# Herding in Equity Crowdfunding *

Thomas Åstebro[†] HEC Paris

Manuel Fernández University of Essex

Stefano Lovo HEC Paris

Nir Vulkan
Said Business School
Oxford University

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**Abstract**

Do equity crowdfunding investors herd? We build a model where informed and uninformed investors arrive sequentially and choose whether and how much to invest. We test the model using data of investments on a leading European equity crowdfunding platform. We show theoretically and find empirically that the size and likelihood of a pledge is affected positively by the size of the most recent pledges, and negatively by the time elapsed since the most recent pledge. The empirical analysis is inconsistent with naïve herding, independent investments, or exogenously correlated investments.

**JEL Codes:** D81, D83, G11, G14

**Keywords:** Equity crowdfunding, Herding

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[†]Corresponding author: Thomas Åstebro. E-mail: astebro@hec.fr. Postal Address: 1, rue de la Libèration, Jouy-en-Josas cedex, France, 78351. Telephone number: (+33) 139 677 000.

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Do equity crowdfunding investors herd? We build a model where informed and uninformed investors arrive sequentially and choose whether and how much to invest. We test the model using data of investments on a leading European equity crowdfunding platform. We show theoretically and find empirically that the size and likelihood of a pledge is affected positively by the size of the most recent pledges, and negatively by the time elapsed since the most recent pledge. The empirical analysis is inconsistent with naïve herding, independent investments, or exogenously correlated investments.

# 1 Introduction

In recent years crowdfunding has emerged as a popular alternative financing channel for entrepreneurs. Funds raised via crowdfunding expanded by 167 percent in 2014 to reach \$16.2 billion, up from \$6.1 billion in 2013 (Massolution, 2015). A number of high-profile campaigns and an increasing appetite to 'cut out the middleman' mean crowdfunding is likely to remain an important part of early-stage-finance for some years to come.

Broadly speaking, crowdfunding can be divided into four main categories: donations, rewards-based (also called pre-selling), lending, and equity crowdfunding. The focus of this paper is on equity crowdfunding, where internet users take an equity stake in the business in much the same way that Venture Capitalist (VC) funding works. Although the typical individual investment ('pledge') is much smaller in equity crowdfunding than for business angels and VCs, the equity raised can be as substantial. Moreover, this model has already become a significant financing vehicle for start-ups, and is growing rapidly. 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]

This paper is motivated by the concerns expressed by practitioners and regulators that crowdfunding investors (backers) can be taken advantage of by investment promoters. For example, the U.S. regulatory framework for equity crowdfunding announced in October 2015[2] has already been criticized by Shiller (2015) for offering too little protection to backers. Yet, little information exists on the investment behaviour of equity crowdfunding backers, making it difficult to provide strong guidance at this stage.[3]

One of the most common concerns is that prior investors' decisions induce future investors to take similar decisions regardless of their initial opinions of the project quality. Regulators may find such behaviour of great concern if weak or even incorrect signals get amplified as a result of information verification being difficult and a herd response overtaking relevant private information. Investment op-

[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 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.

[2] See the Security and Exchange Commission (SEC) final draft at: `http://www.sec.gov/rules/final/2015/33-9974.pdf`

[3] Most analysis of crowdfunding has been limited to rewards-based platforms (for reviews see e.g. Belleflamme et al. (2014); Agrawal et al. (2014)) which avoid equity investment regulation by allowing backers to pre-purchase a product, obtain rewards such as a t-shirt, or simply to donate funds. Recently published empirical work on equity crowdfunding includes Ahlers et al. (2015); Vismara (2016); Vulkan et al. (2016).

portunities presented online may be particularly sensitive to herding as signals in this medium can be propagated easily to a broad audience with little quality control or verification. The theoretical literature on rational herding has analyzed this type of imitative behaviour and shown that past investment decisions can induce future investors to ignore their private information when making their investment choice (e.g., Banerjee, 1992; Welch, 1992). When this happens a so-called information cascade occurs and the market fails to aggregate relevant private information. This could lead to decisions that differ from those that would result had all investors' private information been taken into account.

In this paper we address the following questions about herding in equity crowdfunding: First, is rational herding theoretically possible in equity crowdfunding and if yes, what type of herding? Second, is herding necessarily associated with information cascades? Third, how can rational herding be empirically disentangled from irrational imitative behaviour and what type of herding, if any, is empirically observed?

To answer these questions we analyse backers' behaviour in crowdfunding campaigns using a unique investment-level dataset from one of the leading UK equity crowdfunding platforms, which uses an all-or-nothing funding scheme.[4] To guide our empirical analysis we develop a stylized equilibrium model that reflects the salient features of pledging decisions in equity crowdfunding, in particular, the choice of whether and how much to pledge in a campaign for a project of uncertain quality. This choice may be guided by some private information about the project quality but it is also affected by the public information about how much and when previous backers have pledged. Importantly, the public information does not indicate how many backers choose not to pledge, nor the private information of previous backers.

Our model features a sequence of risk-averse backers who visit a crowdfunding platform. Backers' arrival follows a Poisson process. Each backer can pledge any non-negative amount and is either uninformed or has some private information, positive or negative. Informed backers' private signals are conditional i.i.d. and correlated with the fundamental value of the project to be financed. Past strictly positive pledges are publicly observable, whereas backers' arrivals are not. Thus, backers cannot tell whether the absence of pledges results from the non-arrival of backers or from the fact that backers who arrived chose not to pledge.

We show that, first, in all regular equilibria of a crowdfunding campaign,[5] backers make pledges based on the history of past pledges and their private information. The more positive their privater

[4] In an all-or-nothing funding scheme, investors' pledges are invested only if the total amount pledged reaches a pre-specified threshold by a given date, otherwise all funds are returned to the backers.

[5] We define an equilibrium to be regular if by increasing the size of her pledge a backer cannot decrease the probability that the campaign succeeds.

signal and the public information provided by previous pledges, the more likely is a backer to pledge and to pledge a large amount. Thus large investments provide positive public signals about the project's quality, whereas periods without pledges provide negative public signals. Second, both pledge herding and abstention herding can occur in equilibrium. Namely, past backers' pledges can trigger pledges from future backers that would otherwise not have pledged. Also, the absence of pledges might induce future backers to abstain from pledging. Third, pledge herding is never associated with an information cascade. The reason is that, although noisy, the size of a pledge always provides some information about the backer's belief about the project quality. As opposed to pledge herding, abstention herding is always associated with an information cascade.

This simple model provides us with some testable predictions. First, a pledge size should be increasing in the backer's wealth and the size of the most recent pledge and decreasing in the time elapsed since the most recent pledge. These effects should be present but weaker for pledges further apart in the order of arrival. In our model, the most recent pledge provides complete information about the history of the campaign, but if the signal of the most recent pledge is noisy, the backer will also take into account signals generated by earlier pledges. The most recent pledge would nevertheless have a higher weight. The absence of pledges, on the other hand, makes the backer more pessimistic about the quality of the project, so the time elapsed without pledges is negatively correlated with the size of the backer's optimal pledge. Second, uninformed backers should react more to prior pledges than informed backers. Third, the probability of observing new pledges should be increasing in the size of the most recent pledge and decreasing in the time since the most recent pledge. Fourth, the probability of success of a campaign is highly dependent on the campaign having a good start.

We contrast the four predictions of our model to those of three alternative models. In alternative model 1 (AM1), herding is absent because backers make pledges based only on their own private information. In alternative model 2 (AM2), pledges and their absence solely result from the arrival of public information that is not observable by the econometrician. Similar to AM1, there is no herding in AM2. In alternative model 3 (AM3), herding is extreme and naïve as a backer's pledge only depends on the sum of past pledges. The empirical predictions of AM1 and AM3 substantially differ from those of our model. Our empirical strategy is designed to disentangle our model predictions from those of AM2.

For our empirical analysis we use a dataset kindly shared with us by Seedrs. We analyse 69,699 investments ('pledges') by 22,615 investors ('backers') made between October 2012 and March 2016. Our data detail pledges by the second, making it possible to order all pledges in time and examine Granger causality, while controlling for fixed campaign-specific effects.

We first examine the correlation between the sizes of adjacent pledges in the same campaign and how the strength of this correlation varies as a function of the time elapsed between pledges. Causal interpretation of a positive correlation between adjacent pledges in a campaign is hindered by the possibility that several large pledges might be driven by common factors, like positive news about the campaign as in AM2. We tackle this problem using two alternative sets of instrument. In our main specification, we construct an instrument using the fact that if a campaign fails, the amounts pledged are returned to backers. The returned money can be used by backers for pledges in other future campaigns, and can be plausibly considered exogenous from information arriving about the future campaign. This provides an opportunity to instrument future pledges with the amount returned from the last failed campaign.

The instrument in our main specification uses variation in disposable money among backers that are repeat investors and whose last supported campaign failed. However, the number of backers for which those two conditions hold is a small subset of the sample. We therefore construct an alternative set of instruments based on information on the characteristics of backers that is observed by the econometrician but not to follow-on backers. In particular, we instrument the size of a pledge with (i) the total number of pledges and (ii) the maximum amount pledged by the backer in all previous campaigns, conditional on those pieces of information being unobserved to the public. Since the pledge history of the backer is predetermined and unknown, it is uncorrelated with the stream of new information arriving about a campaign at any point in time. We show that both sets of instruments give similar quantitative results. We also instrument the time elapsed since the most recent pledge.

We find that that both with and without IV, a pledge size is strikingly positively affected by the size of the most recent pledge and negatively affected by the time elapsed since that pledge. Moreover, we show that the strength of the correlation declines if backers are further apart in the order of arrival. For pledges that are not adjacent, the correlation between their sizes is still positive but of smaller magnitude, and after being separated by two or more intervening pledges the correlation is no longer statistically significant. The results suggest some inter-temporal herding that nevertheless quickly dissipates. For example, a doubling of the size of the most recent pledge increases the size of the subsequent pledge by between 8.9 percent and 21.2 percent, depending on the characteristic of the backer of the subsequent pledge, with an average effect size of 11.9 percent. These findings are consistent with our model predictions.

