Herding in Equity Crowdfunding*

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Abstract

Do equity crowdfunding investors rationally or irrationally herd? We build a model of rational information aggregation where both informed and uninformed investors arrive sequentially and rationally choose whether and how much to invest. We compare the predictions of the model to several alternative models of irrational herding and no herding, and test those predictions using data on all investments on a leading European equity crowdfunding platform. We show empirically that the size and likelihood of a pledge is causally affected by the size of the most recent pledge, and by the time elapsed since the most recent pledge. These results are consistent with rational information aggregation, and inconsistent with naïve herding, independent investments, and common information shocks. However, there is still room for negative information cascades to occur. Implications for platform design and regulatory actions are discussed.

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1 Introduction

In recent years crowdfunding and other alternative financing have proved popular channels for entrepreneurs. In the US, this sector has grown 46 percent, from \$289 billion in 2016 to \$422 billion in 2017, or 1,040 percent since 2014 (Ziegler et al., 2018, 2019). The focus of this paper is on equity crowdfunding. Equity crowdfunding is an online-based mechanism that enables broad groups of investors to fund start-up companies and small businesses in return for equity. This mechanism has already become a significant financing vehicle for start-ups, and is growing rapidly from \$600 million in 2014 to \$1.3 billion in 2017. For example, in the UK around 21 percent of all early-stage investment and as much as 35.5 percent of all seed-stage investment deals went through equity crowdfunding sites in 2015 (Beauhurst, 2016).[1]

A young firm can raise funds in exchange for equity by publishing their business idea online and solicit investments on an equity crowdfunding platform. A large number of investors can then express their opinion about the start-up's quality by choosing to invest in the campaign. If one can observe the amount others have already invested, rational investors will take into account the information content of these amounts when choosing whether and how much to invest. Thus, one can view a crowdfunding campaign as a way to aggregate a large number of partially private pieces of information about a project, and this may provide relevant public information about the project's quality. This view is challenged by the idea that the crowd tends to behave as a herd, and may be induced to irrationally invest simply if seeing others invest (Shiller, 2015). It is possible then that the outcome of a campaign may not reflect rational information aggregation but just the opinion of those who arrived early in the campaign and chose to invest, or not to invest.

Broadly speaking, herding is a situation where an investment decision is influenced by investment decisions already taken by other investors. Clearly, herding may occur in equity crowdfunding, and it may be irrational or rational. Whether there are such patterns may affect how crowdfunding platforms are built to reduce or enhance herding; how project owners/entrepreneurs present information about the project to enhance both irrational and rational herding; how they deal with negative information cascades, as their incentive naturally lies in obtaining funding for the project; and whether policy makers

[1]The UK is the fastest-growing country for equity crowdfunding campaigns in the world, both in terms of the number of campaigns and their sizes. This is because the UK has had a clear regulatory framework for equity crowdfunding in place since the end of 2011. Backers of start-ups in the UK also benefit from a very generous tax incentive via the Seed Enterprise Investment Scheme, SEIS, and the Enterprise Investment Scheme, EIS. Both schemes are designed to help small UK-based companies raise finance by offering tax relief on new shares in those companies. The EIS is aimed at wealthier backers who receive 30 percent tax relief but whose pledges cannot be sold or transferred for a minimum lock-in period of three years. The SEIS is more generous and provides tax relief of up to 50 percent on pledges of up to £100,000, and capital gains tax exemption. The maximum investment that can be raised by a company under this scheme is limited to £150,000.

need to be concerned about regulating the provision and presentation of information on these platforms.

In this paper we try to answer the following three broad questions for equity crowdfunding. First, do we observe that investment decisions are causally influenced by investment decisions already taken by other investors? Second, are investors' behaviour consistent with rational aggregation of information? Third, to what extent are investors making irrational investment choices?

To answer these questions we start by building a model of rational information aggregation that consists of an adaptation of Hörner and Herrera (2013) sequential investment model that reflects the specific institutional setting. The model features a project that is either profitable or not, and a sequence of investors (backers henceforth) that sequentially visit the crowdfunding campaign and choose whether and how much to invest (pledge henceforth). Each backer is risk-averse, and is uninformed or possesses some partial information about the project's profitability. When choosing whether and how much to pledge a backer will take into account her private information as well as the information content of the past history of pledges.

To answer whether other forms of investment behaviour may exist, we first contrast our model with two alternative benchmarks where investors do not influence each other. In alternative model 1 (AM1) backers have no private information and their pledges only reflect the arrival of public information about the project's profitability. Alternative model 2 (AM2) reflects a situation in which backers simply use their own private information and ignore the choices made by other backers.[2]

To disentangle whether equity crowdfunding campaigns may rationally aggregate signals from the crowd about the value of business ideas, or whether prior investments are just inducing investors, and particularly unsophisticated investors, to herd, we contrast our model to two other alternative models. In alternative model 3 (AM3) each backer ignores the individual investments already made by others but does react on the cumulative amount already invested. Alternative model 4, (AM4) considers a situation of irrational naïve herding. That is, the first few backers' pledges reflect their private information, but all subsequent backers mimic the first backers. We contrast predictions from these five different theoretical views and empirically test which one better fits the behaviour of investors in one of the two leading UK equity crowdfunding platforms.

Our main model provides the microfoundations for representing rational herding in crowdfunding and derives a number of testable empirical implications. The first group of predictions concern the effect of the most recent pledge on the size and likelihood of a pledge. The size of a pledge and the probability of observing a pledge should be positively correlated with the size of the most recent pledges and negatively correlated

[2] AM2 reflects the approach taken by a number of theoretical papers on crowdfunding that have modelled the funding process as a simultaneous move game.

with the time elapsed since the most recent pledge. These correlations should be stronger when the pledge is made by an uninformed investor rather than an informed investor. The second group of predictions concern the effect of campaign dynamics at launch on backers' behaviour during the remainder of the campaign. The positive correlation between two adjacent pledges, and the negative correlation with the time elapsed since the most recent pledge should be considerably weaker for campaigns that have good start. Campaigns that do not have a good start have little chance to resurrect, that is, too little funding in the beginning of a campaign leads to no pledges in the future.

We contrast these predictions with predictions from the four alternative models. The first two empirical implications of our main model are delivered also by AM1, but AM1 does not have anything in common with the other predictions of the main model. A distinguishing feature of AM2 is that after controlling for campaign fixed effects, the size and timing of the previous pledge should not affect the next pledge. AM3 predicts that after controlling for campaign duration and the cumulative amount pledged, the size and timing of the previous pledge should not affect the next pledge. AM4 predicts that after a very good campaign start, the size and the timing of previous pledges should not affect the next pledge. However, AM4 does not have any other predictions in common with the main model.

We test these model predictions using a rich dataset on over 69,699 pledges in 710 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 of the campaign as well as project-specific information. Because approximately half of the pledges are made anonymously to other backers, we possess information about those backers' identity and past pledge behaviour that is not available to other backers, which turns out to be useful for identification purposes. Since we have the exact timing of every pledge made in every campaign, we can restrict the empirical analysis to within campaign dynamics, controlling for all time-invariant unobserved heterogeneity across campaigns.

We find that both the size and the probability of a pledge are positively correlated with the size of the most recent pledge and negatively correlated with the time elapsed since the most recent pledge. These findings immediately reject AM2 and AM4. We can therefore quickly exclude naïve herding and that backers invest independently. Because these correlations remain after controlling for the cumulative pledge size, we can also exclude AM3.

Disentangling the main model from AM1 is more challenging. Is a backer causally influenced by the most recent pledge as predicted by the main model, or is the correlation between adjacent pledges solely the result from a common hidden factor as in AM1?

To answer this question, we use instrumental variable techniques to scrub out common influences on adjacent pledges. The proposed IV's are based on the prediction from the main theoretical model that the size of a pledge depends on the wealth of investors. We use information available to us but unobserved to backers on the platform about backers' wealth to generate exogenous variation in the size of pledges. We provide auxiliary evidence supportive of the validity of the instruments.

Two alternative IV regressions both identify very similar causal effects on the size of a pledge, and the probability of a pledge, of the size and time since the most recent pledge, consistent with the predictions of the main model, and inconsistent with AM1. We find that a doubling (100% increase) of the value of the most recent pledge is associated with a rise of 11.9 percent in the subsequent amount pledged. For an average pledge size of £1,202, the 11.9 percent increase translates into £143 of extra investment. The causal effects are not statistically significantly different from the effects estimated by OLS, suggesting that our model of rational information aggregation may represent all the correlational effects between adjacent pledges that are observed. In further analysis, we show evidence that these causal effects vary depending on early campaign dynamics and on proxies for the sophistication of an investor in a way that is consistent with the main model's predictions.

The differences between other various equity crowdfunding platforms and Seedrs in how data are presented provide a unique opportunity for us to test and compare different decision-making theories. Seedrs is one of the few equity crowdfunding platforms that displays individual pledges (most others just show cumulative funding).[3] We find that the size of these individual pledges has a positive effect on adjacent individual pledges, while the correlation with cumulative funding is either zero or slightly negative, controlling for individual project fixed effects. The latter most probably reflects that large pledges tend to occur early in the fundraising process on Seedrs, implying that when cumulative funding increases, average pledge size tend to decrease. A possible rationalization is that project owners are advised to go out and find investors that can make large early contributions. Overall, our tests provide most convincing support for that equity crowdfunding backers aggregate investment information rationally. However, we theoretically identify a situation with rational herding when an a priori good campaign does not get initial traction and fails because of a negative information cascade.

There seems little reason to regulate how pledges from backers are presented on equity crowdfunding platforms if they follow the lead of Seedrs. If on the other hand the individual pledges are not presented and dynamically updated, it becomes considerably more difficult for backers to form unbiased estimates based on rational information aggregation from the crowd. Platform designers may consider options to combat negative information cascades, such as using early warning signals prompting actions from

[3]To exemplify, neither Kickstarter, Indiegogo nor Crowdcube show individual pledges by backers.

project owners to further increase efficiency of information aggregation. There may be specific self-investment actions taken by owners of projects to push the crowd in directions favourable only to the project owners. This could be investigated in future research as it may be of considerable interest for regulators and platform operators.

2 Related literature

Empirically, our paper is most closely related to Bursztyn et al. (2014) and Zhang and Liu (2012). Bursztyn et al. (2014) examine investor behaviour in a randomized controlled experiment working closely with a large financial brokerage in Brazil. They investigate the effect on private investment decisions from a) knowing whether a peer – a colleague from work, a friend, or a family member – had a desire to purchase the asset and b) whether the peer actually became in possession of the asset. Both a) and b) were randomized. This set-up allows the authors to disentangle investment herding based on a) social learning, and b) social utility. They find both to be at play with large differences in take-up rates compared to those not informed about peers' investing preferences or behaviour. Bursztyn et al. (2014) are interested in the marginal effect of knowing who made a prior investment. An investor aggregating information rationally would not take this information into account unless the identity of the prior investor was informative of the potential return. In contrast, we study the effect that a pledge was recently made and the signal value of the size of that pledge. By studying only the effects of prior pledges made by anonymous investors we abstract from the effect of knowing who made the pledge. Relative to Bursztyn et al. (2014), we estimate the rational rather than the social signal value of a prior investment.

Another related paper, Zhang and Liu (2012), study pledges made on a peer-to-peer lending web site, *prosper.com*. They use panel field data on daily (and hourly) lending amounts as a function of the cumulative amount of funding up to $t-1$, and its interaction with observable project attributes, while controlling for project fixed effects and observable project attributes. Rational herding is said by the authors to exist if the coefficient for the interaction between the cumulative amount and the project attributes is significant and takes the opposite sign of the project attribute's main effect. The argument made is that for poor (good) project attributes, such as a low (high) credit rating, the cumulative prior funding must signal higher (lower) unobserved quality the lower (higher) the observed attribute. The authors provide evidence that this type of herding is observed in the data. The authors do not present a formal model that would explain how these interactions come about, and why it is the cumulative amount rather than the last pledge that matters for the next investor. The study has led to empirical papers correlating 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 (2016)). The papers do not show whether the herding is rational or irrational. In contrast, our study posits that unless the signal value of a pledge is noisy, the investment that matters is the most recent pledge, since rational backers would consider all prior investment history encapsulated by the most recent pledge. If there is rational herding there would be no reason for the cumulative amount funded to have any additional marginal impact on the next pledge, once controlling for the most recent pledge. We find empirically that after controlling for the size of the most recent pledge, cumulative funding at best has a negative effect on the size of a pledge, supporting our model of rational herding.

In addition, three studies have run randomized controlled experiments where a treatment group receives an early donation and the control group does not (Koning and Model, 2013; Van de Rijt et al., 2014; Zaggl and Block, 2019). Koning and Model (2013) and Zaggl and Block (2019) both find that projects to which they made a small initial contribution (e.g. \$5) significantly decrease the chances of success for a project. Our model rationalizes these results by suggesting that projects that have a poor initial start run the risk of ending up in a negative information cascade.

Our work is also related to the theoretical literature on rational herding (Banerjee, 1992; Welch, 1992; Bikhchandani et al., 1992; Smith and Sorensen, 2000; Hörner and Herrera, 2013), rational herding in financial markets (Avery and Zemsky, 1998; Decamps and Lovo, 2006; Park and Sabourian, 2011) and rational herding in crowdfunding (Cong and Xiao, 2017). Unfortunately, none of these models are fit to guide the detection of herding in our dataset because traded quantities are assumed fixed in these models (i.e., \$1). In the equity crowdfunding setting we consider, tradable quantities are continuous. Further, whereas in most of prior literature a new agent arrives in each period, the number of and arrival time of potential backers to crowdfunding platforms is not deterministic and furthermore not observable by other backers. Instead, to fit the investment setting better, we assume that time is continuous, agents arrive sequentially and the public observe only the agents that actually decide to invest.

The closest paper to our work is Hörner and Herrera (2013) and like them, we predict that periods without pledges make backers more pessimistic. However, whereas in Hörner and Herrera (2013) agents are risk neutral and can only choose between investing 1 dollar and not investing, in our model agents are risk averse, each backer chooses how much to invest and there is dispersion in pledge sizes.

Our paper further contributes to the growing theoretical literature on crowdfunding. Within a private value framework, Belleflamme et al. (2014); Ellman and Hurkens (2016); Chemla and Tinn (2016); Strausz (2017) analyze how reward-based crowdfunding can be used to probe an uncertain demand. Reward-based crowdfunding can under some conditions aggregate information even though backers are not making investments to earn a return. Chen et al. (2016) consider a model with common value where the entrepreneur learns about the value of her project from a rewards-based crowdfunding campaign. In all these papers backers move simultaneously and therefore do not influence each others' investment decisions. In our paper backers instead arrive sequentially and are influenced by previous backers' pledges.

Finally, our paper also contributes to the broader empirical literature on herding behaviour in financial decisions. Several papers have tried to study this using observational data (Hong et al., 2004, 2005; Ivkovic and Weisbenner, 2007; Brown et al., 2008; Banerjee et al., 2012; Li, 2014; Hornuf and Schwienbacher, 2018) and experimental data (Duflo and Saez, 2003; Çelen and Kariv, 2004, 2005; Bursztyn et al., 2014; Beshears et al., 2015). Our paper offers insights into a relatively new type of financial decision that seems to be rapidly growing in size and importance, and for which regulators are showing a keen interest.

The rest of the paper is organized as follows. In Section 3 we describe the institutional context. In Section 4 we present a theoretical model that reflects the institutional context, and derive its empirical implications. We also provide a sketch of four additional models reflecting alternative investor behaviour. Section 5 provides a description of the data used in the analysis. In Section 6 we test if observed data are in line with theoretical predictions, both of the main and the four alternative models. We present several extensions of the model in Section 7. Finally, Section 8 concludes.

3 Institutional Context

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, thereby potentially extending the duration of the campaign beyond 60 days.[4] Backers can pledge any amount above 10 pounds. All shares in a campaign are priced equally.[5]

To become an investor a person has to sign up to the platform. When signing up, individuals have to self-select into one of three investor groups: 'authorized', 'sophisticated' or 'high-net-worth'. If they select one of the latter two groups, they have to acknowledge that they satisfy UK regulatory requirements for being such an investor. Otherwise they have to take and pass a knowledge test to become authorized to invest on the platform.

Investors can also create a profile. Investor profiles are observable to other investors and vary in their information content. Profiles include geographic location, the history

[4]For our analysis we say that as long as the goal has not been reached the campaign is in the *underfunding phase*, whereas after the goal has been reached the campaign is in the *overfunding phase*. The overfunding phase has no time limit.

