliefs are martingale, with the expectation over the possible pledge size $x \in \{0,1,2\}$, which can result as equilibrium play at time t given any history h_t, one must have

$$E[P(h_t+\tilde{x})] = Pr(\tilde{x}>0)P(h_t+x)|_{x>0}+Pr(\tilde{x}=0)P(h_t+x)|_{x=0} = \pi_t$$

thus it must be that $P(h_t+x)|_{x=0} \leq \pi_t$.

■

Proof. [Proof of Corollary 1]

1.(a)-(b) If backer pledges are non-decreasing in the backer's belief, the higher the public belief, the higher will be the probability that a pledge is made and the larger will be its size. Keeping the level of public belief fixed, the backer's pledge is increasing in her private signal θ, and hence the updating function P is non-decreasing in pledge size. Higher past pledges induce higher beliefs in all following backers and hence higher pledges. Periods without pledges correspond to situations in which either no backer arrived or the backer who arrived optimally chose not to pledge. In point 3 of Proposition 1 $P(h_t + 0) \leq \pi_t$, that is, in the absence of pledges, the public belief does not increase. This implies that an absence of pledges is associated with a (weakly) smaller future pledge size and the probability of pledges being made.

1.(c) Because $\Pi(H, \pi) > \Pi(M, \pi) > \Pi(L, \pi)$, monotonicity of pledges in beliefs implies $\sigma(\cdot, H) \geq \sigma(\cdot, M) \geq \sigma(\cdot, L)$. Assumptions (2)-(3) means that backers with signal H (signal L) are more (less) frequent if $\rho = \alpha$ than if $\rho = 0$. That is, in aggregate, pledges will be larger if $\rho = \alpha$ than if $\rho = 0$. Thus the probability that the goal Y is reached by time T is not smaller for a good project than for a bad project.

2. If $z_\tau > \tau/2$, the campaign goal cannot be reached even if in each of the τ remaining periods a backer arrives and pledges the maximum amount $x = 2$. Fix a natural number n and consider a backer who observed history h_t and knows that her and other $n - 1$ future backers' private signals equal H. This backer's belief that $\rho = \alpha$ is

$$\mathbb{P}(\rho = \alpha | h_t, n \text{ future backers have signal } H) = \frac{\pi_t q_{\alpha H}^n}{\pi_t q_{\alpha H}^n + (1 - \pi_t) q_{0H}^n}$$

The threshold $\pi^A(n)$ is the level of π_t such that the expression above equals $1/\alpha$. If $\pi_\tau < \pi^A(\tau)$, then π_τ is so small that the project's expected return is negative even in the most optimistic scenario, where each backer from time τ until the deadline have signal H. Thus, regardless of the future arrival of a backer, the project's expected return is negative, so no backer will trigger the success of the campaign. Because the campaign is doomed to failure, the backer does not pledge.

■

Proof. [Proof of Proposition 2] Let define the thresholds $\underline{\pi}(\theta, w)$ and $\overline{\pi}(\theta, w)$ as flows

$$\underline{\pi}^{OF}(\theta, w) = \sup\{\pi \in [0, 1]\} \ s.t. \ V(0, \theta, w, \pi_\tau) \geq V(1, \theta, w, \pi_\tau)$$

$$\overline{\pi}^{OF}(\theta, w) := \sup\{\pi \in [0, 1]\} \ s.t. \ V(1, \theta, w, \pi_\tau) \geq V(2, \theta, w, \pi_\tau)$$

The thresholds $\underline{\pi}(\theta, w)$ and $\overline{\pi}(\theta, w)$ directly results from the maximization of function (13) with respect to $x \in \mathcal{X}$. Note that in the overfunding phase $S_\alpha(\pi_t, h_t + x) = S_0(\pi_t, h_t + x) = 1$ for any $x >\in \{1, 2\}$. Hence S_ρ satisfy the monotonicity property of point 2 in Proposition 1, thus pledges are increasing in backers' beliefs. The fact that for $\theta = L$ not pledging is optimal follows from $\Pi(\pi_t, L) = 0$. The monotonicity of pledges in backers' wealth follows from point 1 in Proposition 1. ■

Proof. [Proof of Proposition 3]

For $z_1 \geq 1$ the equilibrium strategy $\sigma(1, z, \pi, \theta, w)$ directly follows from the discussion above Proposition 3. For $z_1 = 2$ the last period backer has the choice between triggering the success of the campaign by pledging $x_1 = 2$ and gaining $V(2, \pi, \theta, w)$, or not and letting the campaign failing, thus gaining 0. If $z > 2$ the campaign fails with certainty, regardless of what x is, so $x = 0$ is a best response. ■

Outcome of the numerical calculation of a Markov equilibrium

The values of the exogenous parameters in our numerical calculation of the equilibrium are: $\alpha = 3$, $T = 30$, $Y = 20$, $\lambda = 0.8$, $q_{\alpha H} = 0.6$, $q_{\alpha M} = 0.4$, $q_{\alpha L} = 0$, $q_{0H} = 0.2$, $q_{0M} = 0.4$, $q_{0L} = 0.4$, $w_1 = 1.55$, and $w_2 = 2.55$. Overall, we calculate σ , P, and S_ρ for all possible values of the Markov state variables (τ, z, π), in which we restrict the public belief π to be in the set $\{0, 0.001, 0.002, \ldots, 0.999, 1\}$ and approximate $P(\tau, z, \pi, x)$ to the closest point in this set. Overall, there are 600,000 possible triplets of Markov state variables (τ, z, π), 6 types of backers, and 3 possible actions.