We then examine how the results vary depending on whether the backer is informed or uninformed.

We take uninformed backers to be those backers that are either single-campaign investors, or who have not self-reported as being a sophisticated or high-net-worth backer. We find that all types of backers appear to react to the size of the previous pledge but that the magnitude of the effect is stronger for uninformed backers. This evidence is also consistent with the second prediction of our model.

Analysis supports the third prediction of the model that the probability of a pledge occurring at a given point in time is a decreasing function of the time elapsed since the most recent pledge and increasing in the amounts of the preceding pledges. For example, a doubling of the amount invested at any given hour increases the probability of observing any activity over the next hour by 1.9 percentage points. Since the unconditional probability of observing a pledge is around 5.5 percent, the magnitude of this effect is considerable.

The fourth prediction is that the final success of a campaign is closely correlated with the support it gets at the very early stage of fundraising. This fact has already been documented in the literature (Colombo et al., 2015; Kuppuswamy and Bayus, 2015; Vulkan et al., 2016) and is confirmed in our data. Our model explains the economics behind this result. The absence of pledges at the start of a campaign is indicative that the project is of bad quality. As the public belief about the quality of the project becomes more pessimistic, private signals of arriving investors have to be larger in order to induce another pledge. Absence of pledges reinforces the negative dynamics and leads to the possibility of an abstention information cascade occurring from the outset, so some campaigns fail to get any traction.

All these results are inconsistent with AM1. We reject AM2 because results in the IV specification reject that the remaining correlation between adjacent pledges is caused by a common unobservable shock. That the most recent pledge affects the amount and timing of the subsequent pledge even after controlling for the sum of pledges is inconsistent with AM3. Overall our findings indicate that backers' behaviour are consistent with rational herding and less so with naïve herding. Information cascades due to pledge herding do not occur, whereas long enough periods without pledges can trigger information cascades and lead to the failure of a campaign. Finally, we cannot reject that there may be additional naïve herding, since in some (but not all) specifications, there is a remaining effect of the sum of pledges.

## 1.1 Related literature

Our paper is most closely related to Zhang and Liu (2012) and Bursztyn et al. (2014). Zhang and Liu (2012) study pledges made on a peer-to-peer lending web site, while Bursztyn et al. (2014) examine investor behaviour in a randomized control experiment working closely with a large financial brokerage in Brazil. Zhang and Liu (2012) 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 'listing' attributes, while controlling for listing fixed effects and observable listing attributes. Rational herding is said by the authors to exist if the coefficient for the interaction between the cumulative amount and the listing attributes is significant and takes the opposite sign of the listing attribute's main effect. The argument made is that for poor (good) listing attributes, such as a low (high) credit rating, the incremental increase in 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.

Bursztyn et al. (2014) 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 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.

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). The objective of our model is to guide the empirical analysis of a very rich dataset that details backers identities together with the exact timing and amount of their pledges. Because of their assumptions on the pledgeable amounts and/or backers arrival times none of these herding models is fit to guide the detection of herding in our dataset. In all these models, traded quantities are discrete and both buy-herding and sell-herding can occur and lead to information cascades.[6] In the equity crowdfunding we consider, tradable quantities are continuous, and this make pledge information cascades impossible, but not abstention information cascades. Whereas in most of prior literature time is discrete and a new agent arrives in each period, the number and arrival time of backers to an actual crowdfunding platform is not deterministic and not observable by other backers. To gather this feature, we assume that time is continuous, agents arrivals follows a Poisson process and the public observe only the agents that actually decide to invest. Under this perspective the closest paper to our work is Hörner and Herrera (2013) and like them, we predict that periods without pledges makes backers more pessimistic. However, whereas in Hörner and Herrera (2013) agents are

[6] Avery and Zemsky (1998) and Park and Sabourian (2011) showed that the presence of prices may prevent herding and/or information cascades. However information cascades necessarily occur whever price maker and price takers differ in risk aversion (Decamps and Lovo (2006)).

risk neutral and can only choose between investing 1 dollar and not investing, in equity crowdfunding each backer chooses how much to invest and there is dispersion in pledge sizes. In a recent paper Cong and Xiao (2017) make the link between herding and crowdfunding by analyzing the sequential arrival of partially informed backers who have to choose whether to pledge a fixed amount or not to pledge. They show that the presence of the all-or-nothing funding clause does not eliminate pledging cascades but substantially decreases abstention cascades. Quite the opposite, we find that information cascades can only result from abstention herding.

Our paper also contributes to another 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. Chen et al. (2016) consider a model with common value where the entrepreneur learns about the value of her project from the crowdfunding outcome. In all these papers backers move simultaneously so they do not influence each others' investment decisions. In our paper backers arrive following a Poisson process 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) and experimental data (Duflo and Saez, 2003; 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 2 we present the theoretical model and derive its empirical implications. Section 3 provides a description of the data used in the analysis. In Section 4 we test if observed data are in line with theoretical predictions. Finally, Section 5 concludes.

## 2 A Model of Rational Herding in Equity Crowdfunding

**Firm:** A firm seeks financing from investors (henceforth backers) to implement a risky project. The project's quality can be 'good' or 'bad'. Each dollar invested in the project generates $\rho$ dollars, where $\rho = \alpha > 1$ for a good project, whereas $\rho = 0$ for a bad project. We denote with $\pi_0$ the ex-ante probability that the project is good.

**Investors:** Backers are risk averse with log utility function. Each backer $i$ receives a private signal, $\theta_i \in \{g, b, u\}$. We assume that signals are conditionally i.i.d. across informed backers and satisfy

$$\begin{aligned}
\mathbb{P}[\theta_i = g | \text{ good project}] &= \mathbb{P}[\theta_i = b | \text{ bad project}] = \lambda q, \\
\mathbb{P}[\theta_i = b | \text{ good project}] &= \mathbb{P}[\theta_i = g | \text{ bad project}] = \lambda(1-q), \qquad (2.1) \\
\mathbb{P}[\theta_i = u | \text{ good project}] &= \mathbb{P}[\theta_i = u | \text{ bad project}] = 1-\lambda \qquad (2.2)
\end{aligned}$$

where $q \in (1/2, 1)$. Thus, there are two populations of backers: uninformed backers, who receive signal $u$, and informed backers who receive partially positive information $g$ or a partially negative information $b$ about the quality of the project.[7] As a starting point, we assume all backers have the same initial wealth $W$ and informed backer's signals are binary. We extend the model in Subsection 2.3 to show that qualitatively the predictions do not change if backers' initial wealth are independently distributed or if we allow for multiple signals.

The firm tries to raise funds from backers using a crowdfunding platform. Time is continuous. The crowdfunding campaign starts at $t = 0$ and closes at $t = T$, finite. At $t = 0$ a target fundraising amount $Y$ is announced. If at $t = T$ the total amount of funds committed is at least $Y$, the campaign is successful and committed funds are invested. If not, the campaign fails and backers are returned their funds. Backers arrive at the platform following an exogenous Poisson process with intensity 1. A fraction $\lambda$ of backers are informed whereas the remaining $1 - \lambda$ are uninformed. We assume that a backer can only pledge at the time she arrives to the platform and that pledges cannot be withdrawn.

Let $y_t$ be the total net amount of funds committed by time $t$. We will say that a campaign is in the *underfunding phase* as long as $t < T$ and $y_t < Y$. The campaign enters the *overfunding phase* if $y_t > Y$. Note that, if the overfunding phase does not start before $T$, the campaign fails.

**Histories and strategies:** Pledges are public so that a backer arriving at time $t$ observes all past strictly positive pledges. Importantly, they do not observe backers who visited the platform but chose not to make a pledge. Denote with $h_t$ the history of pledges before time $t$, and with $\mathcal{H}$ the set of all possible histories. A (pure) strategy $\sigma$ for a backer is a mapping from her type and public history into a non-negative pledge, i.e., $\sigma : \{g, b, u\} \times \mathcal{H} \to \mathbb{R}^+$.

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

**Beliefs and success probabilities:** The public belief that the project is good, given $h_t$, is denoted $\pi_t := \mathbb{P}(\rho = \alpha | h_t)$. We denote with $\pi_t^\theta$ the belief of a type $\theta$ backer at time $t$. From Bayes' rule and the assumption of the distribution of private signals, we have:

$$0 \leq \pi_t^b \leq \pi_t = \pi_t^u \leq \pi_t^g, \tag{2.3}$$

where the inequalities are strict for $\pi_t \in (0, 1)$.[8] We denote by $\pi_t(x)$ the time $t$ public belief that results from the observation of a pledge $x_t = x > 0$ at $t$. Given any history $h_t \in \mathcal{H}$, any $\rho \in \{0, \alpha\}$, and any additional pledge $x$ at time $t$, let

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

denote the probability that the campaign succeeds given $h_t$, $x_t = x$, and the project's quality $\rho$. The way $h_t$ affects $\pi_t$ depends on the strategy used by backers until $t$, whereas $S_\rho(x, h_t)$ also depends on the strategies of both the current and future backers.

**Objective function and equilibrium conditions:** We can express the expected payoff for a type $\theta$ backer arriving at time $t$ with wealth $W$ and pledging $x$ as

$$\pi_t^\theta S_\alpha(x, h_t)(\ln(W + (\alpha - 1)x) - \ln(W)) \quad + \quad (1 - \pi_t^\theta) S_0(x, h_t)(\ln(W - x) - \ln(W)). \tag{2.4}$$

An equilibrium strategy profile is $\hat{\sigma}$ such that for any backer $i$, of any type $\theta$ and wealth $W$, after every history $h_t$, she chooses the $x$ that maximizes (2.4), where $\pi_t^\theta$, $S_\alpha(.)$ and $S_0(.)$ are computed taking into account other backers' equilibrium strategies.