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

of pledges made in other campaigns, and, on some occasions, social media contacts and short biographical descriptions. About half of the backers choose to hide their profile when making a pledge, resulting in the pledge being made anonymously.

The platform provides a public abstract of the project, a target goal amount to be raised, fraction of shares issued in the campaign, pre-money valuation (derived from the prior two numbers), days since start of public campaign, total number of backers, total money raised, and percent remaining (see Figure 1 for a visual representation of a typical campaign). The four latter figures are updated dynamically on an hourly basis. All currently ongoing campaigns are listed with this information on an investment page of Seedrs. The campaign on Seedrs that has the highest activity in terms of backers and pledges (the hotness index, to be described) is listed first, followed by the next hottest campaign, and so on. The number of concurrent campaigns per day varied between 1 and 41 (with an average of 14) during our sampling period. The abstract for a campaign leads to a campaign landing page that contains further information on all the entrepreneurs, their own investments in the project, a video, a list of the five largest pledges, and five clickable tabs providing additional information, including a full list of all pledges made and their backers (anonymously if no investor details provided). The list of the five largest pledges and the list of all pledges made are dynamically updated every hour. Visitors to the campaign can therefore follow the evolution of pledges made over time.

During our data collection period Seedrs dynamically presented the top five largest pledges on the landing page of each campaign. We were initially concerned that this would create a discountinuity between the 5th and the 6th largest pledge. During two months and in cooperation with Seedrs we therefore ran a randomized controlled trial where visitors were randomly allocated to either seeing the list of the five largest pledges, or not seeing this list (the space was then blank), while in both cases still having the opportunity to go to the back tab presenting the full list of all pledges. We found no differences in visitor search behaviour on the website or in pledges made between the two arms of the experiment. Regression analysis confirmed no specific discontinuity over the whole sample between the 5th and the 6th largest pledge. (Results available on request.) After our data collection period ended, Seedrs discontinued the practise of presenting the top five pledges on the landing page.

Entrepreneurs are advised by Seedrs to start their campaign with a *private phase* in which the campaign landing page is accessible only to those privately invited to the campaign.[6] Opening with a private phase is a common strategy on most crowdfunding platforms, including Indiegogo and Kickstarter, and is not limited to Seedrs. Most, but not all campaigns on Seedrs start with a private phase. There are two types of potential investors informed about the existence of the private phase. One set are individuals known by the entrepreneurs such as friends, family, and customers and/or supporters.

[6]See https://www.Seedrs.com/learn/help/what-is-private-launch.

On behalf of the entrepreneurs, Seedrs also contact a select set of potential investors such as VCs and angel investors. The private phase is often associated with significant traditional fundraising efforts, such as private meetings with potential investors, as well as larger arranged fundraising events. The private phase is followed by a 60-day *public phase* in which the campaign becomes open to anyone who has a Seedrs account.

4 A Simple Model of the Wisdom of Crowds in Equity Crowdfunding

In this section we modify Hörner and Herrera (2013) to better reflect the institutional context. Our main modification is to allow pledges to take any size. The any-size extension demands that we assume investors to be risk averse.[7] The other modification we make is to simplify the signal space to negative, positive or no information. In Section 7 we discuss how various model assumptions can be relaxed.

A firm seeks financing from investors. Funds will be invested in 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, whereas $\rho = 0$ for a bad project. We denote with π_0 the ex-ante probability that the project is good.

The campaign starts at $t = 0$ and ends at the deadline T. During this period backers arrive at the platform following an exogenous Poisson process with intensity 1. Upon arrival each backer observes the strictly positive pledges made by previous backers, receives a private signal about the project quality, and decides whether to pledge or not and, in the latter case, how much to pledge. Importantly, one cannot observe backers who visited the platform but chose not to make a pledge. We assume that pledges are invested in the project independently of the total amount of pledges reached by the deadline.

Each backer is risk averse with log utility function and initial wealth W. A backer i receives a private signal, $\theta_i \in \Theta := \{g, b, u\}$. Backers' signals are conditionally i.i.d. and satisfy

$$
\begin{aligned}
\mathbb{P}[\theta_i = g| \text{ good project}] &= \mathbb{P}[\theta_i = b| \text{ bad project}] = \lambda q, \\
\mathbb{P}[\theta_i = b| \text{ good project}] &= \mathbb{P}[\theta_i = g| \text{ bad project}] = \lambda(1-q), && (4.1) \\
\mathbb{P}[\theta_i = u| \text{ good project}] &= \mathbb{P}[\theta_i = u| \text{ bad project}] = 1-\lambda && (4.2)
\end{aligned}
$$

where $q \in (1/2, 1)$, implying that signal b and g are partial positive and partial negative informative signals, respectively. Signal u is a non-informative signal. The parameter λ represents the fraction of backers who receive informative signals and the remaining

[7] A risk neutral investor will either invest 0 or all her wealth.

fraction $1-\lambda$ are uninformed backers.[8]

Denote with h_t the history of strictly positive pledges before time t. The public belief that the project is good, given h_t, is denoted $\pi_t := \mathbb{P}(\rho = \alpha | h_t)$. We denote with π_t^θ the belief of a type θ backer at time t. From Bayes' rule and the assumption of the distribution of private signals, we have:

$$0 \le \pi_t^b \le \pi_t = \pi_t^u \le \pi_t^g, \tag{4.3}$$

where the inequalities are strict for $\pi_t \in (0,1)$.[9]

We denote by $\pi_t(x)$ the time t public belief that results from the observation of a pledge $x_t = x > 0$ at t. An equilibrium strategy profile is $\hat{\sigma}$ such that for any backer i, of any type θ and wealth W, after every history h_t, she chooses x that maximizes

$$U(\pi_t, \theta, x) := \pi_t^\theta \left(\ln((\alpha-1)x + W) - \ln(W)\right) + \left(1-\pi_t^\theta\right) \left(\ln((-x+W) - \ln(W)\right), \tag{4.4}$$

the expected gain in utility from investing x in the project, conditional on the information provided by the backer private signal θ and the history of past pledges h_t. The belief π_t^θ, is computed taking into account other backers' equilibrium strategies.

Discussion: Before moving to the equilibrium analysis we discuss some of the simplifying assumptions of this model. First, whereas funds on Seedrs are invested only if the campaign goal is reached (the so-called all-or-nothing clause), backers' pledges are immediately invested in our model. In Section 7.1 we introduce the all-or-nothing clause and show both theoretically and empirically that the main predictions of our simple model are robust to this extension. Second, we assume that all backers have the same wealth and that private signals can only take three values. In reality both wealth and private information can vary substantially across backers. In Section 7.2 we therefore extend the model to the case of heterogeneous wealth and continuous signals and show that also in these cases the main predictions of the model hold.

We can now describe the equilibrium pledge of a type θ backer arriving at time t:

Proposition 4.1. *In equilibrium, a type θ backer arriving at time t pledges only if her belief π_t^θ that the project is good exceeds $1/\alpha$. Conditionally on making a pledge, the size*

[8] Assuming that $\mathbb{P}[\theta_i = g|$ good project$] \neq \mathbb{P}[\theta_i = b|$ bad project$]$, would not qualitatively change the predictions of the model.

[9] Considering that $\mathbb{P}(\rho = \alpha | s; h_t) = \frac{\mathbb{P}(s|\rho=\alpha)\times\mathbb{P}(\rho=\alpha|h_t)}{\mathbb{P}(s|\rho=\alpha)\times\mathbb{P}(\rho=\alpha|h_t)+\mathbb{P}(s|\rho=0)\times\mathbb{P}(\rho=0|h_t)}$, a backer arriving at time t has belief $\pi_t^g = \frac{q\pi_t}{q\pi_t+(1-\pi_t)(1-q)}$, $\pi_t^b = \frac{(1-q)\pi_t}{(1-q)\pi_t+(1-\pi_t)q}$ or $\pi_t^u := \pi_t$ if the backer is of type g, b, or u, respectively.

of the pledge is strictly increasing in the backer's belief π_t^θ and wealth W, and namely

$$\hat{\sigma}(\theta, \pi_t) = \max\left\{0, \frac{\alpha\pi_t^\theta - 1}{\alpha - 1}W\right\}. \tag{4.5}$$

In particular, a backer with signal g, u or b pledges only if the public belief π_t exceeds $\underline{\pi}^g := \frac{1-q}{1-q(2-\alpha)}$, $\underline{\pi}^u := \alpha^{-1}$ or $\underline{\pi}^b := \frac{q}{\alpha-1-q(2-\alpha)}$, respectively. Note that $0 < \underline{\pi}^g < \underline{\pi}^u < \underline{\pi}^b$. Given this pledge behaviour we can analyze the dynamics of the public belief π_t. First, how does the public belief π_t react to the arrival of a pledge x_t? Because the size of a pledge is strictly increasing in the backer's belief it discloses the backer's private signal. It immediately follows that

Proposition 4.2. *If at time t a pledge of size $x_t = \hat{\sigma}(\theta, \pi_t) > 0$ is observed, the public belief moves from π_t to $\pi_t(x_t) = \pi_t^\theta$.*

Second, make $\varepsilon > 0$ small. If between t and $t + \varepsilon$ no pledge is observed, how will π_t compare to $\pi_{t+\varepsilon}$? The fact that no pledge occurred between t and $\pi_{t+\varepsilon}$ can result from two scenarios. Between t and $t + \varepsilon$, either no backer arrived, or the backers who arrived chose not to pledge. If $\pi_t > \underline{\pi}^b$, the public belief π_t is so high that even a backer with a signal b would pledge. In this case, absence of pledges implies no arrival of backers. Because the backers' arrival rate does not depend on the project's quality, no arrival has no information content and $\pi_{t+\varepsilon} = \pi_t$. The same equality results for $\pi_t \leq \underline{\pi}^g$. In this case a backer would not invest no matter her type, and hence absence of pledge has no information content. Things change for $\underline{\pi}^g < \pi_t \leq \underline{\pi}^b$. In this case, had an informed backer arrived between t and $t + \varepsilon$, she would have pledged if her signal was g but not if her signal was b. Because a type g backer (a type b backer) is more (less) likely to arrive for a good project than for a bad project, the absence of a pledge provides negative public information about the project and hence $\pi_{t+\varepsilon} < \pi_t$. In summary, for extreme levels of the public belief π_t, periods of absence of pledges do not change the public belief. However, for intermediate levels of π_t, periods of absence of pledges make all backers more pessimistic about the project's profitability.

The following proposition formalizes this argument.

Proposition 4.3. *If between t and $t' > t$ no pledge is observed then at time t' the public belief is*

$$\pi_{t'} = \begin{cases} \pi_t, & \text{if } \pi_t \leq \underline{\pi}^g \\ \max\left\{\frac{\pi_t}{\pi_t + (1-\pi_t)e^{\lambda(2q-1)(t'-t)}}, \underline{\pi}^g\right\} < \pi_t, & \text{if } \underline{\pi}^g < \pi_t \leq \underline{\pi}^b \\ \pi_t, & \text{if } \pi_t > \underline{\pi}^b \end{cases} \tag{4.6}$$

Consider now the social learning process. Will the pledge history eventually allow us to learn the project's actual quality ρ? We say that an information cascade occurs at time t, if $\pi_t \in (0, 1)$ and for all $t' > t$, $\mathbb{P}(\pi_{t'} = \pi_t) = 1$. That is, if an information cascade occurs at time t, then from time t on the pledge history provides no additional information about the project's quality and social learning about ρ fails. Proposition 4.2 shows that as long as there are pledges, there is social learning. The reason is that each strictly positive pledge size discloses the private information of the backer who made it.

However Proposition 4.3 implies that a long enough time without any pledges can induce all future backers to abstain from pledging no matter their signal thus generating an abstention information cascade. Suppose that $\pi_t \in (\underline{\pi}_g, \underline{\pi}_b)$. From the second expression of (4.6) there is a finite $t' > t$ such that, if there is no pledge between t and t', then $\pi_{t'} = \underline{\pi}^g$.[10] Therefore, from t' on, no arriving backer will ever invest no matter what her private signal is, and the public belief cannot evolve.

4.1 Empirical implications

Propositions 4.1 -4.3 have a number of implications regarding pledge dynamics. In this section we present and compare seven testable predictions of our model and the four alternative models. Table 1 summarizes the seven predictions and contrast them with the alternative models.

First, we address how the most recent pledge affects the next. Consider a backer who arrives at time t with private signal θ, and suppose that the most recent pledge before t occurred at time $t' < t$ and was of size $x_{t'} > 0$. What does time t backer know about time t' backer's total information? Proposition 4.1 shows that strictly positive pledges are invertible in the belief of the backer who makes them. Hence, time t backer can infer from $x_{t'}$ time t' backer's belief $\pi_{t'}^{\theta'}$. This belief incorporates all information provided by the pledge history before t' as well as time t' backer's private signal θ'. The larger $x_{t'}$ the more positive must be this information. Thus, the size of $x_{t'}$ provides relevant information to time t backer. Note that in our model, time t backer can ignore what happened before t' because all information provided by pledges before t' is already embedded in $x_{t'}$. This results from our assumption that all backers have the same wealth. In Section 7.2 we show that when wealth is heterogenous and pledges anonymous, a backer should be influenced not just by the most recent pledge but also by pledges preceding that. This leads to our first empirical implication:

Empirical implication 1: *Pledge size is increasing in the size of the most recent pledges.*

The past history of pledges provides another piece of relevant information to our time t backer: the fact that no pledge occurred between t' and t. According to Proposition

[10] Namely $\pi_{t'} = \underline{\pi}_g$ for $t' = t + \frac{1}{\lambda(2q-1)} \ln\left(\frac{\pi_t(1-\underline{\pi}^g)}{\underline{\pi}^g(1-\pi_t)}\right) > t$.

4.3, the public belief is weakly decreasing in $t' - t$. This leads to our second empirical implication:

Empirical implication 2: *Pledge size is weakly decreasing in the elapsed time since the most recent pledge.*

From Proposition 4.1 we know that a backer will pledge only if her belief π_t^θ is large enough. Because this belief is affected by the most recent pledge size $x_{t'}$ and the time $t' - t$ without pledges, these element will also affect the probability that time t backer will pledge at all. This provides our next two empirical implications.

Empirical implication 3: *The probability of observing a pledge in time t is strictly increasing in the size of the most recent pledge.*

Empirical implication 4: *The probability of observing a pledge in time t is weakly decreasing in the time elapsed since the most recent pledge.*

Our model distinguishes between partially informed backers and uninformed backers. Whereas the former make use of both private and public information, the latter's pledge decision is solely affected by the public information provided by past pledges. This brings our fifth empirical implication:

Empirical implication 5: *Relations described in empirical implications 1 to 4 should be stronger for uninformed than for informed backers*

Both the backers and the dynamics in the private-phase tend to differ from the backers and dynamics in the public phase. From the perspective of the public phase, the outcome of the private phase provides a public signal about private-phase backers' opinion of project quality. In terms of our model, one can interpret the total amount raised during the private phase as a proxy for the public-phase initial belief π_0. In light of our model a $\pi_0 < \underline{\pi}^g$ would lead to an abstention information cascade and to campaign failure, whereas campaign success is much more likely for larger π_0. Also, Proposition 4.2 implies that when $\pi_0 > \underline{\pi}^b$, the negative relation between the lenght of time without any pledges and the next pledge size vanishes. This leads to empirical predictions 6 and 7 below:

Empirical implication 6: *If the total amount pledged during the private phase is particularly low, the probability that the campaign succeeds is strongly reduced.*

Empirical implication 7: *If the total amount pledged during the private phase is particularly high, relations described in empirical implications 1 to 4 should be weaker.*

Table 1 summarizes these predictions and contrasts them with what would result from each of our four alternative models. Let us consider each alternative model separately.

The closest model to our base model is AM1: Here backers respond to common signals unobserved by the econometrician. These common signals could be general news about the startup that are observable to all investors. Alternatively AM1 could be interpreted as a model where groups of investors co-invest at the same time.

In AM1 the timing and sizes of pledges will be correlated, and for that reason predictions 1-4 of AM1 are similar to our base model. Considering prediction 5, AM1 has no relevant prediction regarding investor types as there is no information asymmetry between uninformed and informed backers in that model as all relevant information is public. Prediction 6 differs weakly to our base model: in AM1, exogenously arriving good news can bring back optimism and therefore resurrect a campaign, no matter the length of a no-pledge period preceding. This is not possible in our base model. But the likelihood of good news arriving later when a campaign starts out with bad news is likely small, so it will be difficult to separate these models empirically on this account. On prediction 7 the models differ considerably. In AM1 backers do not influence each other, so the private phase outcome should not affect the correlation between pledges during the public phase. That is why prediction 7 does not apply to AM1.