The belief updating function $P(.)$ was calculated in each of the 600,000 possible values of the Markov state variables and for each of the three possible pledge sizes. For each of the $3 \times 600,000$ points, we iterated $(P^{(i)}, \sigma^i)$ from $i = 0$ to $i = 20$ to obtain the equilibrium posterior public belief function $P(.)$ and strategy $\sigma(.)$. The function $P^{(i)}$ does not converge for 26 out of the 1,200,000 points. The result suggests that equilibrium strategies are almost exclusively in a pure strategy.

The equilibrium strategy was calculated for the 600,000 possible values of the Markov state variables and for each of the 6 possible types of backers. We found that equilibrium strategies are monotonic in signals, i.e., $\sigma(\tau, z, \pi, H, w) \geq \sigma(\tau, z, \pi, M, w) \geq \sigma(\tau, z, \pi, L, w)$ for all possible quadruplets (τ, z, π, w). We find that $\sigma(\tau, z, \pi, \theta, w)$ is not 100% increasing in π. Specifically, for 0.01% of the $600,000 \times 9$ possible quintuplets $(\tau, z, \pi, \theta, w)$, we found

$\sigma(\tau, z, \pi, \theta, w) < \sigma(\tau, z, \pi', \theta, w)$ for some $\pi' < \pi$. Similarly, we found that the public belief posterior $P(\tau, z, \pi, x)$ is increasing in x. That is, for all possible values of the triplet (τ, z, π), we had $P(\tau, z, \pi, 0) \leq P(\tau, z, \pi, 1) \leq P(\tau, z, \pi, 2)$. However, $P(\tau, z, \pi, x)$ is not 100% increasing in the public belief π. Specifically, in 0.05% of the cases, we have $P(\tau, z, \pi, x) < P(\tau, z, \pi', x)$ for some $\pi' < \pi$.

How is it possible that the posterior public belief function $P(.)$ is not always increasing in the prior belief π? To understand this, fix τ and z and consider two levels of public belief $\pi < \pi'$, with π' close to π, and a pledge of size of, say, $x = 1$. Suppose that when the public belief is π, a pledge of $x = 1$ is adopted only by a backer with signal H, and then such a pledge is interpreted as a strong positive signal about ρ. Suppose also that with public belief π', a pledge of size $x = 1$ is optimal not only for backers with signal H but also for backers with signal M. In this case, a pledge of $x = 1$ is interpreted as a partial positive signal about ρ. In situations like this, because π' is close to π, it is possible for $P(\tau, z, \pi, 1) > P(\tau, z, \pi', 1)$ even though $\pi < \pi'$.

Regarding the equilibrium probability of campaign success, we found that, for all possible values of the triplet (τ, z, π), the probability of campaign success is larger if the the project quality is good rather than bad, that is, $S_\alpha(\tau, z, \pi) \geq S_0(\tau, z, \pi)$. Similar to P and σ, the function S_ρ need not always be increasing in π. Whereas $S_0(\cdot, \pi)$ is increasing in π, for S_α we found that in 2.3 % of the cases $S_\alpha(\tau, z, \pi) < S_\alpha(\tau, z, \pi')$ for some $\pi > \pi'$ with π close to π'. Interestingly $S_\rho(\cdot, x)$ need not always be increasing in the pledge size x. Specifically, $S_0(\cdot, x)$ and $S_\alpha(\cdot, x)$ are non-decreasing in x for 99.99% and 85% of the possible values of the campaign state variable.

Appendix B

Vector of controls

The econometric models include broad sets of controls captured in the vectors $Z_{n,c}$ and $W_{n,c}$. We include eleven variables in $Z_{n,c}$: (1) (log) cumulative amount funded at the time of the pledge ($\log y_t$); (2) (log) number of pledges already made at the time of the pledge; (3) the number of days until the end of the campaign (a proxy for τ); (4) the share of the goal that is yet to be financed (z/Y); (5) the number of days until the end of the campaign interacted with the share of the goal that is yet to be financed ($\tau \cdot z/Y$); (6) a variable that equals one if the campaign has already reached the goal at the time of the pledge (if $z \leq 0$ and $\tau > 0$), and zero otherwise; (7) the Seedrs' campaign hotness indicator at the beginning of the day, an index used by the platform to order campaigns on the landing page based on a campaign's relative performance (campaigns with a higher hotness index appear in more prominent positions on the landing page; see Table 2 for further details); (8) an indicator variable that equals one if the Seedrs' campaign hotness indicator rose during the day; (9) the average of the Seedrs' hotness index for all active campaigns except c, capturing overall investment activity on the platform; (10) a Google trend daily index for searches on the campaign's name, a measure of daily interest in the campaign outside the platform; and (11) the FTSE index for the day.