**Herding and information cascades:** We define herding and information cascades similarly to Avery and Zemsky (1998). A backer engages in *pledge herding* if she would have pledged 0 at time 0, but if she arrives after enough other backers have made pledges, she pledges a strictly positive amount. On the contrary, a backer engages in *abstention herding* if she would have pledged a strictly positive amount at time 0, but if she arrives after a long enough period without pledges, she does not pledge. We will

[8] Considering that $\mathbb{P}(\rho = \alpha | s; h_t) = \frac{\mathbb{P}(s|\rho=\alpha) \times \mathbb{P}(\rho=\alpha|h_t)}{\mathbb{P}(s|\rho=\alpha) \times \mathbb{P}(\rho=\alpha|h_t) + \mathbb{P}(s|\rho=0) \times \mathbb{P}(\rho=0|h_t)}$, one has that 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 is $g$, $b$, or $u$, respectively.

say that the economy enters an *information cascade* after history $h_t$ if (on the equilibrium path) for all $t' > t$ one has $\pi_{t'} = \pi_t$, i.e., the additional history provides no information about the project's quality. That is, whereas herding can be transitory, once an information cascade starts it never ends.

## 2.1 Equilibrium Pledging Behaviour

Expression (2.4) shows that a backer's optimal pledge depends on, first, her belief $\pi_t^\theta$ that is a function of $\pi_t$, which in turn depends on the past history of pledges and on the strategies used by past backers. Second, it also depends on the conditional probabilities $S_\alpha(x, h_t)$ and $S_0(x, h_t)$ that the campaign succeeds. This second element is absent during the overfunding phase because $y_t \geq Y$ implies $S_\alpha(x, h_t) = S_0(x, h_t) = 1$. As a result, equilibrium in the overfunding phase is unique and a backer's pledge only depends on her belief $\pi_t^\theta$. In order to describe this equilibrium let us first define for any given backer type $\theta$ the threshold $\underline{\pi}^\theta$ as the level of public belief $\pi_t$ such that $\pi_t^\theta = \alpha^{-1}$. Namely, $\underline{\pi}^g := \frac{1-q}{1-q(2-\alpha)}$, $\underline{\pi}^u := \alpha^{-1}$ and $\underline{\pi}^b := \frac{q}{\alpha-1-q(2-\alpha)}$. Note that $0 < \underline{\pi}^g < \underline{\pi}^u < \underline{\pi}^b$. The following proposition describes the equilibrium of the overfunding phase.

**Proposition 2.1.** *As soon as $y_T \geq Y$, the crowdfunding campaign has a unique equilibrium.*

1. *Pledges: A type $\theta$ backers arriving at time $t$ pledges*

$$\hat{\sigma}(\theta, \pi_t) = \begin{cases} 0, & \text{if } \pi_t \leq \underline{\pi}^\theta \\ \frac{\alpha\pi_t^\theta - 1}{\alpha - 1} W > 0, & \text{if } \pi_t > \underline{\pi}^\theta. \end{cases} \tag{2.5}$$

2. *Evolution of the public belief:*

   (a) *If at time $t$ a pledge of size $\hat{\sigma}(\theta, \pi_t) > 0$ is observed, the public belief $\pi_t$ jumps to $\pi_t^\theta$.*

   (b) *If between $t$ and $t' > t$ no pledge is observed then at time $t'$ the public belief is*

$$\pi_{t'} = \begin{cases} \pi_t, & \text{if } \pi_t \leq \underline{\pi}^g \\ \max\left\{\frac{\pi_t}{\pi_t + (1-\pi_t)e^{\lambda(2q-1)(t'-t)}}, \underline{\pi}^g\right\} < \pi_t, & \text{if } \underline{\pi}_g < \pi_t < \underline{\pi}_b \\ \pi_t, & \text{if } \pi_t \geq \underline{\pi}^b \end{cases} \tag{2.6}$$

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

The proof of the proposition is in Appendix 6.2.1. The proposition says that backers' pledges are increasing in their belief and their wealth (1.). That is, the decision on whether to invest or not depends on the type of the backer and the level of the public belief. A type $\theta$ backer arriving at $t$ pledges only if the public belief $\pi_t$ is above the type specific threshold $\underline{\pi}^{\theta}$. This threshold is lowest (highest) for a positively (resp. negatively) informed backer.[9] Second, conditionally on pledging, the size of the pledge is strictly increasing in $\pi_t^{\theta}$. Thus, a positively informed backers pledges more than an uninformed backer that in turn pledges more than a negatively informed backer, and for all backers the pledge size increases with the public belief $\pi_t$. Third, the size of the pledge increases with the backer's wealth $W$. To summarize, an increase in the public belief $\pi_t$ increases the probability of observing a pledge and its size, that in turn increases with the backer wealth.

This pledging behaviour has an effect on the evolution of the public belief. First, once a pledge is observed, the public can deduce from its size whether it comes from an uninformed backer, a positively informed backer or negatively informed backer (2.a).[10] Thus the pledge size provides public information about the project's quality. Second, absence of pledges provides valuable information as long as the public belief is not extreme (2.b). As long as the public belief is such that $\underline{\pi}^g < \pi_t \leq \underline{\pi}^b$ an informed backer invests only if he has a positive signal. Because negatively informed backers are more common when the project is bad, a period of absence of pledges is more likely if the project is bad than if the project is good. Hence, as long as $\pi_t$ is not extreme, a period of absence of pledges makes backers more pessimistic the longer this period lasts. Things are different when the public belief is extreme. For $\pi_t > \underline{\pi}^b$, in equilibrium all type of backers invest. Hence a period of absence of pledge is only due to the fact that no backer arrived. As this event is not correlated with the project's quality, it does not affect the public belief. For $\pi_t < \underline{\pi}^g$, in equilibrium no backer invests, no information about backers type can be deduce and hence the public belief does not change. Whereas for $\pi_t > \underline{\pi}^b$ the public belief will evolve as soon as a backer arrives and pledges, for $\pi_t \leq \underline{\pi}^g$ backers stop pledging and hence no additional information about the project's comes through the campaign. When this happens we obtain what we call an *abstention information cascade* (3.).

Consider now the underfunding phase. Before the campaign succeeds, a backer has to take into account how her pledge will affect future backers' pledges and, through this, the probabilities of success $S_\alpha(x, h_t)$ and $S_0(x, h_t)$. This implies that the underfunding phase has multiple equilibria.[11] Here we are

[9] This is the same mechanism relating signals and public belief investment threshold in Hörner and Herrera (2013).

[10] Perfect inference comes from the assumption that all backer have the same wealth. This assumption is relaxed in Section 2.3

[11] 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.

interested in equilibria that satisfy a rather compelling regularity condition, that is, by increasing her pledge a backer cannot make the campaign strictly less likely to succeed. Formally:

**Definition 2.2.** *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 $S_\rho(x, h_t) \leq S_\rho(x', h_t)$.*

Finding a closed form solution for a regular equilibrium during the underfunding phase is both difficult and not particularly useful, because one would have to arbitrary pick one across many possible equilibria. The following proposition shows that all regular equilibria of the underfunding phase shares the same qualitative properties of the unique equilibrium of the overfunding phase.[12]

**Proposition 2.3.** *Let $\hat{\sigma}$ be a regular equilibrium of the crowdfunding campaign and let $h_t$ be such that $\mathbb{P}(y_T \geq Y | h_t) > 0$. Then,*

1. *Pledges are (weakly) increasing in $\pi_t$, furthermore*

$$\hat{\sigma}(b, h_t) \leq \hat{\sigma}(u, h_t) \leq \hat{\sigma}(g, h_t).$$

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

   (a) *The change in the public public belief resulting from a pledge is non-decreasing in the pledge size. In particular, if $\hat{\sigma}(b, h_t) \neq \hat{\sigma}(u, h_t) \neq \hat{\sigma}(g, h_t)$, then if at time $t$ a pledge of size $\hat{\sigma}(\theta, \pi_t) > 0$ is observed, the public belief $\pi_t$ jumps to $\pi_t^\theta$.*

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

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.*

The proof of the proposition is in Appendix 6.2.2

## 2.2 Herding and Cascades

What do Propositions 2.1 and 2.3 tell us about the possibility of herding and cascades? First consider how the absence of pledges affects future backers behaviors. Results (2.b) of Propositions 2.1 and 2.3 imply that, for any given $\pi_t$ such that type $b$ backers do not pledge, there is a time interval $\tau$ long enough such that if between $t$ and $t + \tau$ no pledge is observed, then $\pi_{t+\tau} = \underline{\pi}$. Thus, from results (1) we can

[12] The equilibrium of the overfunding phase is trivally regular because $S_\rho(x, h_t) = S_\rho(x', h_t) = 1$, for all $x$, $x'$.

conclude that a long enough period without pledges can induce a backer to engage in abstention herding. The time without pledges required to induce abstention herding for a type $u$ backer is shorter than the one required to induce a type $g$ backer to engage in abstention herding. However, if enough time passes without a pledge, both types will engage in abstention herding and an abstention information cascade occurs. Hence we have:

**Corollary 2.4.** *In a regular equilibrium, if* $\pi_0$ *is such that at time* 0 *type* $b$ *backers would not pledge, then :*

1. *A long enough but finite period without pledges will induce backers to abstain from pledging.*

2. *Uninformed backers engage in abstention herding earlier than positively informed backers.*

3. *An information cascade occurs as soon as positively informed backers engage in abstention herding.*

Consider now the effect of a current pledge on future backer's behavior. As opposed to abstention herding, pledge herding can only affect uninformed backers and never generates an information cascade. If at $t = 0$ an informed backer does not invest, an uninformed backer would not invest either, and an abstention information cascade would start. Hence, consider the case where at time 0 a positively informed backer, but not an uninformed backer would pledge. Then, initially only pledges from informed backers will be made and the public belief $\pi_t$ increases for each pledge. As soon as $\pi_t$ is large enough, an uninformed backer will start pledging, and for $\pi_t$ even larger also negatively informed backer will pledge. Thus, pledge herding can occur. Note, however, that pledge herding cannot generate an information cascade. This is due to two reasons: first, the size of the pledge indicates whether the backer is informed or not; second, when beliefs are such that informed backer pledge only if they have a positive signal, in the time between two pledges the public belief decreases. Hence we have:

**Corollary 2.5.** *In a regular equilibrium, if* $\pi_0$ *is such that at time* 0 *only type* $g$ *backers would pledge, then*

1. *After enough pledges from type* $g$ *backers , the other type backers engages in pledge herding.*

2. *The amount of pledge from type* $g$ *backers necessary to induce pledge herding is larger for type* $b$ *backer than for type* $u$ *backers.*

3. *Pledge herding cannot generate an information cascade.*

## 2.3 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 wealth 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 $\pi_t$ such that $\pi_t^\theta = \alpha^{-1}$. It is easy to verify that $\underline{\pi}^\theta$ is strictly positive and decreasing in $\theta$.