As Table 1 shows none of our seven empirical predictions apply to AM2, which follows the approach taken by a number of theoretical papers in crowdfunding, where the pledges are modelled as a simultaneous move game (see for example Belleflamme et al. (2014); Chang (2016); Chemla and Tinn (2016)). Using our base model terminology each backer bases her pledge solely on her private signal, backers' arrival times are i.i.d., and signals are conditionally i.i.d.[11] If this is the case, the size of the most recent pledge and the time elapsed since the most recent pledge should neither have an effect on pledge size nor on the probability of observing a pledge. This lack of correlation for AM2 holds whether a backer is privately informed or not. Similarly, what happens in the private phase has no impact on pledge behaviour.

AM3 reflects the approach taken by several empirical papers on crowdfunding focusing on the correlation between cumulative amount funded and the size or probability of observing a pledge, ignoring the effect that individual pledges may have on backer's beliefs. In terms of our base model this is equivalent to assuming that upon arrival a

[11]In this case, let h_t^* denote the sequence of public news until time t and let $\pi_t^* = \mathbb{P}(\rho = \alpha | h_t^*)$. Because all relevant information is embedded in h_t^*, the pledge history provides no additional information, i.e., $\pi_t = \pi_t^*$. In this case a backer arriving at time t would pledge $\sigma_{AMj}(\theta, \pi_t) = \max\left\{0, \frac{\alpha\pi_t^*-1}{\alpha-1}W\right\}$.

backer observes the cumulative amount pledged but not how that amount was formed over time (Colombo et al., 2015; Hornuf and Schwienbacher, 2018; Vismara, 2016). AM3 is clearly informationally different to our base model. Consider for example the following two scenarios. In each scenario an uninformed backer arriving at time t observes the same cumulative amount y_t. In scenario 1, y_t results from a single pledge made early on in the campaign. In scenario 2, y_t results from a single pledge made just before t. In our base model, time t uninformed backer will pledge less in scenario 1 than what he would pledge in scenario 2 because compared to scenario 2, in scenario 1 more time has passed since the last pledge. In AM3, time t uninformed backer cannot tell the two scenarios apart and hence will pledge the same amount. Thus according to AM3, after controlling for the cumulative amount pledged and the time since the campaign started, the most recent pledge should not affect the current pledge. AM3 has in common with our main model only prediction 6: a bad start in the private phase might induce public phase backers to abstain and hence the campaign to fail reaching its goal.

In AM4 backers naïvely follow the crowd and invest only if there is a large initial pledge. Hence, conditional on the amount invested at the beginning of the campaign, pledge size and arrival probability should neither depend on the size of the most recent pledge nor the time since the most recent pledge. This again implies different predictions than our base model. For predictions 1-4 AM4 states that they should be zero. Prediction 5 does not apply as there is no information asymmetry between backers in this model. Prediction 6 will be similar to our base model. Empirically it could be difficult to separate AM4 and our base model on this prediction. According to AM4 backers ignore recent pledges. AM4 is therefore silent on prediction 7.

We now bring these testable predictions to the data.

5 Data, Variables, and Descriptives

The data come from the equity crowdfunding platform Seedrs. The information was made available directly to us by Seedrs and comprises the full universe of campaigns from October 2012 up until March 2016. In total, there are 710 campaigns, 22,615 unique backers and 69,699 pledges. These numbers correspond to the final sample after depurating the data. We started with 727 campaigns and 84,761 pledges. We dropped 12 campaigns that didn't have information on the valuation of the projects. More importantly, Seedrs allows investors to regret pledges before a campaign closes. There were 12,373 regretted investments in our sample, and we had 5 campaigns in which all investments are reported as cancelled. We dropped all pledges that were made but later regretted or cancelled. Although we do not have information on the time at which an investment was regretted, the data management department at Seedrs communicated that the majority of regrets happen within minutes of a pledge being made. All estimations shown in the paper have been replicated to include the regretted pledges and the results remain qualitatively unchanged. The main Table with results is repeated in Online Appendix B with regretted investments included.

For each project, we have information about the date the campaign started raising funds, the length of the private campaign, the length of the public campaign, the declared investment target, the pre-money valuation of the company, and the timing and value of each of the pledges received while the campaign was running. Each pledge is also matched to a specific investor associated with some descriptive investor data so that we can analyse the behaviour of both individual campaigns and individual backers. Variable definitions are displayed in Table 2.

Descriptive statistics at the campaign level are provided in Table 3.[12] Out of the 710 campaigns, 243 (34.2%) were successful in raising the declared investment goal. The average campaign goal was £174,215, but there is large heterogeneity in the amounts asked by individual projects, with values that range from £2,500 to more than £1,600,000. This desired investment corresponds to an average equity offered (in pre-money valuation terms) of 12 percent. The level of the investment target and pre-money valuation of the campaigns in Seedrs present a sharp contrast with other non-equity crowdfunding schemes. For example, Mollick (2014), in a study of more than 48,500 projects raising funds on Kickstarter, shows that the average goal is less than $10,000, much lower than what is observed in our sample. The main analysis is performed with campaign fixed effects, effectively controlling for all cross-campaign variation in characteristics such as the pre-money valuation.

Investors have to self-select into one of three groups: 'authorized', 'sophisticated' or 'high-net-worth' (see Table 2 for definitions). Most backers in a campaign (79%) are 'authorized', the rest are either 'sophisticated' (7%) backers, or 'high-net-worth' (14%) backers. Approximately 23 percent of investors in 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 made to a campaign.

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

Some suggestive patterns appear in the descriptives. First, early performance appears to be a major predictor of the likelihood that a campaign will reach the funding goal. Successful campaigns accumulate, on average, 58 percent of the total amount during the private phase, which lasts 10 days on average. In fact, successful campaigns raise 21 percent of the total amount at the end of the first day, and this number increases to

[12] Vulkan et al. (2016) analyse cross-campaign data from the same platform. For this paper we report updated figures for a longer data series.

75 percent after the first week. Failed campaigns, on the other hand, never really get started. Halfway through the time limit these projects have only covered about 15 percent of the total sought. Campaigns that fail to raise the desired capital tend to do so by a large margin, while most successful campaigns overfund, going up to an average among overfunded campaigns of 110 percent of the target. Second, a few large pledges appear to have a major role in driving the success of a campaign. The largest pledge in an average campaign represents a full 15 percent of the total, and for the average successful campaign it accounts for about 31 percent of the total investment sought.

6 Empirical Results

6.1 Econometric Specification

In this section we test the empirical predictions of the main model. We have detailed information on the timing at which decisions were made, and we can also reconstruct the information available to all backers in the platform at the moment of every investment. We use these features of the data to analyse if investors act as predicted by our model, or as predicted by the alternative models.

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 predictions of the model state that a pledge size should be *increasing* in the size of the most recent pledge, but *decreasing* in the time since the most recent pledge. Figure 2 shows suggestive evidence to support this prediction. To construct the figure we first organize all pledges within a campaign in bins of size 5 log points according to the size of (Panel (a)), and time since (Panel (b)), the most recent pledge. We then compute the average amount pledged within each bin. The figure reports the scatter-plot and the correlation between the median point of the bin and the respective averages.

The figure shows that there is a positive correlation between the amounts pledged by current and most recent backers within a campaign, with the slope of the linear fit of the variables (in logs) estimated to be around 0.32. Also consistent with the model is the negative correlation between the time since the most recent pledge and amount pledged, where the slope of the linear fit (in logs) is estimated to be around -0.07.

In an extension of the main model described in Section 7.2, the positive correlation with the most recent pledge becomes distributed over several of the most recent pledges, but the signal value should still be strongest for the most recent pledge. Figure 3 shows supporting evidence for this prediction. The figure is constructed in a similar way as Panel (a) of Figure 2, 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 n-th and $n-2$

pledge in a campaign, while Panels (c) through (d) display correlations between the n-th and all the way until the fifth-lagged pledge. Consistent with the model extension, the size of the positive correlation between pledges declines as the pledges are further separated apart by intervening pledges. The slope of the linear fit of the variables (in logs) goes from 0.32 between the current and most recent pledge, to 0.16 between the n-th and the $n-5$ pledge.

We now move to the econometric analysis. Let all backers who made 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 n-th backer after the start of the *public phase* of the campaign c. Let $T_{(n,n-1),c}$ be the time (in hours) between the $n-1$ and the n-th pledge made to the campaign c. We use a distributed lag model of the form:

$$\log I_{n,c} = \sum\nolimits_{k=1}^{5} \beta_k \log I_{n-k,c} + \beta_6 \log T_{(n,n-1),c} + \alpha W_{n,c} + \gamma Z_{n,c} + \eta_c + \epsilon_{n,c}, \qquad (6.1)$$

where our interest lies in the estimates of the beta coefficients accompanying the values of the investment lags, $\log I_{n-k,c}$, and the time since the most recent pledge, $\log T_{(n,n-1),c}$. η_c is a campaign fixed effect capturing all the time-invariant observed and unobserved campaign characteristics. Campaign fixed effects are particularly important in our set-up since investors choose which campaigns to invest in, a decision that will likely depend on the characteristics (observed and unobserved) of the projects, leading to problems of selection. Including campaign fixed effects implies that we only use within campaign variation for identification in the econometric analysis.

The econometric model includes a set of controls to capture differences in the characteristics of backers. The purpose of the first set of controls is to account for the theoretical prediction of the main model that an agent's optimal strategy depends on her wealth, and her private information. In particular, $W_{n,c}$ is a vector of dummy variables indicating if the backer self-reported as being high-net-worth, sophisticated, or authorized (authorized backers are used as the base). The vector also includes a dummy variable that takes the value of one if the backer is recurrent, and zero otherwise.

In some specifications we include three sets of time-varying controls, all contained in the vector $Z_{n,c}$. The first set of controls capture the history of pledges up to the point where the backer is making the decision, and include the natural logarithm of the total amount funded at $n-1, c$; the total number of pledges at $n-1, c$; and the number of days since the start of the campaign for n. The second set of controls capture the visibility of each campaign in the platform's landing page, which can vary while the campaign is live, potentially affecting pledge dynamics. In particular, we include the Seedrs' campaign hotness indicator at the beginning of the day, an index used by the platform to order campaigns in the landing page[13]; a dummy taking the value one if the Seedrs' campaign hotness indicator rose during the day; and the average of the Seedrs' hotness index for all active campaigns except c. The third set of control variables are intended to capture observable and exogenously arriving information, analogous to the public signals that characterize AM1. Here we include a Google trend daily index for searches of the campaigns name and the FTSE index for the day. We report results including and excluding these three sets of control variables, and show that our main parameter estimates remain quantitatively unchanged.

Conditional on campaign fixed effects, the main identification problem is the possibility that the size of adjacent pledges is driven by common and unobserved factors, as predicted by AM1. For example, positive news about a specific campaign, or even about the sector in which the firm operates, might induce several investors to pledge larger amounts at a given moment in time, generating a positive correlation. Moreover, the length of time between subsequent pledges will also be affected, because more (less) backers will arrive to the campaign when the positive (negative) information shock occurs. We can partly account for these common factors with the variables included as controls, but the predicted pledge dynamics could still be rationalized by unobserved correlated signals, so we need to disentangle the mechanisms proposed by the main model from those of AM1.

Our identification strategy uses an instrumental variable (IV) approach, where the instruments are constructed following the theoretical predictions of the main model. Here we provide a verbal argument for the IV approach. The Online Appendix A.2 provides a technical argument that can be skipped by the general reader. For the IV to work in our context, we need a variable that exogenously affects the size of $\log I_{n-k,c}$, but is uncorrelated with the stream of public information about the campaign. In an ideal scenario, we would change the amount pledged by a random set of investors and analyse if subsequent pledges respond to these changes. We cannot experimentally vary the amounts pledged, but we have information on investors disposable wealth that affects the amounts pledged independently of external information flows. In particular, Equation B.1 (equivalent to Equation 4.5 with heterogeneous wealth) predicts that the size of a pledge is a function of an investor's wealth: higher W leads to larger pledges irrespective of past history of pledges or information shocks. We then use variation in disposable wealth predicted by previous pledging behaviour of a given investor that we observe, but that subsequent backers do not observe.

We use two *alternative* sets of instruments for the size of a prior pledge ($\log I_{n-k,c}$). In our main specification, we construct an instrument using the fact that if a campaign fails, the amounts pledged are returned to the backers. The money that is returned can

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

then be used by recurrent investors for pledges in future campaigns, where the extra disposable income can be thought of as being unexpected. These unexpected extra disposable income should increase the size of the optimal investment via a wealth effect (see Equation B.1). We create a variable that is defined as the inverse hyperbolic sine transformation (IHS)[14] of the total amount returned to a backer in the last failed campaign in which she invested, conditional on that campaign failing before the campaign c started. Since the instrument is pre-determined at the start of campaign c, whatever strategy a backer might be playing as a function of observing the arrival (or non-arrival) of other pledges in the campaign is purged from analysis.

To clarify ideas, we present a sketch of how the instrument is constructed for an individual investor in Figure 4. 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 a campaign was active, which includes the private and public phases. Suppose an investor pledges an amount I_1 at time t_1 to campaign c_1, which fails to reach the target. The amount I_1 is returned to the investor once the campaign fails at t_{fail}, and is the basis of 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 to the investor, which can potentially affect the amount pledged I_2. Furthermore, if $I_1 > I_2$, there is still some disposable income left, $I^* = I_1 - I_2$, which can also affect I_3.We continue 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 any pledges made in that campaign.

We find that close to 8.6 percent of all 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 amount of income returned after a failure of a campaign in which an investor made a pledge and the size of her following pledge in a future campaign 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 average number of days between the failure of a campaign and the next potentially affected pledge (between t_{fail} and t_2 in Figure 4) is 15 days. Since only 8.6 percent of pledges can be affected by disposable income coming from returned money after the failure of a campaign, we use a second set of instruments for $\log I_{n-k,c}$ to validate results. In particular, we use information from investors' profiles that is not public to construct those instruments. Every backer making a pledge to a project appears in the campaign's page, but they can choose whether to have their names and profiles be

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

public or remain anonymous. For backers that choose to be anonymous, only the amount pledged is displayed. Although the past investment history of anonymous profiles is not public, we have access to it in our dataset. We use this information to construct variables that contain relevant information to predict the wealth of an investor, and hence the size of a pledge, which is not observed by follow-on backers. The validity of the instrument relies on the fact that the *past* history of pledges by a backer is pre-determined and hence unrelated to *contemporaneous* information flows.

In the alternative IV strategy, we use two pieces of information as instruments for each prior pledge ($\log I_{n-k,c}$): (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 pledge smaller amounts than single-campaign backers, so the first instrument is expected to have a negative correlation with size of pledge. On the other hand, backers that have previously pledged large amounts are potentially wealthier, so the second instrument is expected to have a positive correlation with pledge size. We have two instruments for each endogenous variable, so we report statistical tests for over-identifying restrictions.

A potential threat to our identification strategy is that wealthier investors might pledge in the same campaigns at the same time. We find this is not the case. In Table B.1 we show the correlation between subsequent values of the pre-determined instruments. These instruments are predicting disposable wealth in alternative ways, so any correlation in their values across subsequent investors would be indicative of problems with our identification strategy. We find no correlation even up to the fifth lagged pledge. In Table B.2 we present a more direct measure: correlations between self-reported types of subsequent investors. Here we are interested in whether being of a certain type (e.g. high-net-worth) has any predictive power on the self-identification of the next investor. Again we find no evidence that this is the case.

Finally, we construct an instrument for the length in time between subsequent pledges, $T_{(n,n-1),c}$. In this case, we need a variable that generates exogenous variation in the arrival time of backers. We use an instrument based on the hour of the day in which the most recent pledge is made. The data shows that the occurrence of pledges tends to be very low before 6 a.m., increases during the morning reaching a peak at 11 a.m., and then monotonically declines for the rest of the day. This pattern reflects typical work schedules. The closer a pledge is to the peak hour, the more likely it is that a subsequent backer will arrive shortly after. We create a variable 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. The validity of the instrument is based on the idea that the time of the day in which people tend to be most active is presumed unrelated with whether the stream of public information about a campaign is positive or negative, while not necessarily unrelated to news in general arriving. For example, public signals might be more likely to arrive at peak hours, but whether those signals are positive or negative should be unrelated to calendar time. The latter condition is the one relevant for our instrument (see Online Appendix A.2). Importantly for identification, close to 75 percent of the tuples $n, n-1$ happen within the same calendar day. There is a strong correlation between our instrument and the time between subsequent pledges when they are made in the same calendar day, but virtually no correlation when they are made in different days.