The vector $W_{n,c}$ is composed of a set of indicator variables for high-net-worth, sophisticated, or authorized (the base) backers. It also includes an indicator that takes a value of one if the backer is recurrent, and zero otherwise.

Detailed instrumentation strategy

There are several identification challenges we need to address. The first is selection of investors to campaigns. Investors choose which campaigns to invest in, a decision that depends on the characteristics (observed and unobserved) of the projects. For example, wealthier investors might self-select into specific campaigns, resulting in a spurious positive correlation between pledge sizes. We deal with this issue in part by including η_c, which are campaign fixed effects to capture all the observed and unobserved project characteristics that remain fixed for the duration of the campaign.[22] Campaign fixed effects are of first-order importance in our setup, and their inclusion implies that we use only *within* campaign variation for identification in the

[22] Examples include the pre-money valuation, campaign goal, equity offered, number and composition of entrepreneurs, and the type of project.

econometric analysis.

The second challenge is the theoretical prediction that pledge sizes depend on both the state of the campaign–as measured by the time left (τ) and the distance to the goal (z_τ)– and backers' characteristics, in particular, their wealth. We need to condition on these factors to isolate the information content of pledge sizes for subsequent investors. We include six variables in vector $Z_{n,c}$ that characterize the state of each campaign at any point in time in a flexible way. The variables are: (1) the (log) cumulative amount funded at the time of the pledge ($\log y_t$); (2) the (log) number of pledges already made at the time of the pledge; (3) the number of days until the end of the campaign (a proxy for τ); (4) the share of the goal that is yet to be financed (z/Y); (5) the number of days until the end of the campaign interacted with the share of the goal that is yet to be financed ($\tau \cdot z/Y$); and (6) a variable that equals one if the campaign has already reached the goal at the time of the pledge (if $z \leq 0$ and $\tau > 0$), and zero otherwise. These are all directly observable to potential backers. We further include vector $W_{n,c}$ of controls, which accounts for some of the heterogeneity in backers' characteristics. This vector is composed of a set of indicator variables for high-net-worth, sophisticated, or authorized (the base) backers. It also includes an indicator that takes a value of one if the backer is recurrent, and zero otherwise.

A third identification challenge is the non-random bunching of pledges or correlated backer types within campaigns. For example, positive news about a specific campaign might induce several investors to pledge larger amounts at a given moment in time, generating a spurious positive correlation. We can account for these common factors in part by including a set of additional control variables in vector $Z_{n,c}$: (1) the Seedrs' campaign hotness indicator at the beginning of the day, an index used by the platform to order campaigns on the landing page based on the campaign's relative performance;[23] (2) an indicator variable that equals one if the Seedrs' campaign hotness indicator rose during the day; (3) the average of the Seedrs' hotness index for all active campaigns except c, which captures overall investment activity on the platform; (4) a Google trend daily index for searches on the campaign's name, a measure of daily interest in the campaign outside the platform; and (5) the FTSE index for the day.

An alternative reason for non-random bunching is that groups of backers might coordinate their investment decisions. We focus on correlations between adjacent (chronologically

[23]Campaigns with a higher hotness index appear in more salient positions on the landing page (see Table 2 for further details).

close) investments, and we include campaign fixed effects. This behavior would be problematic if backers coordinate not only the campaigns in which they choose to invest but also the *timing* of the pledges. But even with the controls included in the model, the predicted pledge dynamics could still be rationalized by unobserved correlated signals. To disentangle these alternative mechanisms from those proposed in the model, we complement the empirical strategy with two alternative instrumental variable (IV) approaches.

Instrumentation strategy (A). For an IV to work in our context, we need a variable that affects the size of $\log I_{n-k,c}$ (relevance) but is unrelated to the pledge sizes of subsequent backers, apart from the indirect influence through its effect on $\log I_{n-k,c}$ (exclusion restriction). Ideally, we would change the amount pledged by a random set of investors and analyze whether subsequent pledges respond to these changes. We cannot experimentally vary the amounts pledged, but we have indicators for investors' liquidity and level of wealth, which the model predicts will affect pledge sizes in a manner that is consistent with the exclusion restriction.

The AoN clause says that if a campaign fails, the amounts pledged are returned to the backers. The money that is returned can then be used by recurrent investors for pledges in future campaigns, in which the extra liquidity can be thought of as unexpected (i.e., a windfall). The unexpected liquidity should increase the size of future optimal investment via the wealth effect (Property 1 of Proposition 1), satisfying the relevance condition. Unless there is a high degree of coordination and communication between investors, which we discuss below, the fact that a backer receives a windfall from the failure of a previous campaign is not known to other backers, so there is no other plausible reason for it to affect their pledges, thus satisfying the exclusion restriction. The instrument is then defined as the inverse hyperbolic sine transformation (IHS)[24] of the total amount returned to a backer in the last failed campaign in which she invested, conditional on the failure of that campaign before the campaign c started.