Then we have:

**Proposition 2.6.** *During the overfunding phase:*

1. *Pledges: A type $\theta$ backers arriving at time $t$ pledges*

$$\hat{\sigma}(\theta, \pi_t) = \begin{cases} 0, & \text{if } \pi_t \leq \underline{\pi}^\theta \\ \frac{\alpha\pi_t^\theta - 1}{\alpha - 1} W > 0, & \text{if } \pi_t > \underline{\pi}^\theta. \end{cases} \tag{2.7}$$

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 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.*

The proof of the proposition is in Appendix 6.2.3.

## 2.4 Empirical Predictions

In this section we discuss the main testable implications of the theory just laid out. These regard, first, how a pledge varies as a function of the size and timing of the most recent pledge, and how these reactions differ for informed and uninformed backers. Second, that a backer will also take into account the sizes of pledges preceding the most recent pledge if the signal from the most recent pledge is noisy. Third, the model provides empirical predictions about how the probability of success of the campaign depends on the history of pledges. We will contrast these predictions to those provided by three alternative models: First, a model where backers are similar to the ones in our model but where each backer bases her pledge solely on her own private information. Second, a model where backers do not have any private information, but where their pledges are determined by the arrival of an exogenous flow of public information non-observable by the econometrician. Third, a model where backers behave like lemmings, placing higher pledges the larger the current cumulative pledge, $y_t$, irrespective of past pledges' order or arrival time. We will call these alternative models AM1, AM2 and AM3, respectively.

The first two sub-predictions of the model concern how the time and size of the most recent pledge affect a pledge. From Propositions 2.3 and 2.6, we have:

**Prediction 1:** *A pledge size should be (i) increasing in the size of the most recent pledge; and (ii) decreasing in the time elapsed since the most recent pledge.*

We further derive a sub-prediction based on our analysis of the impact of investor wealth. If the most recent pledge is not noisy then it provides all information necessary for the subsequent backer to make a pledge. From Section 2.3 we have that if investors' wealth are heterogeneous and unobserved, the signal by the most recent pledge is noisy. The backer would then also take into account signals generated by earlier pledges, but would weight the information of the most recent pledge greatest.

**Prediction 1:** *(iii) After controlling for the time elapsed since the most recent pledge, and if signals are noisy, the backer should condition her pledge on a number of preceding pledges, where nevertheless the most recent pledge should have the highest weight.*

Past pledges affect a future pledge depending on backer type. More specifically, the belief of an uninformed backer is more sensitive to the information provided by prior pledges. Hence we have:

**Prediction 2:** *Uninformed backers react more to prior pledges than informed backers.*

The probability of observing a pledge at any given point in time directly depends on the current public belief. For example, if the public belief is declining because pledges are absent or of a low value, the private signals have to be larger in order to induce a positive investment. But the arrival distribution of all types of backer to a campaign is fixed, so as the public belief falls the probability of observing any activity in the campaign also falls.

**Prediction 3:** *The probability of observing a new pledge is (i) increasing in the amounts of preceding pledges, and (ii) decreasing in the time elapsed since the most recent pledge.*

We can contrast these predictions with those of the alternate models. In AM1 each backer bases her pledge solely on her private signal, and signals are conditionally i.i.d. If this is the case, the size of the most recent pledge and the time elapsed since the most recent pledge should have no effect on the current pledge size nor on the probability of observing a new pledge. In AM2, pledges result from the exogenous arrival of public information. Pledges should cluster around periods in which the positive information arrives and their size should be increasing in the cumulative amount funded up to that point in time. In AM3, conditional on the total amount invested, pledge size and arrival probability should neither depend on the size of the most recent pledge nor the time since the most recent pledge.

The next prediction concerns the probability of success of a campaign. In the model, the absence of pledges is indicative that investors are not arriving with good private signals. If pledges don't arrive, the public belief about the project's quality will decline, and the chance of being successful in raising the target funds falls. Since the quality of a project is unchanged during the campaign, the model predicts that bad projects will have poor campaign development from the outset.

**Prediction 4:** *The probability of success of a campaign is highly dependent on early campaign dynamics: increasing with the number of backers and the amounts invested during the first days of a campaign.*

The same prediction is provided by AM3. However, neither in AM1 nor AM2 will the absence of pledges in the early stage of the campaign play a crucial role.

# 3 Data, Variables, and Some Descriptives

The data used for the analysis 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.[13] A campaign has 60 days to raise funds on the platform. If it does not reach its target all pledges are null and void. Entrepreneurs may accept pledges beyond the campaign target. All shares in a campaign are priced equally.

For each project, we have information about the date the campaign started raising funds, 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 we can analyse the behaviour of both individual campaigns and individual backers. Variable definitions are displayed in Table 1.

Descriptive statistics at the campaign level are provided in Table 2.[14] Out of the 710 campaigns, 243 (34.2%) were successful in raising the declared investment goal. The average campaign goal was £174,216, 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 valuations of the campaigns in Seedrs present a sharp contrast with other non-equity crowd-funding schemes. For example, Mollick (2014), in a study of more than 48,500 projects raising funds in Kickstarter, shows that the average goal is less than $10,000, much lower than what is observed in our sample.

Investors have to sign-up to the platform and create a profile to make a pledge. The profiles vary in their information content, but they include their geographic location, the history of pledges in other campaigns, and, on some occasions, social media contacts or short biographic descriptions. About half of the backers making a pledge to a project choose not to allow their profiles to be seen by others. Investors also have to self-select into one of three groups: 'authorized', 'sophisticated' or 'high-net-worth' (see Table 1 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, but

[13] 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 cancel 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 cancelled. Although we do not have information on the time at which an investment was cancelled, the data management department at Seedrs communicated that the majority of cancellations happen within minutes of a pledge being made. All estimations shown in the paper have been replicated to include the cancelled pledges and the results remain qualitatively unchanged.

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

those investors represent on average 73 percent of the pledges made to a campaign.

The average size of 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, 21 percent of the total amount at the end of the first day, and this number increases to 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.

# 4 Empirical Tests of the Theoretical Model

## 4.1 Econometric Specification

In this section we test the empirical predictions of the 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.

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 prediction of the model states 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 1 shows suggestive evidence to support this prediction. To construct the figure we first organize all pledges 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, 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 the model, the positive correlation between pledges decreases as new information arrives and the public belief evolves. Figure 2 shows supporting evidence for this prediction. The figure is constructed in a similar way as Panel (a) of Figure 1, 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, 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 a linear regression 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 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:

$$\log I_{n,c} = \beta_0 + \sum_{k=1}^{5} \beta_k \log I_{n-k,c} + \beta_6 \log T_{(n,n-1),c} + \alpha W_{n,c} + \gamma Z_{n,c} + \eta_c + \epsilon_{n,c}, \tag{4.1}$$

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, $T_{(n,n-1),c}$.

The econometric model includes a set of controls to capture differences in the characteristics of backers and campaign history. The purpose of the controls is to account for the theoretical prediction that an agent's optimal strategy depends on her wealth, her private information, and the past history of pledges to the campaign. 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. $Z_{n,c}$ is a vector of campaign and time-varying variables including the natural logarithm of the total amount funded in the campaign up that point; the square of the natural logarithm of the total amount funded in the campaign; the total number of pledges in the campaign up to that point; the number of days since the start of the campaign; the Seedrs' campaign's hotness index at the beginning of the day; and a dummy taking the value one if the Seedrs' campaign's hotness index rose during the day, else zero. The hotness index is created by Seedrs to decide the order in which campaigns are presented on its landing page (see Table 1 for further details); campaigns with a higher hotness index are in general more salient. Finally, $\eta_c$ is a campaign fixed effect capturing all the time-invariant observed and unobserved campaign characteristics, and $\epsilon_{n,c}$ is the error term.

The main source of potential bias in our empirical model is the possibility that the size of adjacent pledges is driven by common factors. 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. 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. From the point of view of the theoretical model, the problem would arise if the arrival of agents was endogenous and partly driven by correlated signals.

Our identification strategy uses an instrumental variable (IV) approach. For IV to work in our context, we need a variable that is correlated with the size of a pledge, but uncorrelated with the stream of public information about the campaign and its investors. We use two sets of instruments. 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 then be used by recurrent investors for pledges in future campaigns, where the extra disposable income can be thought of as being partly unexpected. We create a variable that is defined as the inverse hyperbolic sine transformation (IHST)[15] of the total amount returned to a backer in the last failed campaign in which she invested, conditional on that campaign failing before the new pledge was made. Since the instrument is pre-determined at the start of the campaign, whatever strategy a backer might be playing as function of observing the arrival (or non-arrival) of other pledges in the campaign is purged from analysis.

We find that only 6.5 percent of pledges can be affected by disposable income coming from returned money after the failure of a campaign. Hence, we construct a set of alternative instruments to validate the 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 public or remain anonymous. For backers that choose to be public -on average, 50 percent- anyone can see their profile; for those that choose to be anonymous, only the amount pledged is displayed. Although the past investment history of anonymous profiles is not

[15]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, we have access to it in our dataset. We use this information to construct variables that contain relevant information to predict the size of a pledge which is not observed by follow-on backers.

We use two pieces of information as instruments for each investment lag ($\log I_{n-k,c}$): (1) the total number of pledges made by the investor $(n-k)$ in all previous campaigns 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.