6.2 Main Results

The main results are shown in Table 4. The table presents the estimates of Equation 6.1 for five specifications: in the first column we show the OLS estimates without controls; in the second column we add controls on backer characteristics; in the third column we add controls on campaign dynamics; in the fourth we add controls on exogenously arriving information flow.

The last two columns show the Two Stage Least Squares (2SLS) estimates when we instrument each of the lagged pledges and the time between adjacent pledges as described above for our main specification. Note that there are two alternate ways of instrumenting the sizes of the lagged pledges. Version A contains the instrument with the returned money from a pledge in a prior failed campaign and version B contains the instruments with the hidden information about the investor. For version B we have two instruments for each investment lag, and so we can report Hansen's overidentification test for instrument validity. Instruments are found to be statistically relevant in both versions A and B and statistically valid in version B (bottom of the Table). The first stages are presented in the Online Appendix Tables B.3 and B.4.

6.3 Testing Predictions 1 and 2

Examining Prediction 1 of the main model in Table 4, we find that backers who immediately follow pledges of a larger value, on average, invest higher amounts in the campaigns. Moreover, we find that this relation is stronger the 'closer' the pledges are to each other, consistent with the extended model that allows for heterogeneous wealth. For example, in the IV specification in the last column, a doubling (100% increase) of the value of the most recent pledge is associated with a rise of 11.9 percent in the subsequent amount pledged. For an average pledge size of £1,202, the 11.9 percent increase translates into £143 of extra investment. The magnitude of the effect dissipates rapidly: for the backer corresponding to the second most recent pledge, the size of the estimated coefficient declines to 3.8 percent for a similar change. For higher order lags we don't find any statistically significant effect in the IV specification. We therefore find support for Prediction 1, and reject AM1.

The results also show that the amount of time since the most recent pledge is negatively correlated with the size of a pledge, supporting prediction 2 and rejecting AM1. In our IV specification, doubling (100% increase) the time since the last pledge is associated with a fall in the pledge size of 8.2 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 £100. Both descriptive and econometric evidence thus suggests that backers do respond to the sizes of previous pledges, and to the time since arrival of the most recent pledge in a way that is consistent with predictions 1 and 2 of our model of rational information aggregation.

6.4 Testing Predictions 3 and 4

In order to test predictions 3 and 4, we need to change the structure of the data. Since we only observe a backer if she pledges a positive amount, we expand our dataset in such a way that the total duration of a campaign is divided into one hour bins. Using one hour bins is also motivated by the fact that the platform updates information on an hourly basis. We then create a variable the value of which depends on whether there was any activity in the period (bin) or not. In particular, let $DI_{t,c}$ be a dichotomous indicator of activity in campaign c at the hourly bin t after the first investment in the *public phase*. Let $I_{t,c}$ be the amount invested in campaign c at the hourly bin t, where the value is either zero if no investments were made, or the sum of all positive investments within the respective hour. Let $H_{t,c}$ be the number of hours since the last bin in which there was a positive pledge in campaign c. We use two linear probability models that take the form

$$DI_{t,c} = \sum\nolimits_{k=1}^{5} \beta_k \text{IHS}(I_{t-k,c}) + \gamma Z_{t-1,c} + \eta_c + \nu_h + \epsilon_{t,c}, \tag{6.2}$$

$$DI_{t,c} = \beta_1 \log H_{t,c} + \gamma Z_{t-1,c} + \eta_c + \nu_h + \epsilon_{t,c}, \tag{6.3}$$

where we are interested in the estimates of the beta coefficients associated with the amounts invested over the preceding hours (Equation 6.2), and the time since the most recent activity in an hourly bin (Equation 6.3). Given the large number of observations for which the amount invested in the time period is zero, the amount pledged is transformed using the IHS transformation. From the main model, we expect that some activity in previous hours, especially if it reflects large investments, should be associated with a higher probability of observing a pledge in the next hour. Moreover, longer periods without positive pledges should lower the probability of observing a pledge at any point in time.

The econometric models include a vector of controls, $Z_{t-1,c}$, which includes the same variables as in Equation 6.1 except that since we aggregate data across investors over the preceding hours we cannot include investor-specific controls. Finally, η_c is a campaign fixed effect capturing all the time-invariant observed and unobserved campaign characteristics, ν_h is an hour-of-the-day fixed effect, and $\epsilon_{t,c}$ is the error term.

Results are shown in Tables 5 and 6. The tables present the estimates of Equations 6.2 and 6.3 respectively, excluding the controls, including the controls and instrumenting the lagged investments in two different ways. The results support Prediction 3 of the main model that the probability of observing a pledge in a campaign at any point in time is positively affected by the size of previous pledges. In particular, in the IV specifications we estimate that the likelihood of observing a pledge at any given hour increases by between 1.5 to 2.0 percentage points after a doubling of the amount pledged during the previous hour. Since the unconditional probability of observing a pledge is around 5.5 percent, the magnitude of this effect is considerable. Indeed, the probability of observing a new pledge is increasing in the size of the most recent pledge, but the effect decreases with the number of hours since the previous pledge was made. In the second IV model (version D) we cannot reject that the instruments are invalid, and so for this specific regression we cannot claim causal effects.

The results also support Prediction 4 of the main model. If the number of hours since the campaign saw any activity doubles, the probability of observing a pledge declines between 1.9 and 4.5 percentage points. This can also be seen clearly in Figure 5. Here we plot the probability of observing a pledge, measured by the average frequency of positive pledges at any given bin, as a function of the hours since most recent activity in a bin. There is a clear negative correlation between the length of time without positive pledges and the likelihood of observing a pledge. The results reject both AM1 and AM4 since both predict zero correlations where we in fact observe robust non-zero correlations.

6.5 Testing Prediction 5

Following Prediction 5 of the main model, we now analyse whether the reactions are similar across all types of backer. All specifications in which we use a subset of the sample are estimated using IV version B since it provides a much larger source of variation. Table 7 shows the results of estimating Equation 6.1 separately for five different potential types of backer: (i) high-net-worth, (ii) sophisticated, (iii) authorized, (iv) recurrent, and (v) single-campaign backer.[15] The main model predicts that since uninformed backers have no private information, their pledges will be more responsive to the evolution of the

[15]Note that the first three and last two types are mutually exclusive, but not the five altogether.

public belief. Informed backers weigh their own private signals with the public belief, so they are relatively less influenced by the past history of pledges. Although there is no direct mapping between the proposed division of backers and whether they are more or less informed about the quality of a campaign, we do expect a priori that sophisticated and recurrent backers will on average be more informed about the quality of investment opportunities than authorized and single-campaign backers.

All types of backer appear to react to the size of the previous pledge by pledging a larger amount, but the magnitude of the effect is somewhat stronger for authorized (13.6% after a doubling of the most recent pledge) and single-campaign backers (22.7% after a doubling of the most recent pledge), than for high-net-worth (11.8%), sophisticated (-6.2% but not statistically significant), and recurrent backers (8.3%). This evidence is consistent with Prediction 5. However, we also find that sophisticated investors seem to be the most sensitive to the absence of pledges, the opposite of what was predicted. Overall, the standard errors are large enough for the various subgroup estimates that differences in behaviour across investor categories are typically not statistically significant, possibly reflecting the crudeness of the indicators for describing investor types.

6.6 Testing Prediction 6

Prediction 6 states that bad projects will have a poor campaign performance from the outset.

We start with some descriptive information of what typically happens at the outset of successful and unsuccessful campaigns. Figure 6 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 a campaign is active in its public phase. We report two series: one for successful and one for unsuccessful campaigns. The figure shows that there is a clear difference between successful and unsuccessful campaigns in the support during the early stage of a campaign. On average, campaigns that end up raising the target funds are able to 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 never able to rebound at a later time.

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. In terms of our model, one can interpret information about total funds raised during the private phase as a proxy for the public-phase initial belief π_0. 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 that a campaign is ultimately successful. In particular, we are interested in how the probability of being successful changes 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: one without any additional controls; and one controlling for predetermined characteristics of the campaign (pre-money valuation, campaign goal, number of entrepreneurs, and access to tax incentives for investors).[16] The models also contain year * month of start campaign fixed effects.

The econometric results are in line with the prediction that early campaign support is strongly correlated with the probability of 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 larger by 24 percentage points 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. This result is suggestive that the quantity of pledges early on is not nearly as important to improve the chances of success, but that the 'quality' of those initial pledges matters more.

The fact that we can only use campaign-level variation to explore the determinants of the probability of campaign success implies that we are unable to control for campaign-specific characteristics. This is a clear limitation that impedes causal interpretation of these specific results. We interpret the evidence reported in Table 8 with caution, and simply state that it is consistent with predictions of the main model.

6.7 Testing Prediction 7

Further, as stated in Prediction 7 in Table 1, Proposition 4.2 implies that when the initial public belief is very large, subsequent signals are of little importance. The negative relation between periods without pledges and next pledge size and the positive relationship between adjacent pledges should then be greatly reduced. We test these predictions in Table 9.

Table 9 reports IV regressions of our main empirical specification using instrument version B. We report again the main result in the first column for ease of comparison. In the second column we report results for campaigns which reached 15% or less of their campaign goal in the private phase, and in the third column we report results for campaigns which reached more than 15% of their campaign goal in the private phase. For campaigns having generated a strong public signal in the private phase, the coefficient for the time passed since the most recent pledge has no statistically significant impact on subsequent investments, while the sizes of the two most recent pledges still have some

[16]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 since the effects are non-linear by assumption, so they should be read with that caveat in mind.

signaling value. In comparison, for those campaigns having had less success in the private campaign, subsequent signals from pledges made in the public phase matter a lot more. For example, the coefficient for the most recent pledge is 2.6 times as large for weak private phases than for strong private phases. (Other possible cut-offs for defining good and bad private phases generated qualitatively similar results.) Results are consistent with the prediction of the main model, and inconsistent with AM3 that predicted that signal values of investments in the public phase would be similar after weak and strong private phases.

6.8 Summary of Tests of Alternative Models

AM1 predicts that pledges should cluster due to exogenously arriving information or that groups of similar investors tend to invest at the same time. We acknowledge that exogenously arriving public information may affect pledges, and our control variables show that this seems to occur to some extent: the campaign hotness indicator, its intraday rise and the Google trend index are significant in some specifications, and even the FTSE index is significant in one specification. But are pledges solely resulting from these exogenous information and backers not influenced by other backer's pledge?

We explored the opportunity to eliminate such common effects through an IV setting. We used two alternative IV specifications where past pledges are predicted by information about the respective backer that is predetermined of the arrival of information and further not known by subsequent backers. This detaches the estimated correlations between adjacent pledges of common public information. It does not completely eliminate AM1 since we find some room also for exogenously arriving information to explain some of the pledge amounts made. Since the correlations we observe between measurable indexes of arriving information and pledge amounts and pledge probabilities, respectively, do not reduce the size of our target coefficients, and the IV estimates are not significantly different from the OLS estimates, it would be appropriate to say that pledges are affected both by rational herding and by exogenously arriving news.

In all tables we found that the size of most recent pledge and the time elapsed since most recent pledge were both highly predictive of the size and probability of the next pledge, rejecting AM2 and AM3 and AM4. Further, AM2 had nothing to say about the absence of pledges at the early stage of a campaign, although it appeared that such absence was empirically relevant for campaign success. We reject AM2, AM3 and AM4 because they are unable to explain what appears to be empirically relevant behaviour in the data.

7 Model Extensions and Further Analysis

7.1 All-or-nothing Clause

In a Seedrs' campaign, as with most equity crowdfunding platforms, backers' pledges are invested only if by the end of the campaign the total amount raised reaches a pre-specified goal. When this happens we say that the campaign succeeds. If the goal is not reached, the campaign fails, the project is not financed and backers receive their money back. This is the so called "All-or-Nothing" clause (henceforth AoN). Since not all platforms follow this rule, the clause is absent in the more general model of Section 4.

In order to incorporate the AoN clause we add three elements to our main model of Section 4. We denote with $\underline{x} > 0$ the minimum size of a pledge, with $Y > \underline{X}$ the goal amount, and with T the campaign deadline. We then assume that, first, backers' pledges are invested in the project if and only if by time T the cumulative pledges are at least Y and returned to the backers otherwise. Second, if a backer chooses to pledge, she can pledge any amount not smaller than $\underline{x}$.

In the presence of the AoN, as long as the goal is not yet reached, a backer has to take into account not only the information provided by past pledges and her private signal, but also how her pledge will affect future backers' pledges and, through this, the probabilities of success. This implies that as long as the goal is not reached, there are multiple equilibria.[17] Here we are interested in equilibria that satisfy the following compelling regularity condition:

Definition 7.1. *An equilibrium is said to be* regular *if by increasing her pledge a backer cannot make the campaign strictly less likely to succeed.*

In Proposition 7.2 we show that in a regular equilibria, then pledge strategies display the same qualitative properties as our base model without the AoN clause.

Proposition 7.2. *In a regular equilibrium of a crowdfunding campaign with AoN.*

1. *A backer's pledge is (weakly) increasing in the public belief π_t, and in the backer's private signal.*

2. *The public belief evolves according to the following rule:*

   (a) *The change in the public belief resulting from a pledge is non-decreasing in the pledge size.*

   (b) *If between t and $t' > t$ no pledge is observed then $\pi_{t'} \leq \pi_t$.*

[17] In fact, when choosing how much to pledge, each backer is playing a signalling game with the backers who will follow, as future backers have to interpret the information content of her pledge and the way they react will affect her payoff. Thus the multiplicity of equilibria can be extreme.

3. *Information cascade: There is $\underline{\pi} > 0$ such that as soon as $\pi_t < \underline{\pi}$, no backer pledges and for all $t' > t$, $\pi_{t'} = \pi_t$. That is, an abstention information cascade occurs.*

Proposition 7.2 provides the same qualitative empirical implications as the main model. However Proposition 7.2 only concerns regular equilibria, and we cannot exclude a priori that before the goal is reached, backers may coordinate on an equilibrium that is not regular and substantially different from the unique equilibrium emerging once the goal is reached.

This possibility however is rejected by the data. We empirically estimate whether it makes any difference for the coefficients of interest whether a campaign has already reached the goal or not. We do so by separately analysing the data from campaigns before and after the goal is reached. Results are reported in Table 10. As the table shows, the relevant coefficients are similar in the two samples. The estimate of the coefficient capturing the effect of the time passed since the most recent pledge, however, is not statistically significant once we condition on being in the overfunding phase. Intuitively, this makes sense. In the early phase of a campaign pledges are likely to convey more information than in the later stage when the campaign is wrapping up and most private information has already been transmitted.

7.2 The Effects of Multiple Signals and Heterogenous Wealth

In the main model we have assumed that there are only three types of backers and that all backers have the same wealth. In this section we discuss why the predictions of the model would not qualitatively change if we relax these assumptions. Consider first the effect of a richer set Θ of private signals. Let signals in Θ be ordered from the most negative to the most positive. As long as no signal is perfectly informative that the project is of good quality, whenever a backer makes a pledge, the size of her pledge will be strictly increasing in the public belief and in her signal. Also for intermediate levels of π_t, backers with negative enough signals will not pledge, implying that period of absence of pledges translate into a decrease in the public belief π_t. Finally, a small enough π_t will induce even the most optimistic type to refrain from pledging, leading to an abstention cascade.

Now consider heterogeneous wealth. If all backers have the same wealth, it is sufficient to observe the size of the most recent pledge to infer all the relevant information at the disposal of the backer who made that pledge. Hence, the next backer can ignore what happened before the most recent pledge. This is not possible with heterogenously wealthy backers. For example, suppose the most recent pledge is of relative large size x_t. This could result from, say, two possible scenarios. First, the time t backer's wealth is average but she received a strong positive private signal. Second, the time t backer is relatively wealthy, but she received an average private signal.[18] If a backer arriving

[18] Recall that from Proposition 4.1 the size of a backer's pledge is increasing in her wealth.

after t wants to tell the two situations apart, she needs to also examine earlier pledges. In the first scenario the project is more likely to be of good quality than in the second scenario. But then the first scenario x_t is more likely to be preceded by other relatively larger pledges than in the second scenario. Thus, the next backer's pledge will be affected both by x_t and by the sizes of a few pledges preceding x_t.

In the Online Appendix B.1 we provide a formal analysis of the model extended with multiple signals and heterogeneous wealth.