To clarify these ideas, in the Online Appendix (OA) Figure Appendix C.1 we illustrate how the instrument is constructed for an individual investor. In the figure, campaigns to which the investor makes pledges are distributed along the vertical axis, while the horizontal axis represents calendar time. Each horizontal line indicates the time that a campaign was active. Suppose an investor pledges an amount I_1 at time t_1 to campaign c_1, which fails to reach the

[24]The inverse hyperbolic sine transformation can be interpreted in the same way as the standard logarithmic transformation, but it has the property of being defined at zero. This is important because a large number of investors have invested on the platform only once or have not pledged to a failed campaign before.

target. The amount I_1 is returned to the investor after the campaign fails at t_{fail} and is the basis for our instrument. Suppose the same investor makes a pledge of size I_2 at time t_2 to campaign c_3. The returned amount I_1 is unexpected disposable income for the investor, which might affect the amount pledged I_2. Furthermore, if $I_1 > I_2$, some disposable income remains, $I^* = I_1 - I_2$, which can also affect I_3. We continue in this way until all disposable income is potentially used. Finally, note that campaign c_2 started before the failure of c_1, so we abstain from using I_1 to instrument pledges in that campaign (i.e., the instrument takes a value of zero). This implies that the value of the instrument is pre-determined at the start of each campaign.

We find that close to 8.6 percent of the pledges can be affected by disposable income coming from returned money after the failure of a campaign. Among those pledges, the simple correlation between the instrument and the respective endogenous variable is 0.37. Moreover, in 6 percent of the cases, the potentially affected pledge is of exactly the same value as the amount returned. We therefore expect a strong first stage for the instrument.

The exclusion restriction could fail if investors coordinate in such a way that they repeatedly choose together which campaigns to invest in, how much to pledge, and at what point in time. We cannot fully reject that possibility, but we provide three pieces of evidence that suggest coordination is not the driver of the results. First, in a robustness exercise, we reestimate the model using the proposed IV but focus only on responses by single-campaign investors. We can be certain that these one-off investors have not coordinated in previous campaigns. For coordination to exist, a recurrent investor who received a windfall from a previous campaign must be coordinating with people who had never invested in the platform and such coordination must be included the campaign, the timing, and the size of the pledges. Furthermore, this behavior would have to be systemic so that it is captured by regression estimates. We argue that this is highly unlikely. We show that the results from this constrained specification are qualitatively similar to the main estimates.[25] A second piece of evidence of validity is provided in Table Appendix C.2, in which we look at correlations between adjacent values of the IV. If investors are coordinating their pledges, both across campaigns and over time, they would receive positive windfalls from failed campaigns and invest in future campaigns simultaneously. Hence, the value of the instruments (the windfall amount) across adjacent pledges would be positively correlated. Our results show that this is not the case. Finally, the likelihood of coordination might be higher if the investors were of the same type–for example, high-net-worth investors

[25]These results are shown in Table Appendix C.1.

might be more likely to be acquainted with other high-net-worth investors. In Table Appendix C.3 we look for any correlation between adjacent self-reported types of investors, an indication of possible coordination by type. Again, we find no evidence that this is happening.[26]

Although the arrival process of backers is exogenous in the model, the possibility of non-random bunching could also generate a spurious correlation between the time elapsed since the most recent pledge, $\log T_{(n,n-1),c}$, and pledge sizes. For example, if bunching is generated by positive (negative) news about a project, the length of time between subsequent pledges tends to shorten because more (fewer) backers arrive to the campaign when an information shock occurs. We tackle this issue with an IV. In this case, we need a variable that affects the arrival rate of backers to campaigns (relevance) but is unrelated to optimal pledge sizes (exclusion restriction). We define the instrument based on the hour of the day in which the most recent pledge is made. The data show that few pledges tend to occur before 6 a.m., then they increase during the morning and reach a peak at 11 a.m., and then monotonically decline for the rest of the day. This pattern reflects typical work schedules. The closer a pledge is to the peak hour, the greater the likelihood that another backer will arrive shortly afterward. However, there is no direct correlation between the hour at which a pledge is made and its size.[27] The instrument is defined as the (log) absolute value of the difference in hours between the hour of the day in which the most recent pledge is made and 11 a.m.

Instrumentation strategy (B). One pitfall with our preferred (money returned) IV is that the instrument can affect only a small percentage of pledges (8.6 percent). We use a second set of instruments for $\log I_{n-k,c}$ to validate the results. Intuitively, we use information on previous pledging behavior and investors' profiles that we observe in the data but that subsequent backers do not observe. Every backer making a pledge to a project appears on the campaign page, but they can choose whether to have their names and profiles be public or remain anonymous. For backers who choose to be anonymous, only the amount pledged is displayed, so no information on the anonymous backer can be inferred in any way by a subsequent backer. Although the

[26]One additional concern is that investors of a similar type arrive at the same stage of a campaign, generating a spurious correlation in pledge sizes. For example, most active investors keep searching the platform, and they notice a campaign shortly after it starts. Hence, the clustering of contribution timing might mechanically generate the empirical results. To show that this is not the case, we reestimate all the models, excluding days 1, 5, and 7 in campaigns, and the results are robust in each case.