For the length in time between subsequent pledges, $T_{(n,n-1),c}$, we use an instrument based on the hour of the day in which a pledge is made. The data shows that the occurrence of pledges tends to be 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. We create a variable defined as the (log) absolute value of the difference in hours between the hour of the day in which a pledge was made and 11 a.m. If a pledge is made very early or late in the day, the time for a new backer to arrive is potentially longer. 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. 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.

Finally, to complement the IV strategy, we include in the empirical model four additional controls that capture changes in the flow of information about a campaign: 1) the Google Trends index of daily online search volume for every campaign while it was live; 2) the FTSE 100 daily index of the London Stock Exchange; 3) the Seedrs hotness index for the beginning of the day; and 4) an indicator dummy that takes the value of one if the Seedrs hotness index increased during the day, and zero otherwise. Each of these variables will directly capture relevant information shocks to a campaign that could be a source of bias to our estimates.

## 4.2 Main Results

The main results are shown in Table 3. The table presents the estimates of Equation 4.1 for three specifications: in the first column we show the OLS estimates without the inclusion of the additional controls; in the second column we show the OLS adding the controls; the last column shows 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 first that the endogenous variables move very little as we include a range of control variables for the arrival of daily information about the campaign and the economy. Several of the control variables in this specification are however important predictors of pledge amounts, including the cumulative amount funded and its square, the Seedrs hotness index and its intraday rise and the Google Trend index for the campaign. The results of all the first stages of the 2SLS regressions, corresponding to the different endogenous variables, are shown in Table 4.

We find that backers who immediately follow pledges of a larger value invest, on average, higher amounts in the campaigns, supporting Prediction 1 (i). Moreover, we find that this relation is stronger the 'closer' the pledges are to each other. For example, in our preferred 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. 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 9.6 percent for a similar change. For higher order lags we don't find any statistically significant effect in the IV specification. We therefore also find support for Prediction 1 (iii).

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 1 (ii). In our IV specification, doubling (100% increase) the time since the last pledge is associated with a fall in the pledge size of 7.7 percent. 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 Prediction 1.

The results from the alternative set of instrumental variables is shown in Table 5. Given that we have two instruments for each investment lag, we also report Hansen's overidentification test for instrument validity. Instruments are found to be both statistically relevant and valid. The results of all the first stages of the 2SLS regressions, corresponding to the different endogenous variables, are shown in Table 6. The specification with the alternative set of instrumental variables provide a message very similar to our preferred specification, both qualitatively and quantitatively.

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 the alternative IV's, since they provide a much larger source of variation. Table 7 shows the results of estimating Equation 4.1 separately for five different potential types of backer: (i) high-net-worth, (ii) sophisticated, (iii) authorized, (iv) recurrent, and (v) single-campaign backer.[16] Prediction 2 states that since uninformed backers have no private information, their pledges follow more closely the evolution of the 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.

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 stronger for authorized (13.5% after a doubling of the most recent pledge) and single-campaign backers (21.2% after a doubling of the most recent pledge), than for high-net-worth (12.6%), sophisticated (-2.8% but not statistically significant), and recurrent backers (8.9%). This evidence is consistent with Prediction 2.

Prediction 3 (i) and (ii) follow from the result that agents invest a positive amount only if their belief that the project is good is above a given threshold. The size of past pledges, and periods of time without positive pledges, affect this belief. Through that channel, they influence the probability of observing any activity in a campaign at any point in time. In order to test these predictions 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. 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. 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

$$DI_{t,c} = \beta_0 + \sum\nolimits_{k=1}^{5} \beta_k \text{IHST}(I_{t-k,c}) + \gamma Z_{t-1,c} + \eta_c + \nu_h + \epsilon_{t,c}, \tag{4.2}$$

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

$$DI_{t,c} = \beta_0 + \beta_1 \log H_{t,c} + \gamma Z_{t-1,c} + \eta_c + \nu_h + \epsilon_{t,c}, \tag{4.3}$$

where we are interested in the estimates of the beta coefficients associated to the amounts invested over the preceding hours (Equation 4.2), and the time since the most recent activity in an hourly bin (Equation 4.3). Given the large number of observations for which the amount invested in the time period is zero, the amount pledged is transformed using the IHST transformation. From the 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 includes a vector of controls, $Z_{t-1,c}$, which includes the same variables as in Equation 4.1. Finally, $\eta_c$ is a campaign fixed effect capturing all the time-invariant observed and unobserved campaign characteristics, $\nu_h$ is an hour-of-the-day fixed effect, and $\epsilon_{t,c}$ is the error term.

Results are shown in Tables 8 and 9. The tables present the estimates of Equations 4.2 and 4.3 respectively for four specifications: excluding and including the controls, and separating the first two weeks and later weeks of the campaigns. The first two specifications are performed to also test alternative models, while the latter two specifications are performed to examine robustness. We will discuss test results of alternative models and robustness analysis in more detail in subsequent sections.

The results support Prediction 3 (i) that the probability of observing a pledge in a campaign at any point in time is positively correlated with the size of previous pledges. In particular, we estimate that the likelihood of observing a pledge at any given hour increases by 1.8 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 pledges was made. The results also show that this prediction holds for both the first two weeks and later stages of the campaign, but the estimated coefficients are of a larger magnitude during the first two weeks of the campaign.

The results also support Prediction 3 (ii). If the number of hours since the campaign saw any activity doubles, the probability of observing a pledge declines between 1.4 and 3.3 percentage points. This can also be seen clearly in Figure 3. 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 possitive pledges and the likelihood of observing a pledge.

Prediction 4 follows from the fact that the absence of pledges to a campaign is indicative that backers are not arriving with good private signals. Since the quality of a project is unchanged during the campaign, the model predicts that bad projects will have a poor campaign performance from the outset.

Figure 4 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. 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 stages 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 they never able to rebound at a later time.

We now formalize the graphical evidence in a regression framework. Table 10 reports the average marginal effect of a change in a set of measures of early campaign support on the probability that a campaign is ultimately successful. In particular, we are interested in how the probability of being successful changes with the number of backers and the total cumulative investment in the first week of a campaign. The table reports three specifications: one without any additional controls; one controlling for predetermined characteristics of the campaign (pre-money valuation, desired investment, number of entrepreneurs, and access to tax incentives for investors); and one controlling for both predetermined characteristics of the campaigns and other variables describing campaign dynamics while it was active (share of recurrent, authorized and high-net-worth investors, total number of pledges, average amount pledged, and maximum amount invested by a single backer). The econometric model corresponds to a probit model, and standardized effects[17] are reported at the bottom of the table.

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 percentage of the desired investment covered during the first week 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, and the effect of the number of backers is null or even negative in some specifications.

[17] 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.

This result is suggestive that the quantity of pledges early on is not sufficient to improve the chances of success, but that the 'quality' of those initial pledges matters.

The fact that we can only use campaign-level variation to explore the determinants of the probability of 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 10 with caution, and simply state that it is consistent with predictions of the theoretical model.

### 4.3 Robustness Analysis

As in most crowdfunding platforms, Seedrs recommends campaign promotors run their campaign in two phases. The first being a 'private' phase, and the second a 'public' phase. In the private phase the entrepreneur is given a private *url* for the campaign which they can share privately with anyone. Entrepreneurs are urged to increase the chances that the public campaign will succeed by showing enough traction with private investments, using various methods for raising funds in the private phase from "the business' personal network of customers, followers, fans, friends and family."[18] Some common approaches used by entrepreneurs are to have a local launch party, and private meetings with select potential investors. The private phase lasts between one-to-two weeks. It is not immediately clear what effects the private phase would have on our estimates of herding. It could be that potential backers more easily get to know each other and therefore coordinate their investments offline during the private phase. It could also be that informed backers who choose to be anonymous when listed on the campaign's website on Seedrs are more likely to become known to other backers during the private phase. Finally, it could be that in the early stages of a campaign there is less public information, and pledges from informed backers matter even more. All three mechanisms would suggest that the coefficients for inter-temporal correlation from the private phase may be larger. This type of social influence would be just part and parcel of the mechanisms suggested by Banerjee (1992) and others, and identified by, for example, Bursztyn et al. (2014) as driving herding in financial decision-making.

It is, however, simple for us to separately estimate coefficients for the private and public phases of the campaigns. We do this by separating data for the first two weeks and for the rest of the campaign days. Results are provided in Table 11 which details effects of the sequence of arriving backers. As the table shows, the results are not remarkably different for the two phases of the campaign. The magnitudes of coefficients are larger for the private phase, but not significantly so. Recall that Table 8,

[18] See for example `https://www.Seedrs.com/learn/help/what-is-private-launch`.

which examined hourly data, also contained separate estimates for the first two weeks and later weeks in the campaign. Let us focus on the results for the probability that a pledge occurs within the next hour as displayed in Table 8. This table shows that the correlation between the amount pledged in the most recent hour and the probability of a new pledge occurring in the next hour is approximately 50 percent higher in the first two weeks of the campaign than in the later weeks of the campaign, and the coefficients are statistically significantly different from each other. The difference in the sizes of the coefficients across the two phases subsequently drops as one looks at the effects of pledges in the prior two hours, to become indistinguishable after the second hour. There is therefore some evidence that pledge herding is stronger in the private phase of campaigns, but that this moderating effect quickly becomes indistinguishable across the two phases as time passes.

In addition, our theory was precise to the overfunding phase, but there were potentially multiple equilibria for the underfunding phase. We can estimate whether, empirically, it makes any difference for the herding coefficients whether a campaign is in the underfunding phase or overfunding phase. We do so by separately analysing the data from campaigns in the overfunding and the underfunding phase. Results are reported in Table 12. As the table shows, the relevant coefficients are very similar in the two samples. The estimate of the coefficient capturing the effect of the time passed since the most recent pledge 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.