8 Conclusions

In this paper we provide a detailed study using micro-level data of investments by the crowd on a major equity crowdfunding platform. Equity crowdfunding is an important and fast-growing economic phenomena. 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 U.S. in years to come as regulation for its provision was 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 which should have been funded may not get funded, and vice versa. However, through the process of information aggregation, the crowd can provide information in the absence of much else information about the value of entrepreneurial projects. We developed a microfounded model that captures what we believe to be the main rational information aggregation process in one investment platform. The model is able to predict much of the dynamics of campaign funding based on the random arrival of investors with different private information about the projects. The model makes precise the value of the information aggregated from the public without resorting to costly signalling 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 neither Crowdcube, the other major equity crowdfunding platform, nor Kickstarter or Indiegogo, the two major rewards-based platforms, show the size of each individual pledge.

We show that the amount pledged and the probability of a pledge in a campaign is robustly affected by the size of the most recent pledge. This is because a large pledge signals to the public that the backer making the pledge potentially knows something about the project that others may not. This in turn may cause follow-on investors to alter their investment strategies, even though they don't actually observe the information of the investor making the pledge. The model also predicts that the time elapsed since the most recent pledge has a negative effect on the amounts pledged and the probability of pledge occurring. This is because the absence of pledges is indicative that investors are not arriving to the campaign with sufficiently good private signals. Our IV estimates are similar in size to the OLS estimates, suggesting that rational information aggregation captures all the pledge-on-pledge correlation in the data.

Consistent with other studies about early campaign dynamics in crowdfunding, and with a few experimental paper where small pledges were randomly made at the very beginning of a campaign, we show that the probability that a campaign is successful depends largely on the support it gets at the early stage of fundraising. The model rationalises why low or absent pledges have a negative effect on the initial public belief about the project. Lack of support to a campaign is indicative that only a few investors are arriving with positive signals. Having a bad start makes potential backers more pessimistic that the project is of good quality, so that they either pledge lower amounts or decide not to invest at all. In this context an abstention information cascade may occur at the outset, and failed campaigns end up missing the mark by a large margin. Having a good start on the other hand makes signals from pledges made later have less informational value. Empirical results are consistent with that the crowd is able to aggregate information rationally, at least for those campaigns which do not have a very bad start. On the other hand, the theoretical results, together with some graphs and correlations we provide suggests that information provision could be improved on this platform to try and avoid negative information cascades.

Our results are important for entrepreneurs running equity crowdfunding projects, designers of equity crowdfunding platforms, and for regulators as well. Seedrs is a relatively unique platform in that it provides information about each individual pledge. We are able to show that this helps investors form rational beliefs about project value based on rational information aggregation. Other equity crowdfunding platforms may consider voluntarily adopting this practice, and regulators may consider recommending it.

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Tables and Figures

Figure 1: Example of a Typical Campaign in Seedrs

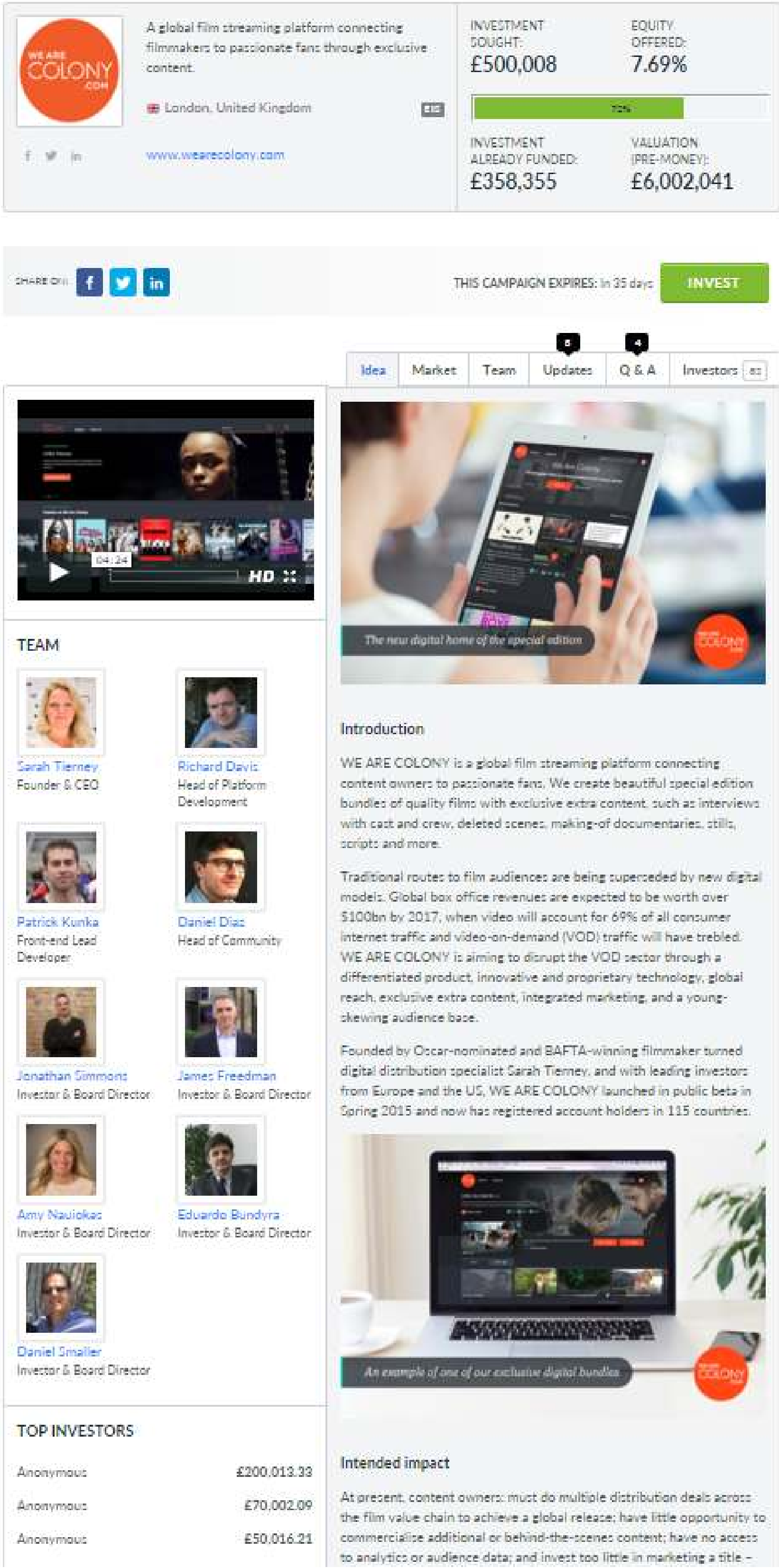
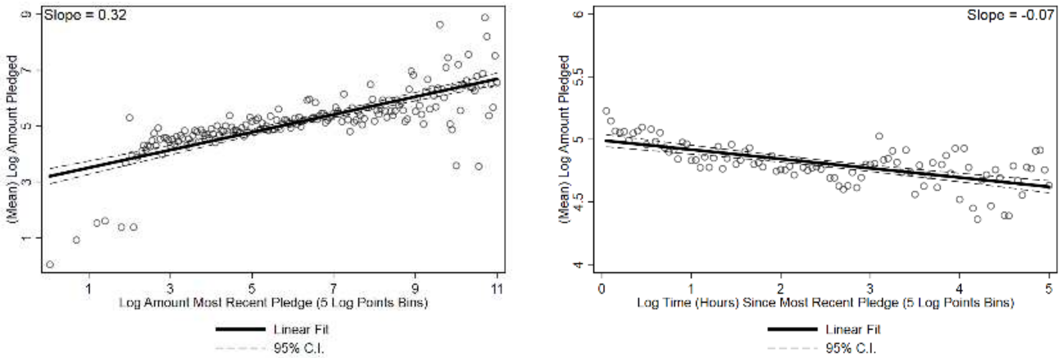


Figure 2: Correlations Between the Amount Pledged by an Investor and the Timing and Size of the Most Recent Pledge

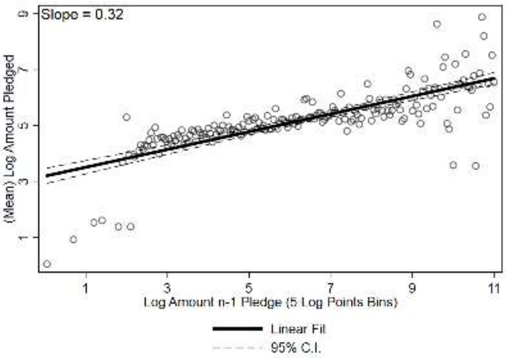
(a) Size of Most Recent Pledge (b) Time Since Most Recent Pledge



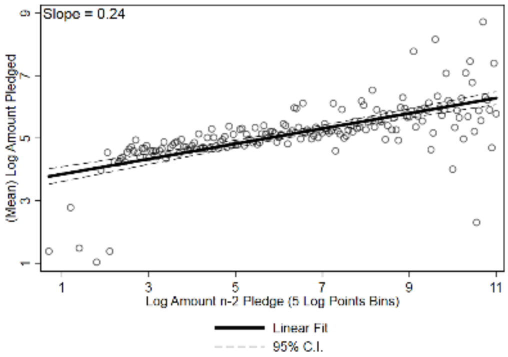
Notes: All pledges are organized in bins of size 5 log points according to the size of the most recent pledge (Panel (a)), and the time elapsed (in hours) since the most recent pledge (Panel (b)). Each panel shows the relation between the median value of the respective bin and the average amount invested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

Figure 3: Correlations Between the Amounts Pledged by Adjacent Backers in a Campaign

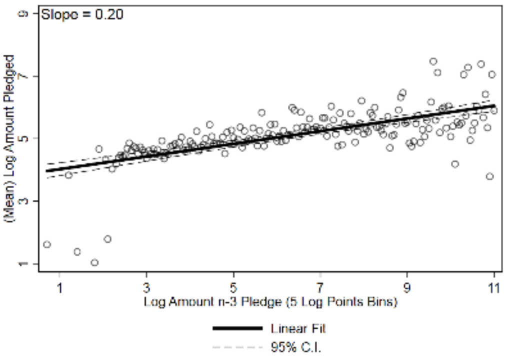
(a) $(n, n-1)$



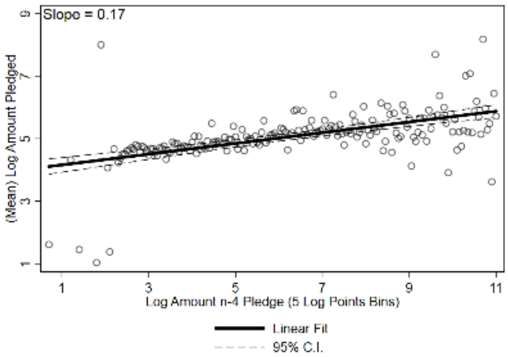
(b) $(n, n-2)$



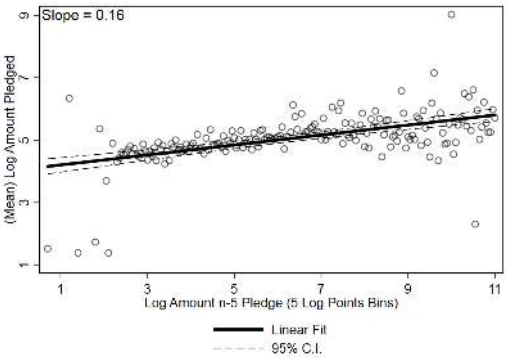
(c) $(n, n-3)$



(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 $k = \{1, 2, 3, 4, 5\}$. Each panel shows the relation between the median value of the respective bin and the average amount invested by the backers.

Figure 4: Sketch of the Construction of the Preferred Instrument

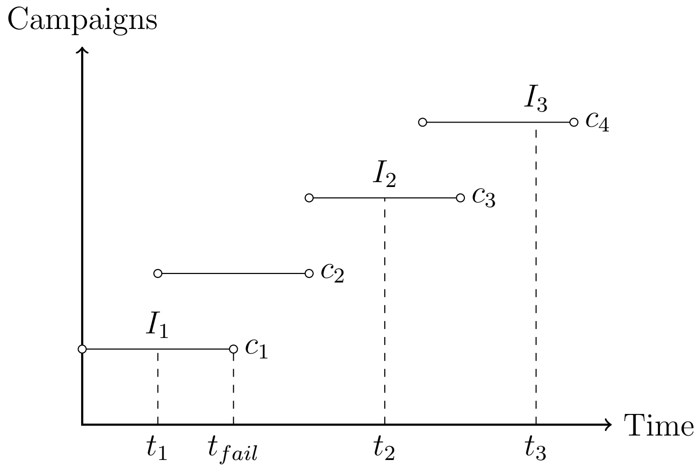
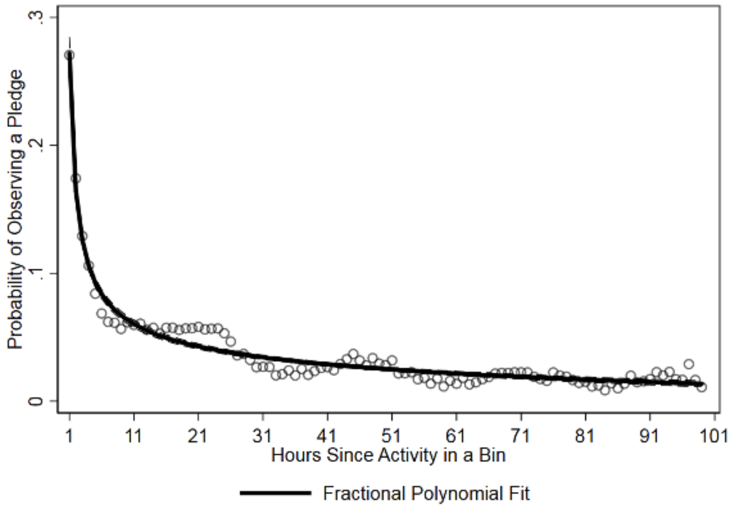


Figure 5: Probability of Observing a Pledge at Any Given Hour as a Function of Time Since Most Recent Activity in an Hourly Bin

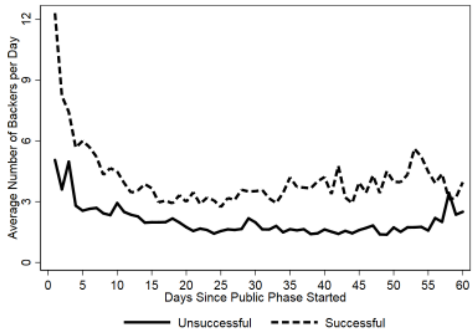


Notes: The total time that a campaign is running is divided into bins of length one hour. For each bin we create two variables: a dummy equal to one if there was at least one positive pledge, and zero otherwise; and a variable equal to the number of hours since the most recent pledge. The figure reports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

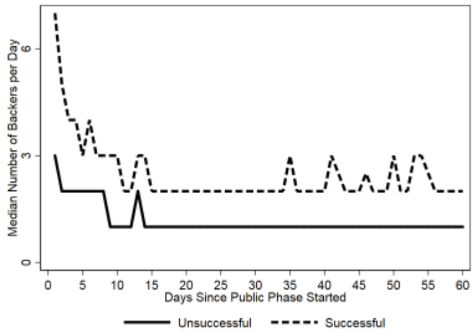
Figure 6: Number of Backers and Cumulative Investments to the Campaigns Across Time During the Public Phase: Successful and Unsuccessful Campaigns

Average and Median Number of Backers per Day

(a) Mean

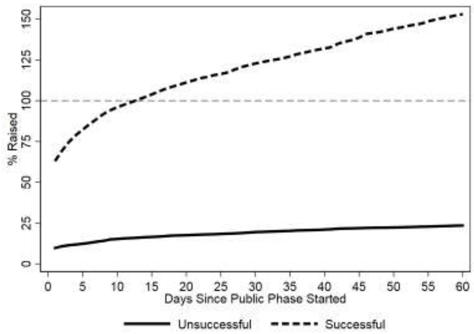


(b) Median

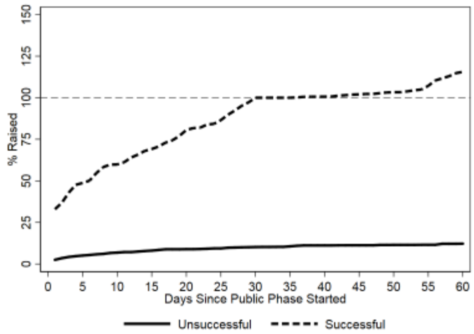


Number of Days to Reach a Given Percentage of the Investment Target

(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: Empirical Predictions of the Model Compared with Predictions of Alternative Models

Predictions	Model	AM1	AM2	AM3	AM4
1. Relation between the size of the most recent pledge and pledge size	$+$	$+_{co}$	$\emptyset$	$\emptyset^{CA}$	$\emptyset^{P1}$
2. Relation between the time elapsed since the most recent pledge and pledge size	$-$	$-_{co}$	$\emptyset$	$\emptyset^{CA}$	$\emptyset^{P1}$
3. Relation between the size of the most recent pledge and the probability of observing a pledge	$+$	$+_{co}$	$\emptyset$	$\emptyset^{CA}$	$\emptyset^{P1}$
4. Relation between the time elapsed since the most recent pledge and the probability of observing a pledge	$-$ (absorbing)	$-_{co}$ (non-absorbing)	$\emptyset$	$\emptyset^{CA}$	$\emptyset^{P1}$
5. Relations 1 and 2 should be stronger for uninformed than for informed backers	Yes	N.A.	N.A.	N.A.	N.A.
6. If the total amount pledged during the private phase is particularly low, the probability campaign succeeds	Nil	Low	Low	Nil	Nil
7. If the total amount pledged during private phase is particularly high, relations 1 and 2 at the beginning of the the public phase should be:	Weak	N.A.	N.A.	N.A.	N.A.