[27]We test this claim by estimating a model similar to the one specified in Equation 16 but using hour-of-the-day dummies as IVs, instead of investment lags, $\log I_{n-k,c}$, and the time since most recent pledge, $\log T_{(n,n-1),c}$. None of the hour-of-the-day dummies are statistically significant, regardless of the base category used. The results are available upon request.

past investment history of anonymous profiles is not public, we have access to it in our data set. We use this information to construct variables that contain relevant information to predict the wealth of an anonymous investor, and hence the size of a pledge, but that is not observed by subsequent backers, so it cannot directly influence their pledging behavior.

We use two pieces of information as instruments for each prior pledge ($\log I_{n-k,c}$):[28] (1) the total number of pledges made by the investor $(n-k)$ in all previous campaigns before campaign c started is interacted with the anonymous indicator; and (2) the largest single amount pledged by the backer $(n-k)$ in previous campaigns is interacted with the anonymous indicator. Recurrent backers tend to pledge smaller amounts than single-campaign backers, so the first instrument is expected to have a negative correlation with pledge size. At the same time, backers who previously pledged large amounts are potentially wealthier (Property 1 of Proposition 1), so the second instrument is expected to have a positive correlation with pledge size.

[28]By using two instruments for each pledge, the model is overidentified, so we can report standard Hansen test statistics for overidentifying restrictions.

Appendix C

Appendix Tables and Figures

Figure Appendix C.1: Sketch of the Construction of the Preferred Instrument

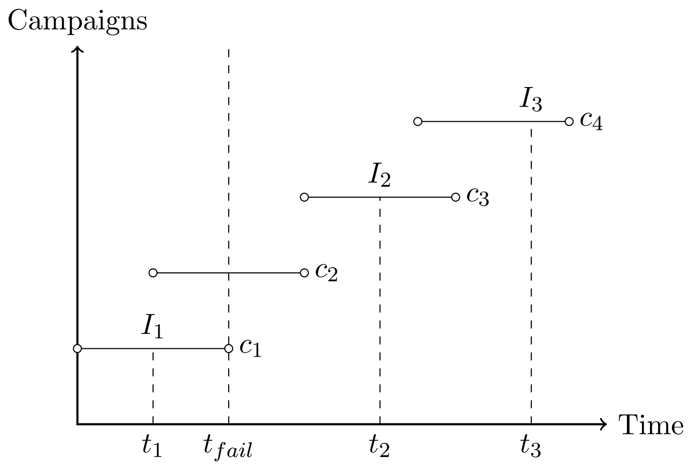

Table Appendix C.1: The Effect of Prior Pledges and the Time Since the Most Recent Pledge: Single Campaign Investors

	Dependent Var: log amount pledged (£)					
	Model	Model Controls I	Model Controls II	Model Controls Full	IV-A	IV-B
Prior pledges						
Log amount pledged (n-1)	0.121***	0.116***	0.115***	0.112***	0.155**	0.196**
	(0.017)	(0.016)	(0.017)	(0.016)	(0.054)	(0.068)
Log amount pledged (n-2)	0.060***	0.056***	0.055***	0.054***	0.418	0.035
	(0.012)	(0.012)	(0.011)	(0.011)	(0.439)	(0.051)
Log amount pledged (n-3)	0.033***	0.033***	0.032***	0.031**	0.285	0.011
	(0.010)	(0.010)	(0.010)	(0.010)	(0.295)	(0.066)
Log amount pledged (n-4)	0.025**	0.022**	0.022**	0.020**	-0.459	0.022
	(0.010)	(0.010)	(0.010)	(0.010)	(0.413)	(0.046)
Log amount pledged (n-5)	0.031**	0.031**	0.032**	0.031**	0.175	-0.059
	(0.011)	(0.011)	(0.010)	(0.010)	(0.417)	(0.073)
Log time (hours) since most recent pledge	-0.009	-0.001	0.005	0.017	0.010	-0.021
	(0.044)	(0.044)	(0.043)	(0.042)	(0.152)	(0.104)
Controls investor						
Dummy high-net-worth		1.413***	1.411***	1.402***	1.384***	1.392***
		(0.125)	(0.125)	(0.123)	(0.137)	(0.127)
Dummy sophisticated		0.519***	0.520***	0.520***	0.487***	0.506***
		(0.101)	(0.100)	(0.099)	(0.120)	(0.103)
Controls campaign						
Log total amount funded up to n-1			-0.027	-0.031	-0.119	0.012
			(0.102)	(0.102)	(0.265)	(0.124)
Log number of pledges up to n-1			0.093	0.086	0.197	0.094
			(0.088)	(0.096)	(0.311)	(0.112)
Share amount left n-1			-0.014	0.006	0.316	0.443
			(0.304)	(0.296)	(0.414)	(0.397)
Share amount left n-1 × Days left			0.002	0.002	-0.001	-0.004
			(0.005)	(0.006)	(0.008)	(0.007)
Days left in the campaign			-0.004*	-0.004*	-0.005	-0.005**
			(0.002)	(0.002)	(0.003)	(0.003)
=1 if goal already reached			-0.127	-0.130	-0.086	-0.088
			(0.097)	(0.089)	(0.097)	(0.093)
Standardized Campaign hotness at start of the day				0.041	0.002	-0.015
				(0.038)	(0.070)	(0.055)
Dummy campaign hotness intraday rise				0.276***	0.221**	0.215**
				(0.059)	(0.080)	(0.072)
Standardized average campaign hotness rest of campaigns				-0.032	0.005	-0.011
				(0.036)	(0.053)	(0.042)
Standardized Google trend index				-0.070*	-0.090*	-0.087**
				(0.037)	(0.046)	(0.038)
Standardized FTSE 100 index				0.008	0.054	0.048
				(0.065)	(0.076)	(0.074)
Observations	13,203	13,203	13,203	13,203	12,205	12,205
Average pledge (£)	2,772	2,772	2,772	2,772	2,752	2,752
SD pledge (£)	17,494	17,494	17,494	17,494	15,573	15,573
Average time (hours) since most recent pledge	8.6	8.6	8.6	8.6	8.7	8.7
S.D. time (hours) since most recent pledge	31.7	31.7	31.7	31.7	30.1	30.1
Kleibergen and Paap rk statistic					13.45	70.61
Hansen J statistic P-Val					.	0.22
Campaign FE	Yes	Yes	Yes	Yes	Yes	Yes