### 4.4 Tests of Alternative Models

There are three alternate models to test. In AM1 each backer bases her pledge solely on her private signal, backers' arrival times are i.i.d., and signals are conditionally i.i.d. If this is the case, past pledge size and time elapsed since the most recent pledge should have no effect on the current pledge size nor on the probability of observing a new pledge. In AM2, pledges result from the exogenous arrival of public information. Pledges should cluster around periods in which the positive information arrives and their size should be increasing in the cumulative amount invested up to that point in time. Also, pledges should be rare in periods in which negative information arrives. In AM3, backers naïvely follow the crowd and invest more the larger the total amount already invested in the campaign. Hence, conditional on the total amount invested, pledge size and arrival probability should neither depend on the size of the most recent pledge nor the time since the most recent pledge.

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. Further, AM1 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 AM1 because it is unable to explain what appears to be empirically relevant herding behaviour in the data.

AM2 predicts that pledges should cluster due to exogenously arriving information. Whereas 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, while the FTSE index is not) we explore the opportunity to eliminate such common effects through an IV setting. We use two alternative IV specifications where past pledges are predicted by information about the respective backer that is predetermined of the arrival of information and not known by subsequent backers. This detaches the estimated correlations between adjacent pledges of common public information and eliminates AM2 as the cause of our empirical results demonstrating that backers do take into account the information provided by past pledges.

Further, AM2 and AM3 both have predictions regarding the impact of the cumulative amount funded on subsequent pledges. In all tables we therefore include a control for the cumulative amount funded (and its square). We still find that Predictions 1 through 3 of our theory are supported and not much affected by the inclusion of the cumulative amount funded. It also turns out that contrary to much of past work, the coefficients for the cumulative amount funded are not robust to alternative specifications. Specifically, in Table 5 the coefficient for cumulative amount funded (log amount funded) is large and significant, but in Table 8 the coefficient for cumulative amount funded is not significant. These results are not particularly supportive of AM2 or AM3. At the most, one might argue that under some specifications (but not others) we cannot reject the possibility that AM2 or AM3 can explain some alternative types of naïve herding behaviour.

# 5 Conclusions

In this paper we provide a detailed study using micro-level data of herding on a major equity crowdfunding platform. Equity crowdfunding is an important and fast-growing economic phenomenon. It has already had a significant impact on early-stage funding in the UK, and is likely to become an important avenue for entrepreneurial finance in the U.S. in years to come as regulation for its provision was recently introduced.

Herding is likely to be common in all types of crowdfunding. It is what we expect in a situation with so much uncertainty: the decisions of the crowd provide some information in the absence of much else. We developed a model which captures what we believe to be the main information asymmetries in these investment platforms. 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.

We show that the amount pledged by an investor to a campaign is affected by the sizes of prior pledges. This is because a large pledge signals to the public that the backer making the pledge potentially knows something about the project that others might 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 large pledge. We find that in IV regressions, a doubling of the size of a pledge is associated with a subsequent pledge that is between 8.9 percent and 21.2 percent larger. Proxies for investor type indicate that better informed investors react less to large pledge signals, as they should if they have private information.

The model also predicts that the time elapsed between pledges has a negative effect on the amounts pledged. This is because the absence of pledges is indicative that investors are not arriving to the campaign with sufficiently good private signals. In IV regressions, we find that a doubling of the time since the most recent pledge is associated with a subsequent pledge that is 7.7 percent 9.7 percent lower.

Consistent with other studies about campaign dynamics in crowdfunding, 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 also rationalises this observation by the effect low or absent pledges have on the 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 is likely to occur from the outset, and failed campaigns end up missing the mark by a large margin.

Equity crowdfunding is a new and important phenomena which is already having a large impact on early-stage financing. It is part of what is sometimes known as the democratisation of finance. Here members of the crowd make their investment decisions directly and without the help (and without paying commission) of professional intermediaries. The success of this movement depends largely on there being wisdom in the crowd. This paper provides a first step at understanding these important phenomena.

# References


Agrawal, A., Catalini, C. and Goldfarb, A. (2014). Some Simple Economics of Crowdfunding. *NBER Innovation Policy & the Economy* 14(1): pp. 63–97.

Ahlers, G. K., Cumming, D., Gnther, C. and Schweizer, D. (2015). Signaling in equity crowdfunding. *Entrepreneurship Theory and Practice* 39: 955–980, doi:10.1111/etap.12157.

Avery, C. and Zemsky, P. (1998). Multidimensional Uncertainty and Herd Behavior in Financial Markets. *American Economic Review* 88: 724–748.

Banerjee, A. (1992). A Simple Model of Herd Behavior. *The Quarterly Journal of Economics* 107: pp. 797–817.

Banerjee, A., Chandrasekhar, A. G., Duflo, E. and Jackson, M. O. (2012). The Diffusion of Microfinance. NBER Working Papers 17743, National Bureau of Economic Research, Inc.

Beauhurst (2016). The Deal. Review of Equity Investment Landscape. [Online Report] http://about.beauhurst.com/the-deal-h1-16.

Belleflamme, P., Lambert, T. and Schwienbacher, A. (2014). Crowdfunding: Tapping the Right Crowd. *Journal of Business Venturing* 29(14): pp. 585–609.

Beshears, J., Choi, J. J., Laibson, D., Madrian, B. C. and Milkman, K. L. (2015). The Effect of Providing Peer Information on Retirement Savings Decisions. *Journal of Finance* 70: 1161–1201.

Bikhchandani, S., Hirshleifer, D. and Welch, I. (1992). A Theory of Fads, Fashion, Custom, and Cultural Change as Informational Cascades. *Journal of Political Economy* 100(5): pp. 992–1026.

Brown, J. R., Ivkovic, Z., Smith, P. A. and Weisbenner, S. (2008). Neighbors Matter: Causal Community Effects and Stock Market Participation. *Journal of Finance* 63: 1509–1531.

Bursztyn, L., Ederer, F., Ferman, B. and Yuchtman, N. (2014). Understanding Mechanisms Underlying Peer Effects: Evidence From a Field Experiment on Financial Decisions. *Econometrica* 82: 1273–1301, doi:10.3982/ECTA11991.

Chemla, G. and Tinn, K. (2016). Learning through Crowdfunding. CEPR Discussion Papers 11363, C.E.P.R. Discussion Papers.

Chen, L., Huang, Z. and De, L. (2016). Pure and hybrid crowds in crowdfunding markets. *Financial Innovation* 2: 1–18.

Colombo, M. G., Franzoni, C. and Rossi-Lamastra, C. (2015). Internal Social Capital and the Attraction of Early Contributions in Crowdfunding. *Entrepreneurship Theory and Practice* 39: 75–100, doi:10.1111/etap.12118.

Cong, L. W. and Xiao, Y. (2017). Up-Cascaded Wisdom of the Crowd. Tech. rep.

Decamps, J.-P. and Lovo, S. (2006). A note on risk aversion and herd behavior in financial markets. *The Geneva Risk and Insurance Review* 31: 35–42, doi:10.1007/s10713-006-9466-x.

Duflo, E. and Saez, E. (2003). The Role of Information and Social Interactions in Retirement Plan Decisions: Evidence from a Randomized Experiment. *The Quarterly Journal of Economics* 118: pp. 815–842, doi:10.1162/00335530360698432.

Ellman, M. and Hurkens, S. (2016). Optimal Crowdfunding Design. Working Papers 871, Barcelona Graduate School of Economics.

Hong, H., Kubik, J. D. and Stein, J. C. (2004). Social Interaction and Stock-Market Participation. *Journal of Finance* 59: 137–163.

Hong, H., Kubik, J. D. and Stein, J. C. (2005). Thy Neighbor's Portfolio: Word-of-Mouth Effects in the Holdings and Trades of Money Managers. *Journal of Finance* 60: 2801–2824.

Hörner, J. and Herrera, H. (2013). Biased Social Learning. *Games and Economic Behavior of Finance* 80: 131–146.

Ivkovic, Z. and Weisbenner, S. (2007). Information Diffusion Effects in Individual Investors' Common Stock Purchases: Covet Thy Neighbors' Investment Choices. *The Review of Financial Studies* 20: pp. 1327–1357, doi:10.1093/revfin/hhm009.

Kuppuswamy, V. and Bayus, B. (2015). Crowdfunding Creative Ideas: The Dynamics of Project Backers in Kickstarter. UNC Kenan-Flagler Research Paper No. 2013-15.

Li, G. (2014). Information Sharing and Stock Market Participation: Evidence from Extended Families. *The Review of Economics and Statistics* 96: 151–160.

Massolution (2015). The Crowdfunding Industry Report. [Online Report] http://reports.crowdsourcing.org/index.php?route=product/product&product_id=54.

Mollick, E. (2014). The Dynamics of Crowdfunding: An Exploratory Study. *Journal of Business Venturing* 29(14): pp. 1–16.

Park, A. and Sabourian, H. (2011). Herding and contrarian behavior in financial markets. *Econometrica* 79: 973–1026.

Shiller, R. (2015). Crowdfunding or Crowdphishing?. [Op-ed]. https://www.project-syndicate.org/commentary/sec-crowdfunding-regulations.

Smith, L. and Sorensen, P. (2000). Pathological Outcomes of Observational Learning. *Econometrica* 68: 371–398.

Strausz, R. (2017). A Theory of Crowdfunding: A Mechanism Design Approach with Demand Uncertainty and Moral Hazard. *American Economic Review* 107: 1430–1476.

Vismara, S. (2016). Information cascades among investors in equity crowdfunding. *Entrepreneurship Theory and Practice* : n/a–n/adoi:10.1111/etap.12261.

Vulkan, N., Åstebro, T. and Fernandez, M. (2016). Equity Crowdfunding: A New Phenomena. *Journal of Business Venturing Insights* 5: 37 – 49, doi:http://dx.doi.org/10.1016/j.jbvi.2016.02.001.

Welch, I. (1992). Sequential Sales, Learning, and Cascades. *The Journal of Finance* 47(2): pp. 695–732.

Zhang, J. and Liu, P. (2012). Rational Herding in Microloan Markets. *Management Science* 58(5): pp. 892–912.