Notes: signs "$+$", "$-$" and "$\emptyset$" indicate a positive causal relation, negative causal relation, and no relation, respectively. "$+_{co}$", "$-_{co}$" indicate positive and negative correlations, respectively, without causal effect of one variable on the other. "CA" stands for after controlling for cumulative amount pledged, "P1" stands for after controlling for the first pledge, "N.A." indicates that the model does not have a prediction.

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.
SEIS tax relief	=1 if investors in the campaign have access to the Seed Enterprise Investment Scheme (SEIS) tax relief, zero otherwise. The SEIS Scheme encourages investment in qualifying new seed-stage startups companies by providing individuals with 50 percent of their investment back in income tax relief. Investors can also benefit from 50 percent capital gains tax relief on gains which are reinvested in SEIS eligible shares. Any gain arising on the disposal of the shares may also be exempt from capital gains tax, and loss relief is available if the disposal results in a loss.
EIS tax relief	=1 if investors in the campaign have access to the Enterprise Investment Scheme (EIS) tax relief, zero otherwise. The EIS scheme is designed to encourage investment in qualifying slightly later-stage companies than the SEIS by providing investors with up to 30% of their investment back in income tax relief. Investors can also defer any capital gains tax on gains which are reinvested in EIS eligible shares, gains arising on the disposal of the shares may be exempt from capital gains tax, and loss relief is available if the disposal results in a loss.
% 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 qualify as investors.
Recurrent investor	=1 if investor has made pledges in more than one campaign; =0 otherwise.
Mean Pledge	Average value in pounds of the pledges made to the campaign.
Median pledge	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.
Mean time between pledges	Average time in hours between adjacent pledges in a campaign.

Table 3: Summary Statistics

	All	Successful (34.2%)	Unsuccessful	Difference
Campaigns				
Pre-money valuation (£)	1,845,466 (5,028,624)	2,793,642 (7,834,238)	1,352,090 (2,426,414)	1,441,552***
Equity offered	11.95 (7.66)	8.82 (6.43)	13.57 (7.75)	-4.75***
Campaign goal (£)	174,215 (327,598)	176,629 (252,718)	172,959 (360,711)	3,670
% EIS tax relief	34.51 (47.57)	46.50 (49.98)	28.27 (45.08)	18.24***
% SEIS tax relief	57.18 (49.52)	45.68 (49.92)	63.17 (48.29)	-17.49***
% Raised	76.40 (195.39)	179.06 (306.91)	22.98 (28.57)	156.07***
# Entrepreneurs	3.28 (1.97)	3.74 (2.07)	3.04 (1.87)	0.70***
# Backers	83.44 (126.38)	169.47 (174.62)	38.68 (50.99)	130.78***
# Pledges	96.48 (146.15)	199.03 (200.67)	43.12 (56.99)	155.91***
% Anonymous pledges	51.40 (18.60)	54.22 (9.50)	49.93 (21.76)	4.30***
Hotness indicator (start of day)	11.13 (13.08)	21.39 (14.80)	5.79 (7.95)	15.60***
Intraday increase in hotness indicator	0.76 (0.24)	0.82 (0.17)	0.74 (0.27)	0.08**
# Days the campaign is active	54.70 (38.46)	58.19 (38.56)	52.89 (38.32)	5.30*
Type of Investor				
% Authorized	79.20 (15.58)	76.49 (11.45)	80.62 (17.19)	-4.12***
% High-net-worth	13.57 (12.72)	14.83 (10.30)	12.92 (13.77)	1.92*
% Sophisticated	7.22 (8.24)	8.68 (4.92)	6.47 (9.44)	2.21***
% Recurrent investors	72.64 (27.54)	79.16 (19.99)	69.25 (30.22)	9.91***
Investments				
Mean pledge (£)	1,202.46 (2,949.49)	1,745.97 (3,472.27)	919.64 (2,596.24)	826.33***
Median pledge (£)	354.32 (2,336.11)	571.29 (3,146.97)	241.42 (1,767.18)	329.87*
Max pledge (£)	38,201.94 (158,251.56)	81,341.40 (259,065.82)	15,754.64 (42,113.87)	65,586.76
Max pledge / goal	0.15 (0.19)	0.31 (0.22)	0.07 (0.10)	0.23
Timing				
Mean time between pledges (hours)	56.57 (109.83)	9.96 (8.98)	82.04 (129.56)	-72.08***
Days in private phase	10.61 (28.22)	10.09 (34.17)	10.89 (24.46)	-0.80
% Covered in private phase	29.73 (118.70)	58.30 (182.47)	10.28 (12.49)	48.02***
% Covered in day 1	9.08 (20.96)	21.11 (30.79)	2.82 (7.83)	18.30***
% Covered in week 1	30.79 (165.42)	75.47 (276.97)	7.54 (14.45)	67.93***
% Covered in month 1	53.32 (187.78)	126.66 (306.94)	15.16 (21.33)	111.50***
Observations	710	243	467	

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

Notes: Each cell is computed by taking the average across the campaigns. The mean time between pledges corresponds to the average across all pledges. 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***	0.075***	0.076***	0.075***	0.140**	0.119***
	(0.007)	(0.006)	(0.007)	(0.007)	(0.062)	(0.020)
Log amount pledged (n-2)	0.034***	0.032***	0.032***	0.031***	0.090	0.038**
	(0.005)	(0.005)	(0.005)	(0.005)	(0.068)	(0.018)
Log amount pledged (n-3)	0.021***	0.021***	0.022***	0.021***	0.063	0.003
	(0.004)	(0.004)	(0.004)	(0.004)	(0.059)	(0.018)
Log amount pledged (n-4)	0.015***	0.013**	0.014***	0.013**	-0.006	0.009
	(0.004)	(0.004)	(0.004)	(0.004)	(0.059)	(0.018)
Log amount pledged (n-5)	0.013**	0.014**	0.015***	0.014***	0.031	0.005
	(0.004)	(0.004)	(0.004)	(0.004)	(0.063)	(0.017)
Log time (hours) since most recent pledge	-0.038**	-0.015	-0.023	-0.012	-0.059	-0.082**
	(0.018)	(0.017)	(0.017)	(0.017)	(0.040)	(0.038)
Controls						
Dummy high-net-worth		1.203***	1.204***	1.200***	1.186***	1.190***
		(0.037)	(0.037)	(0.037)	(0.037)	(0.037)
Dummy sophisticated		0.452***	0.452***	0.451***	0.430***	0.439***
		(0.037)	(0.037)	(0.037)	(0.039)	(0.038)
Dummy recurrent investor		-0.647***	-0.640***	-0.636***	-0.621***	-0.623***
		(0.047)	(0.047)	(0.046)	(0.047)	(0.048)
Log total amount funded up to n-1			-0.060*	-0.066**	-0.163**	-0.100**
			(0.033)	(0.033)	(0.070)	(0.040)
Log number of pledges up to n-1			0.074	0.074	0.138*	0.080
			(0.046)	(0.047)	(0.076)	(0.050)
Log days from start of campaign			0.021	0.028	0.081**	0.096**
			(0.034)	(0.035)	(0.041)	(0.043)
Standardized Campaign hotness at start of the day				0.035**	-0.009	-0.005
				(0.015)	(0.022)	(0.022)
Dummy campaign hotness intraday rise				0.188***	0.135***	0.140***
				(0.021)	(0.025)	(0.026)
Standardized average campaign hotness rest of campaigns				-0.005	0.005	0.005
				(0.011)	(0.012)	(0.012)
Standardized Google trend index				-0.012	-0.016	-0.022*
				(0.012)	(0.013)	(0.013)
Standardized FTSE 100 index				-0.010	0.012	0.010
				(0.024)	(0.023)	(0.025)
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					19.08	208.47
Hansen J statistic P-Val						0.46
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.

Table 5: Probability of Observing a Pledge at Any Given Hour and Amount Invested in Previous Hours

	Dependent Var: Dummy Investment in the Hourly Bin				
	Model	Model Controls I	Model Controls Full	IV C	IV D
Prior pledges					
IHS total amount pledged hour bin t-1	0.018***	0.018***	0.017***	0.020***	0.015***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
IHS total amount pledged hour bin t-2	0.014***	0.014***	0.013***	0.015***	0.015***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
IHS total amount pledged hour bin t-3	0.011***	0.011***	0.010***	0.012***	0.011***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
IHS total amount pledged hour bin t-4	0.010***	0.009***	0.008***	0.011***	0.009***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
IHS total amount pledged hour bin t-5	0.008***	0.007***	0.006***	0.007***	0.006***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Controls					
Log total amount funded up to bin t-1		0.012**	0.006	0.005	0.006
		(0.005)	(0.005)	(0.004)	(0.005)
Log number of pledges up to t-1		-0.013	-0.022	-0.022	-0.022
		(0.017)	(0.016)	(0.015)	(0.016)
Log days from start of campaign		-0.021**	-0.008	-0.005	-0.007
		(0.007)	(0.007)	(0.006)	(0.007)
Standardized Campaign hotness at start of the day			0.025***	0.022***	0.024***
			(0.001)	(0.001)	(0.001)
Dummy campaign hotness intraday rise			0.008***	0.007***	0.008***
			(0.001)	(0.001)	(0.001)
Standardized average campaign hotness rest of campaigns			-0.005***	-0.005***	-0.005***
			(0.001)	(0.001)	(0.001)
Standardized FTSE 100 index			0.002	0.002	0.002
			(0.002)	(0.002)	(0.002)
Standardized Google trend index			0.004***	0.003***	0.004***
			(0.001)	(0.001)	(0.001)
Observations	706,429	706,429	706,429	706,429	706,429
R2	0.066	0.069	0.075	0.074	0.075
Frequency of Investments per Hour	0.060	0.060	0.060	0.060	0.060
SD of Frequency of Investments per Hour	0.238	0.238	0.238	0.238	0.238
Kleibergen and Paap rk statistic				166.286	294.078
Hansen J statistic P-Val				.	0.001
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 dataset 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 (C) is instrumented using the inverse hyperbolic sine transformation (IHS) of the maximum amount of money returned to any of the backers as a result of a campaign failure. The total amount pledged in the IV setting (D) 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.

Table 6: Probability of Observing a Pledge at Any Given Hour and Time Since Last Pledge

	Dependent Var: Dummy Investment in the Hourly Bin			
	Model	Model Controls I	Model Controls Full	IV E
Log Hours since most recent activity in bin	-0.024***	-0.021***	-0.019***	-0.045**
	(0.001)	(0.001)	(0.001)	(0.022)
Controls				
Log total amount funded up to bin t-1		0.017**	0.008	-0.105*
		(0.006)	(0.006)	(0.060)
Log number of pledges up to t-1		-0.032	-0.046**	-0.292**
		(0.020)	(0.018)	(0.127)
Log days from start of campaign		-0.012	0.009	0.509**
		(0.008)	(0.007)	(0.253)
Standardized Campaign hotness at start of the day			0.034***	-0.025
			(0.002)	(0.032)
Dummy campaign hotness intraday rise			0.013***	-0.044
			(0.001)	(0.033)
Standardized average campaign hotness rest of campaigns			-0.008***	0.006
			(0.001)	(0.010)
Standardized FTSE 100 index			0.002	0.000
			(0.002)	(0.017)
Standardized Google trend index			0.005***	-0.007
			(0.001)	(0.011)
Observations	681,541	681,541	681,541	641,707
R2	0.017	0.022	0.033	-4.759
Frequency of Investments per Hour	0.063	0.063	0.063	0.062
SD of Frequency of Investments per Hour	0.242	0.242	0.242	0.242
Kleibergen and Paap rk statistic				3.580
Campaign FE	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 dataset is then organized as a panel in which the time dimension corresponds to the hours passed since the start of the campaign. The time since the most recent pledge in IV setting (D) 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.

Table 7: The Effect of Prior Pledges: Heterogeneous Effects by Investor Type (IV-B)

	Dependent Var: log amount pledged (£)					
	All	High-Net-Worth	Sophisticated	Authorized	Recurrent	Single Campaign
Prior pledges						
Log amount pledged (n-1)	0.119***	0.118**	-0.062	0.136***	0.083***	0.227**
	(0.020)	(0.047)	(0.064)	(0.027)	(0.017)	(0.072)
Log amount pledged (n-2)	0.038**	0.065	0.160	0.023	0.040**	0.043
	(0.018)	(0.053)	(0.161)	(0.021)	(0.017)	(0.051)
Log amount pledged (n-3)	0.003	0.023	0.023	0.004	0.003	0.013
	(0.018)	(0.080)	(0.059)	(0.019)	(0.020)	(0.068)
Log amount pledged (n-4)	0.009	0.057	0.007	-0.004	0.011	0.008
	(0.018)	(0.052)	(0.077)	(0.019)	(0.018)	(0.044)
Log amount pledged (n-5)	0.006	-0.062	-0.006	0.026	0.015	-0.049
	(0.017)	(0.069)	(0.065)	(0.018)	(0.017)	(0.072)
Log time (hours) since most recent pledge	-0.082**	-0.024	-0.256**	-0.070	-0.072**	0.010
	(0.037)	(0.089)	(0.115)	(0.043)	(0.035)	(0.097)
Observations	55,052	7,216	4,489	43,213	42,793	12,205
Average pledge (£)	1,228	3,102	1,694	863	791	2,752
SD pledge (£)	12,169	13,171	11,045	12,075	10,963	15,573
Average time (hours) since most recent pledge	11.4	10.9	9.7	11.6	12.2	8.7
S.D. time (hours) since most recent pledge	38.5	39.8	30.8	39.0	40.6	30.1
Kleibergen and Paap rk statistic	209.78	106.41	77.60	195.69	217.92	71.92
Hansen J statistic P-Val	0.39	0.28	0.48	0.32	0.58	0.02
Campaign FE	Yes	Yes	Yes	Yes	Yes	Yes

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

Notes: Robust standard errors, clustered by campaign. All the 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 Table 2 for the definitions used to classify investors.

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.

Table 9: 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 $\in (0, 15]$	Private Phase Share > 15
Prior pledges			
Log amount pledged (n-1)	0.119***	0.230***	0.086***
	(0.020)	(0.048)	(0.023)
Log amount pledged (n-2)	0.038**	-0.021	0.044**
	(0.018)	(0.053)	(0.021)
Log amount pledged (n-3)	0.003	0.063**	-0.003
	(0.018)	(0.030)	(0.024)
Log amount pledged (n-4)	0.009	-0.011	0.002
	(0.018)	(0.030)	(0.027)
Log amount pledged (n-5)	0.006	0.048	0.007
	(0.017)	(0.040)	(0.022)
Log time (hours) since most recent pledge	-0.082**	-0.186**	-0.066
	(0.037)	(0.084)	(0.046)
Observations	55,052	8,692	26,958
Average pledge (£)	1,228	1,585	1,091
SD pledge (£)	12,169	23,759	8,280
Average time (hours) since most recent pledge	11.4	16.9	9.3
S.D. time (hours) since most recent pledge	38.5	50.4	27.6
Kleibergen and Paap rk statistic	204.61	43.64	102.35
Hansen J statistic P-Val	0.62	0.11	0.88
Campaign FE	Yes	Yes	Yes

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

Notes: Robust standard errors, clustered by campaign. 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.