*** 1 percent ** 5 percent * 10 percent

Notes: Robust standard errors, clustered by campaign. Single Campaign Investors. Each lagged pledge in the IV setting (A) is instrumented using the inverse hyperbolic sine transformation (IHS) of the amount of money returned to the backer if the last campaign she supported failed. Each lagged pledge in the IV setting (B) has two instruments: (i) total number of pledges made by the investor in all campaigns interacted with the anonymous indicator; and (ii) the largest single amount pledged by the investor in previous campaigns interacted with the anonymous indicator. The time since the most recent pledge is instrumented in (A) and (B) with the (log) absolute value of the difference in hours between the hour in the day in which the previous pledge is made and 11am. See Section 7 for a detailed description.

Table Appendix C.2: Correlation Between Adjacent Values of the Pre-Determined Instruments

	Dependent Var:		
	IHS Amount Returned	Number of Pledges × Anonymous	Max Amount Invested × Anonymous
Inst. A			
IHS amount returned (n-1)	0.012 (0.008)		
IHS amount returned (n-2)	0.013 (0.009)		
IHS amount returned (n-3)	0.010 (0.007)		
IHS amount returned (n-4)	0.015 (0.010)		
IHS amount returned (n-5)	0.001 (0.006)		
Inst. B1			
Number of pledges (n-1) × Anonymous (n-1)		0.001 (0.006)	
Number of pledges (n-2) × Anonymous (n-2)		-0.014 (0.011)	
Number of pledges (n-3) × Anonymous (n-3)		-0.005 (0.006)	
Number of pledges (n-4) × Anonymous (n-4)		-0.004 (0.006)	
Number of pledges (n-5) × Anonymous (n-5)		-0.014 (0.012)	
Inst. B2			
Max amount invested (n-1) × Anonymous (n-1)			-0.006 (0.008)
Max amount invested (n-2) × Anonymous (n-2)			-0.016 (0.013)
Max amount invested (n-3) × Anonymous (n-3)			-0.003 (0.009)
Max amount invested (n-4) × Anonymous (n-4)			-0.001 (0.010)
Max amount invested (n-5) × Anonymous (n-5)			-0.016 (0.011)
Observations	55,052	55,052	55,052
Full Set Controls	Yes	Yes	Yes
Campaign FE	Yes	Yes	Yes

*** 1 percent ** 5 percent * 10 percent

Notes: Robust standard errors, clustered by campaign. The full set of controls from Table 4 are included but not reported.

Table Appendix C.3: Correlation Between Self-Reported Types of Adjacent Investors

	Self Reported Investor Type Dummy		
	Authorized	High-net-worth	Sophisticated
Authorized			
Dummy authorized n-1	-0.002		
	(0.005)		
Dummy authorized n-2	0.007		
	(0.005)		
Dummy authorized n-3	-0.002		
	(0.004)		
Dummy authorized n-4	0.006		
	(0.005)		
Dummy authorized n-5	0.003		
	(0.005)		
High-net-worth			
Dummy high-net-worth n-1		-0.006	
		(0.005)	
Dummy high-net-worth n-2		0.010	
		(0.008)	
Dummy high-net-worth n-3		-0.010	
		(0.007)	
Dummy high-net-worth n-4		0.004	
		(0.005)	
Dummy high-net-worth n-5		0.001	
		(0.005)	
Sophisticated			
Dummy sophisticated n-1			-0.006
			(0.005)
Dummy sophisticated n-2			-0.002
			(0.005)
Dummy sophisticated n-3			0.000
			(0.005)
Dummy sophisticated n-4			0.004
			(0.005)
Dummy sophisticated n-5			-0.003
			(0.005)
Observations	55,052	55,052	55,052
Campaign FE	Yes	Yes	Yes

*** 1 percent ** 5 percent * 10 percent

Notes: Robust standard errors, clustered by campaign.