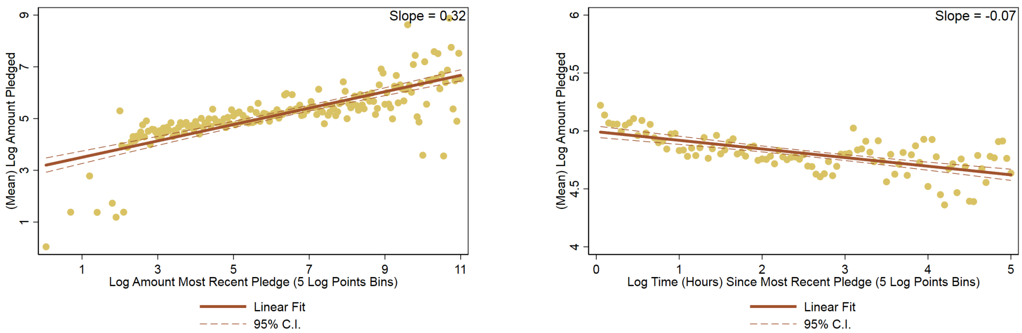
# 6 Appendix

## 6.1 Tables and Figures

Figure 1: Correlations Between the Amount Pledged by an Investor and the Timing and Size of the Most Recent Pledge

(a) Size of Most Recent Pledge

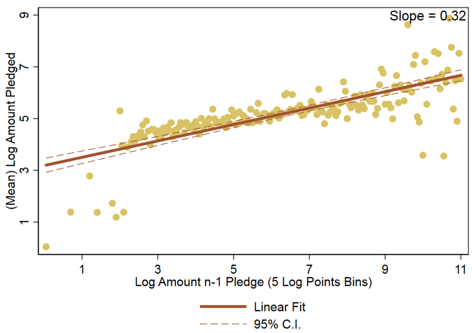
(b) Time Since Most Recent Pledge



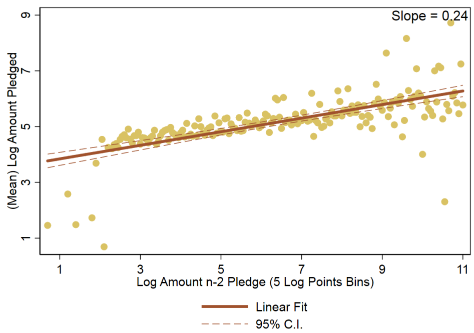

Notes: All pledges are organized in bins of size 5 log points according to the size of the most recent pledge (Panel (a)), and the time elapsed (in hours) since the most recent pledge (Panel (b)). Each panel shows the relation between the median value of the respective bin and the average amount invested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

Figure 2: Correlations Between the Amounts Pledged by Adjacent Backers in a Campaign

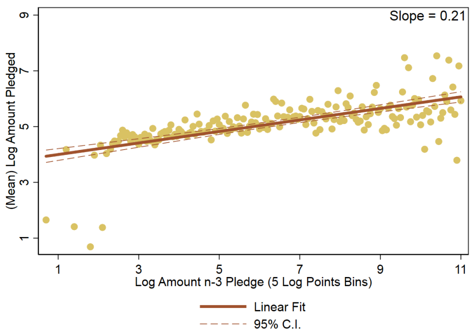
(a) $(n, n-1)$



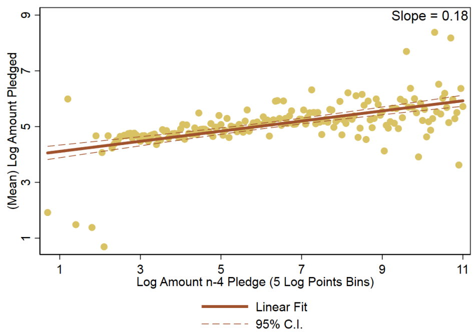

(b) $(n, n-2)$



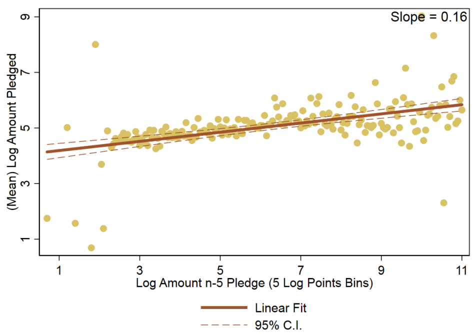

(c) $(n, n-3)$




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

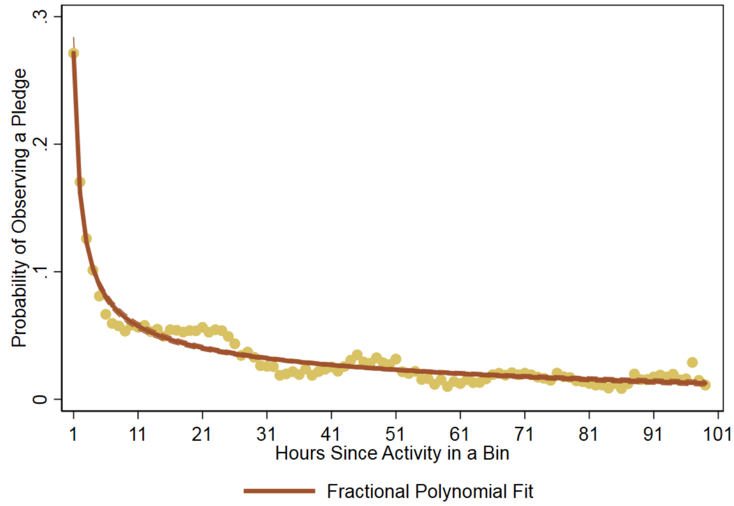



(e) $(n, n-5)$




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

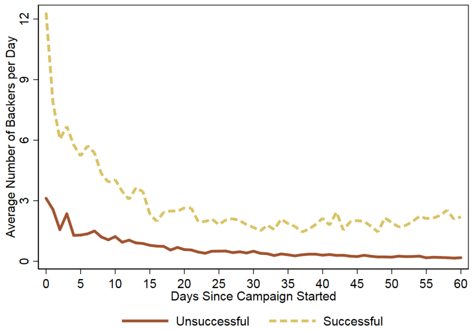



Notes: The total time that a campaign is running is divided into bins of length one hour. For each bin we create two variables: a dummy equal to one if there was at least one positive pledge, and zero otherwise; and a variable equal to the number of hours since the most recent pledge. The figure reports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

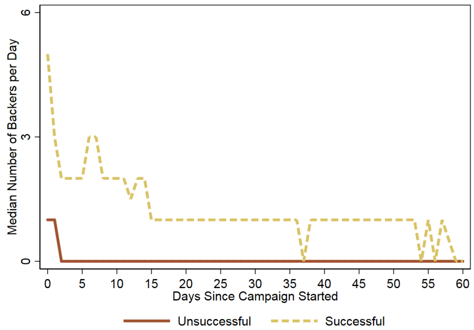
Figure 4: Number of Backers and Cumulative Investments to the Campaigns Across Time: Successful and Unsuccessful Campaigns

Average and Median Number of Backers per Day

(a) Mean

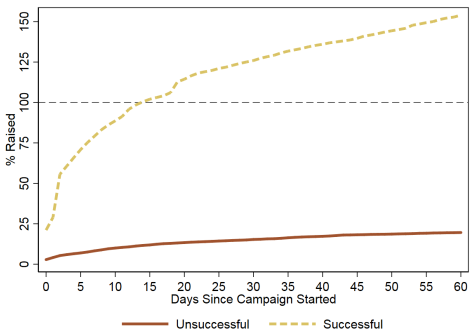



(b) Median

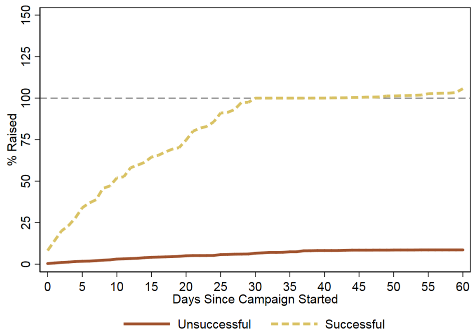



Number of Days to Reach a Given Percentage of the Investment Target

(c) Mean




(d) Median




Notes: Panel (a) and (b) depict the average and median number of backers making pledges to a campaign each day, 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, conditional on whether they end up being successful or not.

Table 1: 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 2: Summary Statistics