Table 10: The Effect of Prior Pledges and the Time Since the Most Recent Pledge: Underfunding and Overfunding Stages of a Campaign (IV-B)

	Dependent Var: log amount pledged (£)		
	Baseline	Underfunding Phase	Overfunding Phase
Prior pledges			
Log amount pledged (n-1)	0.119***	0.107***	0.129***
	(0.020)	(0.028)	(0.035)
Log amount pledged (n-2)	0.038**	0.034	0.044
	(0.018)	(0.022)	(0.033)
Log amount pledged (n-3)	0.003	0.007	-0.011
	(0.018)	(0.023)	(0.026)
Log amount pledged (n-4)	0.009	0.011	-0.002
	(0.018)	(0.018)	(0.048)
Log amount pledged (n-5)	0.006	0.006	0.004
	(0.017)	(0.020)	(0.029)
Log time (hours) since most recent pledge	-0.082**	-0.113**	0.040
	(0.037)	(0.041)	(0.078)
Observations	55,052	39,332	15,707
Average pledge (£)	1,228	1,106	1,532
SD pledge (£)	12,169	7,129	19,783
Average time (hours) since most recent pledge	11.4	13.3	6.6
S.D. time (hours) since most recent pledge	38.5	42.2	26.7
Kleibergen and Paap rk statistic	209.23	196.49	64.97
Hansen J statistic P-Val	0.38	0.53	0.20
Campaign FE	Yes	Yes	Yes

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

Notes: Robust standard errors, clustered by campaign. All the controls from Table 4 are included but not reported. A campaign is said to be in the overfunding phase if it has already raised the target amount, but has not reached the time limit. 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.

A Appendix

A.1 Proofs

A.1.1 Proof of Proposition 4.1

Differentiating the r.h.s of (4.4) with respect to x and solving for the f.o.c., it is easy to see that the backer objective function is maximized for $x = \frac{\alpha\pi_t^\theta - 1}{\alpha - 1}W$, that is negative for $\pi_t < \underline{\pi}^\theta$. Because pledges cannot be negative, we get expression (4.5). Q.E.D.

A.1.2 Proof of Proposition 4.2

Because of the monotonicity of pledges with respect to beliefs and because signals are informative, the optimal size of pledges differs across backer type. Hence the public can deduce the backer type from the size of her pledge. Q.E.D.

A.1.3 Proof of Proposition 4.3

When $\pi_t > \underline{\pi}^b$ a backer pledges a positive amount no matter her signal, hence observing no pledge only means that no backer arrived, an event whose distribution does not depend on the project's quality. Similarly, if $\pi_t \leq \underline{\pi}^g$, no backer pledges, hence observing no pledge provides no information about backer's signals and the project's quality. For $\underline{\pi}^u < \pi_t \leq \underline{\pi}^b$ only uninformed backers and positively informed backers pledge. The probability of observing no pledge between t and t' is $e^{-(\lambda q + 1 - \lambda)(t-t')}$ if the project is good, and $e^{-(\lambda(1-q)+1-\lambda)(t-t')}$ if the project is bad. Applying Bayes' rule and simplifying one gets expression (4.6). Q.E.D.

A.1.4 Proof of Proposition 7.2

We show that for any regular equilibrium and any history that does not lead the campaign to fail with certainty, a backer's pledge is an increasing function of her belief. Because there are more positively informed backers if the project is good than if the project is bad, the first result implies that a campaign for a bad project is not more likely to succeed than a campaign for a good project. Because the likelihood ratio on good and bad project success probability is bounded, the positive information, given campaign success, cannot overwhelm negative enough priors, so abstention information cascades are always possible. Given these properties the evolution of beliefs immediately follows.

We first introduce some notation. Let y_t denote the total amount of funds pledged by time t and let $\underline{x} > 0$ be the minimum amount that a backer has to commit if she chooses to pledge. For a given project quality ρ and an pledge history h_t, let

$$S_\rho(x, h_t) := \mathbb{P}(y_T \geq Y | \rho, x, h_t)$$

denote the equilibrium probability that the campaign succeeds if at time t a backer pledges, $x_t = x$, conditional on h_t and ρ. Then, a type θ backer arriving at time t with wealth W solves

$$\max_{x \in 0 \cup [\underline{x}, \infty]} \pi_t^\theta S_\alpha(x, h_t)(\ln(W + (\alpha - 1)x) - \ln(W)) \quad + \quad (1 - \pi_t^\theta) S_0(x, h_t)(\ln(W - x) - \ln(W)). \tag{A.1}$$

With this notation we can formally define regular equilibria as follows:

Definition A.1. *An equilibrium is said to be* regular *if for any x, x' with $0 \leq x < x'$, any history $h_t \in \mathcal{H}$ and any project quality $\rho \in \{0, \alpha\}$, one has $S_\rho(x, h_t) \leq S_\rho(x', h_t)$.*

Note that if h_t is such that $y_t \geq Y$, the goal has already been reached. In this case $S_\alpha(x, h_t) = S_0(x, h_t) = 1$ and we are back to our main model, that indeed describes the unique pledging equilibrium of the campaign during the overfunding phase. Note that this equilibrium is regular.

Second we describe some useful properties of S. Take any finite history s of backers' arrivals, that is $s := \{(t_1, s_1), \ldots, (t_n, s_n), \ldots\}$, where for all $n > 0$, $0 \leq t_n < t_{n+1} \leq T$ and $s_n \in \{b, g, u\}$. Let $\mathcal{S}$ denote the set of all possible such histories. Because arrival time does not depend on the project quality, and $q \in (0, 1)$, for any subset $S \subseteq \mathcal{S}$ we have that

$$\begin{aligned} \mathbb{P}(S|\text{bad project}) \in (0,1) \quad &\Leftrightarrow \quad \mathbb{P}(S|\text{good project}) \in (0,1) \Rightarrow \\ \mathbb{P}(S|\text{bad project}) \quad &\neq \quad \mathbb{P}(S|\text{good project}). \end{aligned} \tag{A.2}$$

Now consider a history of pledges h_t completed with a pledge x_t and let $\mathcal{X}(h_t, x_t) \subset \mathcal{H}$ denote the set of pledge histories that start with h_t, x_t, lead the campaign to succeed, and are compatible with the equilibrium strategies. To any history $h \in \mathcal{X}(h_t, x_t)$ corresponds a history of backers' arrival $z(h) \in \mathcal{S}$ that leads to the observation of h. Then the probability that the campaign succeeds conditional on h_t, x_t and the project's quality ρ can be written as

$$S_\rho(x, h_t) = \mathbb{P}(y_T \geq Y | h_t, x_t = x, \rho) = \mathbb{P}(\cup_{h \in \mathcal{X}(h_{t-1}, x_t = x)} z(h) | h_{t-1}, x_t = x, \rho),$$

that in a regular equilibrium is a non-decreasing function of x.

1. We can now prove that backers' pledges are increasing in their belief. A type θ backer arriving at time t with wealth W solves:

$$\max_{x \in 0 \cup [\underline{x}, \infty]} \pi_t^\theta S_\alpha(x, h_t)(\ln(W + (\alpha - 1)x) - \ln(W)) \quad + \quad (1 - \pi_t^\theta) S_0(x, h_t)(\ln(W - x) - \ln(W)). \tag{A.3}$$

Equivalently,

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

where we define

$$\begin{aligned} A(x) &:= S_\alpha(x, h_t)(\ln(W + (\alpha - 1)x) - \ln(W)) + S_0(x, h_t)(\ln(W) - \ln(W - x)) \\ B(x) &:= S_0(x, h_t)(\ln(W - x) - \ln(W)). \end{aligned}$$

Observe that $\mathbb{P}(y_T \geq Y | h_t, x_t) > 0$ and (A.2) imply $S_\rho(x, h_t) > 0$ for $\rho \in \{0, \alpha\}$. Thus, because the equilibrium is regular, $A(x)$ is a strictly increasing function. Now take two backers, one with belief π and the other with belief $\pi' > \pi$, and let x and x' be their respective optimal pledges. We want to show $x' \geq x$. Observe that x and x' must satisfy

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

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

Because $\pi_t^b < \pi_t^u < \pi_t^g$, it immediately follows that $\hat{\sigma}(b, W, h_t) \leq \hat{\sigma}(u, W, h_t) \leq \hat{\sigma}(g, W, h_t)$. Because there are more positively informed backers when the project is good, it immediately follows that the probability that the campaign succeeds is not smaller for a good project than for a bad project:

$$S_0(x, h_t) \leq S_\alpha(x, h_t). \tag{A.4}$$

2.a Because pledges are non-decreasing in a backer's belief, larger pledges must be associated with more positive private information. When pledges are strictly monotonic in beliefs the public can deduce the backer type from the size of her pledge.

2.b Because pledges are non-decreasing in backers' beliefs, absence of pledges between t and t' can only result from three equilibrium scenarios between t and t': first, no type of backer pledges, second, all types of backers pledge, and third, informed backers pledge only if they have a positive signal. In the first two scenarios absence of pledge provides no information about the project quality and hence the public belief does not change hence $\pi_{t'} = \pi_t$. In the second scenario absence of pledge is more likely if the project is of bad quality because in this case positively informed backers are less likely to arrive. Hence $\pi_{t'} < \pi_t$.

3. Because pledges are non-decreasing in backer's beliefs it is sufficient to show that there is $\underline{\pi}$ such that when $\pi_t < \underline{\pi}$, then a positively informed backer does not invest. If this happens, then an abstention information cascade must occur. Take a type g backer arriving at time t and pledging x and let's consider the expected net-cash flow of the project conditional on the campaign succeeding. This is equal to

$$ECF_t(x) := \frac{\pi_t^g S_\alpha(x, h_t)}{\pi_t^g S_\alpha(x, h_t) + (1 - \pi_t^g) S_0(x, h_t)}\alpha - 1.$$

If $ECF_t(x) \leq 0$ for all $x > 0$, then a risk-averse backer will strictly prefer abstention to investing. Equation (A.2) implies that $S_\alpha(x, h_t) > 0$ if and only if $S_0(x, h_t) > 0$. If for all $x < Y - y_t$ one has $S_\alpha(x, h_t) = 0$ then the campaign fails with certainty unless the backer triggers success by pledging at least $Y - y_t$. For $x > Y - y_t$, one has $S_\alpha(x, h_t) = S_0(x, h_t) = 1$ and so if π_t is such that $\alpha > \pi_t^g$, then $ECF_t(x)$ is negative and not pledging is optimal even to a positively informed backer. For this case, the statement is satisfied by setting $\underline{\pi}$ such that $\frac{\underline{\pi} q}{\underline{\pi} q + (1 - \underline{\pi})(1 - q)} = \alpha$. Now, suppose that $S_\alpha(x, h_t) > 0$ for some $x < Y - y_t$ and take any of such x. Observe that $ECF_t(x)$ is an increasing function of the likelihood ratio $\frac{S_\alpha(x,h_t)}{S_0(x,h_t)}$ that is strictly positive. Suppose that there exists $M > 0$ finite such that $\frac{S_\alpha(x,h_t)}{S_0(x,h_t)} < M$, then

$$ECF_t(x) \leq \frac{\pi_t^g M}{\pi_t^g M + 1 - \pi_t^g}\alpha - 1.$$

Let $\underline{\underline{\pi}} > 0$ be such that the r.h.s. of the above expression is nil for $\pi_t^g = \underline{\underline{\pi}}$ and let $\underline{\pi} > 0$ be such that $\underline{\pi} q / (\underline{\pi} q + (1 - \underline{\pi})(1 - q)) = \underline{\underline{\pi}}$. Then, for $\pi_t < \underline{\pi}$, one has that $ECF_t(x) < 0$, that is, even a positively informed backer will strictly prefer not to pledge.

What remains to be shown is the following Lemma.

Lemma A.2. *There exists $M > 0$ finite such that if $S_\alpha(x, h_t) > 0$, then $\frac{S_\alpha(x,h_t)}{S_0(x,h_t)} < M$.*

Proof. The fact that $S_\alpha(x, h_t) > 0$ implies that $S_0(x, h_t) > 0$ and hence the ratio $\frac{S_\alpha(x,h_t)}{S_0(x,h_t)}$ is well defined and not smaller than 1 because of (A.4). Note that the project's quality ρ affects the distribution of signals among backers but not their arrival time. Hence $\frac{S_\alpha(x,h_t)}{S_0(x,h_t)}$ is maximized when backers pledge only if their signals are positive, and the number of pledges required for the campaign to succeed is large. Now, without loss of generality, let's set the minimum pledge size $\underline{x} = 1$ dollar. Then, $\frac{S_\alpha(x,h_t)}{S_0(x,h_t)}$ is maximized when only positively informed backers pledge, pledges are of 1 dollar each, and no pledge has yet been made. Under these three conditions, the campaign succeeds only if by time T there are at least Y backers with signal g. Considering that the probablity of having exactly i positively informed bakers by time T is equal to $\frac{(\lambda qT)^i}{i!}e^{-\lambda qT}$, if $\rho = \alpha$, and to $\frac{(\lambda(1-q)T)^i}{e}^{-\lambda(1-q)T}$, if $\rho = 0$, we have:

$$\frac{S_\alpha(x,h_t)}{S_0(x,h_t)} \leq \frac{1-\sum_{i=0}^{Y-1}\frac{(\lambda qT)^i}{i!}e^{-\lambda qT}}{1-\sum_{i=0}^{Y-1}\frac{(\lambda(1-q)T)^i}{i!}e^{-\lambda(1-q)T}}. \tag{A.5}$$

Thus we can set M equal to the r.h.s. of (A.5) that is strictly positive and finite because Y is finite and $q \in (1/2, 1)$.

Q.E.D.

A.2 Technical Description of Instrumentation Strategy

Take the simplest specification of the empirical model. We omit additional controls, campaign fixed effects, and campaign indexes to reduce notation. For simplicity of presentation we consider only one lag.

$$\log I_n = \beta \log I_{n-1} + \gamma \log T_{(n,n-1)} + e_n \tag{A.6}$$

where I_n is the amount invested by the nth backer. $T_{(n,n-1)}$ is the time between investment n and $n-1$, and e_n is the error term. Conditional on campaign fixed effects, which absorb all unobserved heterogeneity across campaigns, the key identification problem is one of omitted variable bias. Suppose backer n makes the pledge at calendar time t. It is possible that the error term has the following structure:

$$e_n = \theta_t + \epsilon_n, \tag{A.7}$$

where ϵ_n is a 'pure' stochastic shock and θ_t is some public information shock –not captured by our explicit controls or by the campaign fixed effects– that arrived at or before t and is visible to the backer n. Importantly, it could also be visible to backer $n-1$. Suppose information can be good (=1), irrelevant/non-existent (=0), or bad (=-1): $\theta_t \in \{-1, 0, 1\}$. The endogeneity comes from the idea that:

$$Cov(\log I_n, \theta_t) > 0, \tag{A.8}$$

$$Cov(\log I_{n-1}, \theta_t) \geq 0, \tag{A.9}$$

$$Cov(\log T_{(n,n-1)}, \theta_t) \leq 0, \tag{A.10}$$

where the first two inequalities arise because good news leads people to invest more, and the last inequality follows from the proposition that, at the margin, good news leads people to invest (at least a positive amount). Both independent variables are potentially endogenous, so we need two instruments, one for each.

A.2.1 First Instrument

Let X_{n-1} be an instrument for $\log I_{n-1}$. In our case X_{n-1} is either i. income returned to investor $n-1$ after previous failed campaign or iia. max amount pledged in the past by investor $n-1$ and iib. number of pledges in the past. In both cases, X_{n-1} must satisfy:

$$Cov(\log I_{n-1}, X_{n-1}) \neq 0, \tag{A.11}$$

$$Cov(\theta_t, X_{n-1}) = 0. \tag{A.12}$$

The relevance of the instruments can be tested with the data, and we argue that the exogeneity condition applies. The amount returned in previous pledges from other campaigns, the max amount invested in previous campaigns or the number of pledges in previous campaigns by backer $n-1$ should be unrelated to the public information shock about the campaign θ_t. In all cases X_{n-1} is only defined for events that happen before the campaign starts, so it's fully predetermined and uncorrelated with the stream of information arriving during the life of the campaign.

A.2.2 Second Instrument

Let G_n be an instrument for $\log T_{(n,n-1)}$. In our case G_n is the absolute length of time between the most recent pledge and 11 a.m., which is the hour of the day in which people are most active on the platform. The instrument must satisfy:

$$Cov(\log T_{(n,n-1)}, G_n) \neq 0, \tag{A.13}$$

$$Cov(\theta_t, G_n) = 0. \tag{A.14}$$

Rather mechanically, the length of time between two adjacent pledges should be smaller the closer the first one is to 11 a.m., something we observe in the data. What about the second condition? Is the time of the day in which a pledge is made correlated with θ_t? The only threat is that particular forms of information shock (news) arrive close to 11 a.m. and others do not. News can be positive, negative or irrelevant/non-existent (=0). If the likelihood that positive news arrives close to 11 a.m. is higher than the likelihood that negative news arrives close to 11 a.m., then the correlation is positive. If the likelihood that negative news arrives close to 11 a.m. is higher than the likelihood that positive news arrives close to 11 a.m., then the correlation is positive. If the likelihood is the same then the correlation is zero. The threat to validity then requires that the timing of the arrival of information not captured in our controls is non-random and that the direction of the signal (positive/negative) is skewed around 11 a.m..