Table Appendix C.4: The Effect of Prior Pledges and the Time Since the Most Recent Pledge: First Stages IV-A

	First Stage Regressions					
	$\log I_{n-1,c}$	$\log I_{n-2,c}$	$\log I_{n-3,c}$	$\log I_{n-4,c}$	$\log I_{n-5,c}$	$\log T_{(n,n-1),c}$
IHS amount returned (n-1)	0.068***	-0.002	-0.006	-0.004	-0.004	-0.001
	(0.007)	(0.005)	(0.005)	(0.004)	(0.004)	(0.003)
IHS amount returned (n-2)	-0.003	0.069***	-0.000	-0.006	-0.005	-0.004
	(0.005)	(0.008)	(0.005)	(0.005)	(0.004)	(0.003)
IHS amount returned (n-3)	0.002	-0.001	0.069***	0.004	-0.006	-0.003
	(0.005)	(0.005)	(0.008)	(0.005)	(0.005)	(0.003)
IHS amount returned (n-4)	0.002	0.003	-0.003	0.065***	0.002	-0.003
	(0.005)	(0.005)	(0.005)	(0.008)	(0.005)	(0.003)
IHS amount returned (n-5)	-0.004	0.001	0.003	-0.004	0.067***	-0.001
	(0.004)	(0.005)	(0.005)	(0.005)	(0.008)	(0.003)
Log hours since midday (n-1)	-0.079***	-0.033**	0.003	0.012	0.003	0.254***
	(0.012)	(0.011)	(0.011)	(0.011)	(0.010)	(0.011)
Observations	55,052	55,052	55,052	55,052	55,052	55,052
Campaign FE	Yes	Yes	Yes	Yes	Yes	Yes

*** 1 percent ** 5 percent * 10 percent

Notes: Robust standard errors, clustered by campaign. The full set of controls from Table 4 are included but not reported. Each lagged pledge in the IV setting is instrumented using the inverse hyperbolic sine transformation (IHS) of the amount of money returned to the backer if the last campaign she supported failed. The time since the most recent pledge is instrumented with the (log) absolute value of the difference in hours between the hour in the day in which the previous pledge is made and 11am. See Section 7 for a detailed description.

Table Appendix C.5: The Effect of Prior Pledges and the Time Since the Most Recent Pledge: First Stages IV-B

	First Stage Regressions					
	$\log I_{n-1,c}$	$\log I_{n-2,c}$	$\log I_{n-3,c}$	$\log I_{n-4,c}$	$\log I_{n-5,c}$	$\log T_{(n,n-1),c}$
Number of pledges (n-1) × Anonymous (n-1)	-0.689***	-0.005	-0.015	-0.026	0.018	-0.059***
	(0.023)	(0.022)	(0.022)	(0.024)	(0.022)	(0.016)
Number of pledges (n-2) × Anonymous (n-2)	-0.028	-0.706***	-0.014	-0.017	-0.027	-0.046**
	(0.019)	(0.023)	(0.022)	(0.021)	(0.024)	(0.016)
Number of pledges (n-3) × Anonymous (n-3)	-0.047**	-0.049**	-0.716***	-0.020	-0.015	-0.007
	(0.021)	(0.020)	(0.024)	(0.022)	(0.022)	(0.016)
Number of pledges (n-4) × Anonymous (n-4)	0.001	-0.048**	-0.050**	-0.726***	-0.027	-0.022
	(0.022)	(0.020)	(0.020)	(0.024)	(0.023)	(0.015)
Number of pledges (n-5) × Anonymous (n-5)	-0.021	-0.013	-0.074***	-0.073***	-0.749***	0.009
	(0.023)	(0.022)	(0.021)	(0.020)	(0.025)	(0.017)
Max amount invested (n-1) × Anonymous (n-1)	0.553***	0.022	0.003	-0.014	-0.020	-0.019
	(0.086)	(0.020)	(0.013)	(0.013)	(0.018)	(0.012)
Max amount invested (n-2) × Anonymous (n-2)	0.016	0.586***	0.052**	0.008	-0.006	-0.007
	(0.021)	(0.074)	(0.019)	(0.014)	(0.012)	(0.008)
Max amount invested (n-3) × Anonymous (n-3)	0.020	0.025	0.574***	0.037	0.019	-0.006
	(0.013)	(0.019)	(0.085)	(0.023)	(0.013)	(0.009)
Max amount invested (n-4) × Anonymous (n-4)	-0.010	0.017	0.014	0.576***	0.048**	0.003
	(0.012)	(0.013)	(0.020)	(0.077)	(0.017)	(0.009)
Max amount invested (n-5) × Anonymous (n-5)	-0.014	-0.015	0.020*	0.014	0.572***	-0.003
	(0.024)	(0.013)	(0.012)	(0.017)	(0.093)	(0.009)
Log hours since midday (n-1)	-0.065***	-0.026**	0.005	0.014	0.004	0.255***
	(0.011)	(0.010)	(0.010)	(0.010)	(0.010)	(0.011)
Observations	55,052	55,052	55,052	55,052	55,052	55,052
Campaign FE	Yes	Yes	Yes	Yes	Yes	Yes

*** 1 percent ** 5 percent * 10 percent

Notes: Robust standard errors, clustered by campaign. The full set of controls from Table 4 are included but not reported. Each lagged pledge has two instruments: (i) total number of pledges made by the investor in all campaigns interacted with the anonymous indicator; and (ii) the largest single amount pledged by the investor in previous campaigns interacted with the anonymous indicator . The time since the most recent pledge is instrumented with the (log) absolute value of the difference in hours between the hour in the day in which the previous pledge is made and 11am. See Section 7 for a detailed description.