B Online Appendix

Not for Publication

Herding in Equity Crowdfunding (T. Astebro, M. Fernandez, S. Lovo, and N. Vulkan)

Table B.1: Correlation Between Subsequent 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)	0.010 (0.007)		
IHS amount returned (n-2)	0.013 (0.008)		
IHS amount returned (n-3)	0.009 (0.006)		
IHS amount returned (n-4)	0.010 (0.016)		
IHS amount returned (n-5)	0.004 (0.006)		
Inst. B1			
Number of pledges (n-1) × Anonymous (n-1)		0.000 (0.006)	
Number of pledges (n-2) × Anonymous (n-2)		-0.013 (0.026)	
Number of pledges (n-3) × Anonymous (n-3)		-0.003 (0.006)	
Number of pledges (n-4) × Anonymous (n-4)		-0.003 (0.006)	
Number of pledges (n-5) × Anonymous (n-5)		-0.011 (0.016)	
Inst. B2			
Max amount invested (n-1) × Anonymous (n-1)			-0.006 (0.007)
Max amount invested (n-2) × Anonymous (n-2)			-0.015 (0.034)
Max amount invested (n-3) × Anonymous (n-3)			-0.003 (0.008)
Max amount invested (n-4) × Anonymous (n-4)			-0.001 (0.010)
Max amount invested (n-5) × Anonymous (n-5)			-0.015 (0.015)
Observations	56,042	56,042	56,042
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 B.2: Correlation Between Self-Reported Types of Subsequent Investors

	Self Reported Investor Type Dummy			
	Authorized	High-net-worth	Sophisticated	Recurrent
Dummy authorized n-1	-0.002			
	(0.004)			
Dummy high-net-worth n-1		-0.007		
		(0.005)		
Dummy sophisticated n-1			-0.006	
			(0.005)	
Dummy recurrent investor				0.064
				(0.073)
Log total amount funded up to n-1	-0.005	0.002	0.003	0.056***
	(0.006)	(0.005)	(0.004)	(0.008)
Log number of pledges up to n-1	0.018**	-0.006	-0.012**	-0.048***
	(0.006)	(0.005)	(0.004)	(0.010)
Log days from start of campaign	-0.005	-0.003	0.008**	-0.017**
	(0.005)	(0.004)	(0.004)	(0.007)
Standardized Campaign hotness at start of the day	-0.010**	0.004	0.006**	-0.016**
	(0.003)	(0.003)	(0.002)	(0.005)
Dummy campaign hotness intraday rise	-0.014**	0.014***	0.000	-0.020***
	(0.005)	(0.004)	(0.003)	(0.005)
Standardized average campaign hotness rest of campaigns	-0.003	0.003	-0.000	0.005*
	(0.002)	(0.002)	(0.001)	(0.003)
Standardized Google trend index	0.003	-0.004*	0.002	-0.007
	(0.003)	(0.002)	(0.002)	(0.005)
Standardized FTSE 100 index	-0.003	0.001	0.003	0.005
	(0.006)	(0.004)	(0.004)	(0.007)
Observations	56,992	56,992	56,992	56,992
Campaign FE	Yes	Yes	Yes	Yes

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

Notes: Robust standard errors, clustered by campaign.

Table B.3: 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***	-0.003	-0.005	-0.005	-0.005	0.002
	(0.007)	(0.005)	(0.005)	(0.004)	(0.004)	(0.003)
IHS amount returned (n-2)	-0.001	0.069***	-0.001	-0.005	-0.005	-0.001
	(0.005)	(0.008)	(0.005)	(0.004)	(0.004)	(0.003)
IHS amount returned (n-3)	0.000	0.001	0.069***	0.002	-0.006	0.000
	(0.005)	(0.005)	(0.008)	(0.005)	(0.005)	(0.003)
IHS amount returned (n-4)	0.002	0.001	-0.001	0.066***	0.001	0.001
	(0.004)	(0.005)	(0.005)	(0.008)	(0.005)	(0.003)
IHS amount returned (n-5)	-0.004	0.001	0.002	-0.002	0.068***	0.003
	(0.004)	(0.004)	(0.005)	(0.005)	(0.008)	(0.003)
Log hours since 11am (n-1)	-0.080***	-0.034**	0.004	0.011	0.003	0.264***
	(0.012)	(0.011)	(0.011)	(0.011)	(0.010)	(0.010)
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 IHS can be interpreted in the same way as the standard logarithmic transformation, but it has the property that is defined at zero. 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.

Table B.4: 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	-0.016	-0.028	0.024	-0.071***
	(0.024)	(0.022)	(0.021)	(0.024)	(0.023)	(0.016)
Number of pledges (n-2) × Anonymous (n-2)	-0.029	-0.706***	-0.013	-0.017	-0.030	-0.053**
	(0.019)	(0.024)	(0.022)	(0.021)	(0.024)	(0.016)
Number of pledges (n-3) × Anonymous (n-3)	-0.047**	-0.053**	-0.716***	-0.020	-0.016	-0.012
	(0.021)	(0.020)	(0.024)	(0.022)	(0.022)	(0.016)
Number of pledges (n-4) × Anonymous (n-4)	0.002	-0.046**	-0.053**	-0.726***	-0.028	-0.026*
	(0.022)	(0.020)	(0.020)	(0.024)	(0.023)	(0.015)
Number of pledges (n-5) × Anonymous (n-5)	-0.024	-0.011	-0.072***	-0.077***	-0.750***	0.006
	(0.023)	(0.022)	(0.021)	(0.020)	(0.025)	(0.017)
Max amount invested (n-1) × Anonymous (n-1)	0.561***	0.009	0.010	-0.012	-0.017	-0.017
	(0.090)	(0.016)	(0.012)	(0.013)	(0.018)	(0.011)
Max amount invested (n-2) × Anonymous (n-2)	0.011	0.597***	0.041**	0.015	-0.002	-0.003
	(0.018)	(0.077)	(0.018)	(0.014)	(0.011)	(0.009)
Max amount invested (n-3) × Anonymous (n-3)	0.016	0.020	0.588***	0.024	0.028**	-0.005
	(0.013)	(0.017)	(0.090)	(0.020)	(0.013)	(0.010)
Max amount invested (n-4) × Anonymous (n-4)	-0.007	0.013	0.010	0.586***	0.036**	0.007
	(0.013)	(0.013)	(0.018)	(0.080)	(0.015)	(0.009)
Max amount invested (n-5) × Anonymous (n-5)	-0.018	-0.016	0.018	0.018	0.570***	-0.001
	(0.024)	(0.014)	(0.012)	(0.018)	(0.091)	(0.009)
Log hours since 11am (n-1)	-0.065***	-0.027**	0.005	0.014	0.004	0.266***
	(0.011)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
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.

Table B.5: 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)	0.113***	0.104***	0.104***	0.103***	0.206**	0.133***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.081)	(0.017)
Log amount pledged (n-2)	0.031***	0.029***	0.030***	0.029***	0.084	0.029
	(0.005)	(0.005)	(0.005)	(0.005)	(0.086)	(0.018)
Log amount pledged (n-3)	0.022***	0.021***	0.022***	0.021***	0.077	0.018
	(0.004)	(0.004)	(0.004)	(0.004)	(0.074)	(0.019)
Log amount pledged (n-4)	0.017***	0.016***	0.017***	0.016***	0.020	-0.017
	(0.004)	(0.004)	(0.004)	(0.004)	(0.081)	(0.015)
Log amount pledged (n-5)	0.020***	0.018***	0.019***	0.019***	0.086	0.011
	(0.004)	(0.004)	(0.004)	(0.004)	(0.082)	(0.014)
Log time (hours) since most recent pledge	-0.041**	-0.021	-0.027	-0.019	-0.013	-0.050
	(0.017)	(0.017)	(0.017)	(0.017)	(0.039)	(0.036)
Controls						
Dummy high-net-worth		1.161***	1.162***	1.158***	1.128***	1.150***
		(0.035)	(0.035)	(0.035)	(0.035)	(0.035)
Dummy sophisticated		0.463***	0.464***	0.463***	0.438***	0.456***
		(0.036)	(0.036)	(0.036)	(0.037)	(0.037)
Dummy recurrent investor		-0.611***	-0.606***	-0.603***	-0.584***	-0.588***
		(0.046)	(0.046)	(0.046)	(0.045)	(0.047)
Log total amount funded up to n-1			-0.071**	-0.074**	-0.196***	-0.089**
			(0.028)	(0.028)	(0.056)	(0.034)
Log number of pledges up to n-1			0.060	0.062	0.159**	0.060
			(0.037)	(0.039)	(0.058)	(0.041)
Log days from start of campaign			0.034	0.039	0.061*	0.086**
			(0.028)	(0.029)	(0.032)	(0.039)
Standardized Campaign hotness at start of the day				0.026*	-0.004	0.004
				(0.015)	(0.019)	(0.020)
Dummy campaign hotness intraday rise				0.177***	0.134***	0.150***
				(0.021)	(0.023)	(0.026)
Standardized average campaign hotness rest of campaigns				-0.003	0.002	0.002
				(0.010)	(0.010)	(0.012)
Standardized Google trend index				-0.015	-0.010	-0.022*
				(0.012)	(0.011)	(0.012)
Standardized FTSE 100 index				-0.003	0.007	0.007
				(0.023)	(0.019)	(0.024)
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					17.78	210.82
Hansen J statistic P-Val					.	0.62
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.

B.1 Online Appendix: The Effect of Heterogenous Wealth and Multiple Signals

In the baseline model we have assumed that there are only three types of backer and that all backers have the same wealth. In this section we discuss why the predictions of the model would not qualitatively change if we relax these assumptions. For this purpose we focus on the unique equilibrium of the overfunding phase. First, suppose that backers' wealth are i.i.d. on the interval $[0, 1]$ with density z, and that a backer's wealths is not correlated with the project's quality or the backer's private information. Second, suppose that backers receive conditionally i.i.d. private signals that are drawn from a 'smooth' density f on the interval $[\underline{\theta}, \overline{\theta}]$ and c.d.f. F. Without loss of generality, we can order signals so that the monotone likelihood ratio property holds:

$$L(\theta) := \frac{f(\theta|\rho = \alpha)}{f(\theta|\rho = 0)} \text{ is increasing in } \theta.$$

Thus $\theta < \theta'$ implies $\pi_t^\theta < \pi_t^{\theta'}$, where $\pi_t^\theta = \frac{\pi_t L(\theta)}{\pi_t L(\theta)+1-\pi_t}$. We further assume that $L(\underline{\theta}) \geq 0$ and $L(\overline{\theta})$ is bounded. This implies that for any $\pi_t \in (0, 1)$ we have that $\pi_t^\theta < 1$. Let's denote with $\underline{\pi}^\theta$, the level of public belief π_t such that $\pi_t^\theta = \alpha^{-1}$. It is easy to verify that $\underline{\pi}^\theta$ is strictly positive and decreasing in θ.

Then we have:

Proposition B.1. *During the overfunding phase:*

1. *Pledges: A type θ backer arriving at time t pledges*

$$\hat{\sigma}(\theta, \pi_t) = \begin{cases} 0, & \text{if } \pi_t \leq \underline{\pi}^\theta \\ \frac{\alpha\pi_t^\theta - 1}{\alpha - 1} W > 0, & \text{if } \pi_t > \underline{\pi}^\theta. \end{cases} \tag{B.1}$$

2. *The public belief evolves according to the following rules:*
   (a) *During the periods of absence of pledges the public belief strictly decreases $\pi_t \in (\underline{\pi}^{\overline{\theta}}, \underline{\pi}^{\underline{\theta}}]$ and does not change for $\pi_t \notin (\underline{\pi}^{\overline{\theta}}, \underline{\pi}^{\underline{\theta}}]$.*
   (b) *The public belief $\pi_t(x)$ resulting from a pledge of $x > 0$ at time t is strictly increasing in x.*

3. *Information cascade: An information cascade occurs if and only if $\pi_t \leq \underline{\pi}^{\overline{\theta}}$ and leads all backers to abstain from pledging.*

Proof.

1. The proof is identical to the proof of Proposition 4.1.

2.a Let's denote with $\theta^*(\pi) > 0$ backers of type θ such $\underline{\pi}^{\theta} = \pi$. It is easy to verify that $\theta^*(\pi)$ satisfies $L(\theta^*(\pi)) = \frac{1-\pi}{\pi(\alpha-1)}$ and is decreasing in π. If the public belief is π, then a backer pledges only if her type is $\theta > \theta^*(\pi)$. Let's consider the instantaneous probability of observing no pledges between t and $t+dt$. This corresponds to the chance of no backer arriving, $1-\lambda$, plus the chance of one informed backer arriving, λ, times the probability that the informed backer does not pledge. Given (1.), a backer does not pledge only if $\pi_t^{\theta} \leq \underline{\pi}^{\theta}$, which is equivalent to $\theta < \theta^*(\pi_t)$. The probability that $\theta < \theta^*(\pi_t)$ given ρ is $F(\theta^*(\pi_t)|\rho)$. Applying Bayes' rule we have that

$$\frac{\partial \pi_t}{\partial t} = \frac{\pi_t(\lambda F(\theta^*(\pi_t)|\rho = \alpha) + 1 - \lambda)}{\lambda(\pi_t F(\theta^*(\pi_t)|\rho = \alpha) + (1-\pi_t)F(\theta^*(\pi_t)|\rho = 0)) + 1 - \lambda} - \pi_t.$$

For $\pi < \underline{\pi}^{\overline{\theta}}$ no backer invests. Thus $F(\theta^*(\pi_t)|\rho = \alpha) = F(\theta^*(\pi_t)|\rho = 0) = 1$ and $\frac{\partial \pi_t}{\partial t} = 0$. For $\pi > \underline{\pi}^{\underline{\theta}}$ all types of backer invest. Thus $F(\theta^*(\pi_t)|\rho = \alpha) = F(\theta^*(\pi_t)|\rho = 0) = 0$ and $\frac{\partial \pi_t}{\partial t} = 0$. To see that $\frac{\partial \pi_t}{\partial t} < 0$ for $\pi_t \in (\underline{\pi}^{\overline{\theta}}, \underline{\pi}^{\underline{\theta}}]$ it is sufficient to note that because pledges are strictly increasing in the backer's signals and signals satisfy the monotone likelihood ratio property, we have that $F(\cdot|\rho = \alpha)$ first order stochastically dominate $F(\cdot|\rho = 0)$, that is, for $\pi_t \in (\underline{\pi}^{\overline{\theta}}, \underline{\pi}^{\underline{\theta}}]$, we have $F(\theta^*(\pi_t)|\rho = \alpha) < F(\theta^*(\pi_t)|\rho = 0)$ implying $\frac{\partial \pi_t}{\partial t} < 0$.

2.b For any $x > 0$, π_t and $W \in [0,1]$, let $\theta(x, W, \pi_t)$ be the θ such that $x = \max\left\{0, \frac{\pi_t^{\theta}\alpha-1}{\alpha-1}W\right\}$ and if no such θ exists set $\theta(x, W, \pi_t) > \overline{\theta}$. That is $\theta(x, W, \pi_t)$ is the backer type who would invest x if her wealth is W and the public belief is π_t. Let $x < x'$ and fix W. We have that

$$\mathbb{P}(\rho = \alpha|x, W, h_t) = \frac{\pi_t L(\theta(x, W, \pi_t)}{\pi_t L(\theta(x, W, \pi_t)) + 1 - \pi_t}$$

that is in $L(\cdot)$. Because pledges are increasing in θ we have that $\theta(x, W, \pi_t) < \theta(x', W, \pi_t)$. Because $L(\theta)$ is an increasing function we have that for all W,

$$\mathbb{P}(\rho = \alpha|x, W, h_t) < \mathbb{P}(\rho = \alpha|x', W, h_t).$$

Because posterior beliefs are martingales, and the distribution of wealth and signals are independent we have

$$\pi_t(x) = E[\mathbb{P}(\rho = \alpha|x, \tilde{W}, h_t)] < \pi_t(x') = E[\mathbb{P}(\rho = \alpha|x', \tilde{W}, h_t)]$$

where the expectation is taken with respect to the possible wealth.

3. The proof is identical to the proof of Proposition 4.3 and Corollary **??**.