Table Appendix C.6: The Effect of Prior Pledges and the Time Since the Most Recent Pledge. Including Regretted Investments

	Dependent Var: log amount pledged (£)					
	Model	Model Controls I	Model Controls II	Model Controls Full	IV A	IV B
Prior pledges						
Log amount pledged (n-1)	0.111***	0.103***	0.103***	0.101***	0.182**	0.131***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.081)	(0.019)
Log amount pledged (n-2)	0.032***	0.029***	0.030***	0.029***	0.090	0.036**
	(0.005)	(0.004)	(0.004)	(0.004)	(0.086)	(0.018)
Log amount pledged (n-3)	0.024***	0.022***	0.023***	0.022***	0.075	0.014
	(0.004)	(0.004)	(0.004)	(0.004)	(0.076)	(0.019)
Log amount pledged (n-4)	0.014***	0.014***	0.015***	0.014***	0.023	-0.027
	(0.004)	(0.004)	(0.004)	(0.004)	(0.084)	(0.026)
Log amount pledged (n-5)	0.021***	0.020***	0.021***	0.020***	0.066	0.025*
	(0.004)	(0.004)	(0.004)	(0.004)	(0.081)	(0.014)
Log time (hours) since most recent pledge	-0.041**	-0.020	-0.016	-0.007	-0.019	-0.052
	(0.017)	(0.016)	(0.017)	(0.017)	(0.041)	(0.038)
Controls investor						
Dummy high-net-worth		1.162***	1.162***	1.159***	1.130***	1.148***
		(0.036)	(0.036)	(0.035)	(0.035)	(0.035)
Dummy sophisticated		0.463***	0.464***	0.463***	0.440***	0.455***
		(0.036)	(0.036)	(0.036)	(0.038)	(0.037)
Dummy recurrent investor		-0.611***	-0.604***	-0.602***	-0.584***	-0.587***
		(0.046)	(0.046)	(0.046)	(0.046)	(0.047)
Controls campaign						
Log total amount funded up to n-1			-0.103**	-0.100**	-0.178***	-0.094**
			(0.037)	(0.037)	(0.054)	(0.041)
Log number of pledges up to n-1			0.053*	0.058*	0.170**	0.084**
			(0.028)	(0.030)	(0.058)	(0.038)
Share amount left n-1			-0.081	-0.034	0.192	0.190
			(0.119)	(0.119)	(0.117)	(0.141)
Days left in the campaign			-0.003***	-0.003***	-0.002**	-0.003***
			(0.001)	(0.001)	(0.001)	(0.001)
Share amount left n-1 × Days left			-0.002	-0.002	-0.004**	-0.005**
			(0.002)	(0.002)	(0.002)	(0.002)
=1 if goal already reached			-0.096**	-0.095**	-0.078**	-0.082**
			(0.031)	(0.032)	(0.026)	(0.033)
Standardized Campaign hotness at start of the day				0.033**	0.001	0.007
				(0.014)	(0.018)	(0.020)
Dummy campaign hotness intraday rise				0.171***	0.132***	0.144***
				(0.021)	(0.023)	(0.026)
Standardized average campaign hotness rest of campaigns				-0.002	0.004	0.004
				(0.011)	(0.011)	(0.012)
Standardized Google trend index				-0.020	-0.015	-0.027**
				(0.012)	(0.013)	(0.013)
Standardized FTSE 100 index				0.001	0.005	0.006
				(0.024)	(0.021)	(0.025)
Observations	70,136	70,136	70,136	70,136	64,844	64,844
Average pledge (£)	1,225	1,225	1,225	1,225	1,221	1,221
SD pledge (£)	12,624	12,624	12,624	12,624	12,395	12,395
Average time (hours) since most recent pledge	9.6	9.6	9.6	9.6	9.8	9.8
S.D. time (hours) since most recent pledge	35.2	35.2	35.2	35.2	34.8	34.8
Kleibergen and Paap rk statistic					16.83	206.17
Hansen J statistic P-Val						0.52
Campaign FE	Yes	Yes	Yes	Yes	Yes	Yes

*** 1 percent ** 5 percent * 10 percent

Notes: Robust standard errors, clustered by campaign. Each lagged pledge in the IV setting (A) is instrumented using the inverse hyperbolic sine transformation (IHS) of the amount of money returned to the backer if the last campaign she supported failed. Each lagged pledge in the IV setting (B) has two instruments: (i) total number of pledges made by the investor in all campaigns interacted with the anonymous indicator; and (ii) the largest single amount pledged by the investor in previous campaigns interacted with the anonymous indicator. The time since the most recent pledge is instrumented in (A) and (B) with the (log) absolute value of the difference in hours between the hour in the day in which the previous pledge is made and 11am. See Section 7 for a detailed description.