| | All | Successful (34.2%) | Unsuccessful | Difference |
|---|---|---|---|---|
| **Campaigns** | | | | |
| Pre-money valuation (£) | 1,845,449<br>(5,028,629) | 2,793,642<br>(7,834,238) | 1,352,064<br>(2,426,423) | 1,441,578*** |
| Equity offered | 11.95<br>(7.66) | 8.82<br>(6.43) | 13.57<br>(7.75) | -4.76*** |
| Campaign goal (£) | 174,216<br>(327,598) | 176,630<br>(252,718) | 172,959<br>(360,711) | 3,670 |
| % EIS tax relief | 34.51<br>(47.57) | 46.50<br>(49.98) | 28.27<br>(45.08) | 18.24*** |
| % SEIS tax relief | 57.18<br>(49.52) | 45.68<br>(49.92) | 63.17<br>(48.29) | -17.49*** |
| % Raised | 76.37<br>(195.13) | 178.95<br>(306.45) | 22.99<br>(28.57) | 155.96*** |
| # Entrepreneurs | 3.28<br>(1.96) | 3.74<br>(2.07) | 3.04<br>(1.87) | 0.70*** |
| # Backers | 83.44<br>(126.38) | 169.46<br>(174.62) | 38.68<br>(50.99) | 130.78*** |
| # Pledges | 96.48<br>(146.15) | 199.03<br>(200.68) | 43.13<br>(56.99) | 155.90*** |
| % Anonymous pledges | 51.40<br>(18.60) | 54.22<br>(9.50) | 49.93<br>(21.75) | 4.29*** |
| Hotness indicator (start of day) | 11.13<br>(13.08) | 21.39<br>(14.80) | 5.79<br>(7.95) | 15.60*** |
| Intraday increase in hotness indicator | 0.76<br>(0.24) | 0.82<br>(0.17) | 0.74<br>(0.27) | 0.08** |
| # Days the campaign is active | 54.70<br>(38.46) | 58.19<br>(38.56) | 52.89<br>(38.32) | 5.30* |
| **Type of Investor** | | | | |
| % Authorized | 79.21<br>(15.57) | 76.50<br>(11.45) | 80.63<br>(17.17) | -4.13*** |
| % High-net-worth | 13.55<br>(12.73) | 14.82<br>(10.31) | 12.89<br>(13.79) | 1.92* |
| % Sophisticated | 7.23<br>(8.24) | 8.68<br>(4.91) | 6.48<br>(9.44) | 2.20*** |
| % Recurrent investors | 72.64<br>(27.54) | 79.16<br>(19.99) | 69.25<br>(30.22) | 9.91*** |
| **Investments** | | | | |
| Mean pledge (£) | 1,202.71<br>(2,949.49) | 1,745.98<br>(3,472.27) | 920.03<br>(2,596.30) | 825.95*** |
| Median pledge (£) | 354.32<br>(2,336.11) | 571.29<br>(3,146.97) | 241.42<br>(1,767.18) | 329.87* |
| Max pledge (£) | 38,201.94<br>(158,251.56) | 81,341.40<br>(259,065.82) | 15,754.64<br>(42,113.87) | 65,586.76*** |
| Max pledge / goal | 0.15<br>(0.19) | 0.31<br>(0.22) | 0.07<br>(0.10) | 0.23*** |
| **Timing** | | | | |
| Mean time between pledges (hours) | 56.57<br>(109.83) | 9.96<br>(8.98) | 82.04<br>(129.56) | -72.08*** |
| % Covered in day 1 | 9.07<br>(20.94) | 21.07<br>(30.77) | 2.83<br>(7.84) | 18.24*** |
| % Covered in week 1 | 30.79<br>(165.41) | 75.47<br>(276.97) | 7.55<br>(14.45) | 67.92*** |
| % Covered in month 1 | 53.33<br>(187.77) | 126.66<br>(306.94) | 15.17<br>(21.33) | 111.49*** |
| Observations | 710 | 243 | 467 | |

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: *** 1 percent ** 5 percent * 10 percent.

Table 3: The Effect of Prior Pledges and the Time Since the Most Recent Pledge

| | *Dependent Var*: log amount pledged (£) | | |
|---|---|---|---|
| | Model | Model + Controls | IV |
| **Prior pledges** | | | |
| Log amount pledged (n-1) | 0.096*** | 0.086*** | 0.119** |
| | (0.007) | (0.006) | (0.060) |
| Log amount pledged (n-2) | 0.041*** | 0.037*** | 0.098* |
| | (0.005) | (0.004) | (0.058) |
| Log amount pledged (n-3) | 0.029*** | 0.026*** | 0.047 |
| | (0.004) | (0.004) | (0.048) |
| Log amount pledged (n-4) | 0.021*** | 0.017*** | 0.041 |
| | (0.004) | (0.004) | (0.051) |
| Log amount pledged (n-5) | 0.018*** | 0.016*** | -0.014 |
| | (0.004) | (0.004) | (0.051) |
| Log time (hours) since most recent pledge | -0.028 | 0.017 | -0.077* |
| | (0.017) | (0.017) | (0.040) |
| **Controls** | | | |
| Log amount funded | | 0.261** | 0.276** |
| | | (0.087) | (0.094) |
| Log amount funded squared | | -0.015*** | -0.016*** |
| | | (0.005) | (0.005) |
| Dummy high-net-worth | | 1.167*** | 1.151*** |
| | | (0.038) | (0.039) |
| Dummy sophisticated | | 0.421*** | 0.401*** |
| | | (0.034) | (0.036) |
| Dummy recurrent investor | | -0.576*** | -0.559*** |
| | | (0.047) | (0.048) |
| Campaign hotness at start of the day | | 0.003*** | -0.000 |
| | | (0.001) | (0.001) |
| Dummy campaign hotness intraday rise | | 0.175*** | 0.097*** |
| | | (0.019) | (0.024) |
| Total pledges (/100) | | 0.004 | 0.017* |
| | | (0.009) | (0.009) |
| Days from start of campaign | | 0.004*** | 0.005*** |
| | | (0.001) | (0.001) |
| Google trend index | | -0.001* | -0.001* |
| | | (0.000) | (0.000) |
| FTSE 100 index | | 0.000 | 0.000 |
| | | (0.000) | (0.000) |
| Observations | 66,347 | 66,347 | 61,426 |
| Average pledge (£) | 1,247 | 1,247 | 1,244 |
| SD pledge (£) | 12,151 | 12,151 | 11,859 |
| Average time (hours) since most recent pledge | 11.2 | 11.2 | 11.4 |
| S.D. time (hours) since most recent pledge | 40.4 | 40.4 | 40.2 |
| Kleibergen and Paap rk statistic | | | 44.76 |
| Campaign FE | Yes | Yes | Yes |

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

Notes: Robust standard errors, clustered by campaign. Each lagged pledge in the IV setting is instrumented using the inverse hyperbolic sine transformation (IHST) of the amount of money returned to the backer if the last campaign she supported failed. The IHST 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 4: The Effect of Prior Pledges and the Time Since the Most Recent Pledge: First Stages of the Preferred IV Regression

| | First Stage Regressions | | | | | |
|---|---|---|---|---|---|---|
| | $\log I_{n-1,c}$ | $\log I_{n-2,c}$ | $\log I_{n-3,c}$ | $\log I_{n-4,c}$ | $\log I_{n-5,c}$ | $\log T_{(n,n-1),c}$ |
| IHST amount returned (n-1) | 0.093*** | 0.004 | -0.002 | -0.005 | -0.006 | -0.004 |
| | (0.010) | (0.005) | (0.005) | (0.005) | (0.005) | (0.004) |
| IHST amount returned (n-2) | -0.002 | 0.094*** | 0.006 | -0.000 | -0.002 | -0.003 |
| | (0.006) | (0.010) | (0.005) | (0.005) | (0.005) | (0.004) |
| IHST amount returned (n-3) | 0.002 | 0.002 | 0.096*** | 0.010* | -0.002 | -0.006* |
| | (0.005) | (0.006) | (0.010) | (0.005) | (0.005) | (0.003) |
| IHST amount returned (n-4) | 0.003 | 0.004 | 0.002 | 0.094*** | 0.011** | -0.007* |
| | (0.005) | (0.005) | (0.006) | (0.010) | (0.005) | (0.004) |
| IHST amount returned (n-5) | 0.003 | 0.004 | 0.004 | 0.001 | 0.095*** | -0.003 |
| | (0.005) | (0.005) | (0.006) | (0.006) | (0.010) | (0.003) |
| Log hours since 11am (n-1) | -0.083*** | -0.035*** | -0.005 | 0.006 | -0.001 | 0.252*** |
| | (0.011) | (0.010) | (0.010) | (0.011) | (0.010) | (0.010) |
| Observations | 61,426 | 61,426 | 61,426 | 61,426 | 61,426 | 61,426 |
| 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 3 are included but not reported. Each lagged pledge in the IV setting is instrumented using the inverse hyperbolic sine transformation (IHST) of the amount of money returned to the backer if the last campaign she supported failed. The IHST can be interpreted in the same way as the standard logarithmic transformation, but it has the property that is defined at zero.

Table 5: The Effect of Prior Pledges and the Time Since the Most Recent Pledge: Alternative IV

| | *Dependent Var*: log amount pledged (£) | | |
|---|---|---|---|
| | Model | Model + Controls | IV |
| **Prior pledges** | | | |
| Log amount pledged (n-1) | 0.096*** | 0.086*** | 0.120*** |
| | (0.007) | (0.006) | (0.018) |
| Log amount pledged (n-2) | 0.041*** | 0.037*** | 0.042** |
| | (0.005) | (0.004) | (0.019) |
| Log amount pledged (n-3) | 0.029*** | 0.026*** | 0.022 |
| | (0.004) | (0.004) | (0.017) |
| Log amount pledged (n-4) | 0.021*** | 0.017*** | -0.011 |
| | (0.004) | (0.004) | (0.018) |
| Log amount pledged (n-5) | 0.018*** | 0.016*** | 0.016 |
| | (0.004) | (0.004) | (0.017) |
| Log time (hours) since most recent pledge | -0.028 | 0.017 | -0.097** |
| | (0.017) | (0.017) | (0.036) |
| **Controls** | | | |
| Log amount funded | | 0.261** | 0.356*** |
| | | (0.087) | (0.092) |
| Log amount funded squared | | -0.015*** | -0.019*** |
| | | (0.005) | (0.005) |
| Dummy high-net-worth | | 1.167*** | 1.164*** |
| | | (0.038) | (0.038) |
| Dummy sophisticated | | 0.421*** | 0.409*** |
| | | (0.034) | (0.036) |
| Dummy recurrent investor | | -0.576*** | -0.563*** |
| | | (0.047) | (0.049) |
| Campaign hotness at start of the day | | 0.003*** | -0.000 |
| | | (0.001) | (0.001) |
| Dummy campaign hotness intraday rise | | 0.175*** | 0.108*** |
| | | (0.019) | (0.026) |
| Total pledges (/100) | | 0.004 | 0.013 |
| | | (0.009) | (0.009) |
| Days from start of campaign | | 0.004*** | 0.005*** |
| | | (0.001) | (0.001) |
| Google trend index | | -0.001* | -0.001** |
| | | (0.000) | (0.000) |
| FTSE 100 index | | 0.000 | 0.000 |
| | | (0.000) | (0.000) |
| Observations | 66,347 | 66,347 | 61,426 |
| Average pledge (£) | 1,247 | 1,247 | 1,244 |
| SD pledge (£) | 12,151 | 12,151 | 11,859 |
| Average time (hours) since most recent pledge | 11.2 | 11.2 | 11.4 |
| S.D. time (hours) since most recent pledge | 40.4 | 40.4 | 40.2 |
| Kleibergen and Paap rk statistic | | | 207.66 |
| Hansen J statistic P-Val | | | 0.64 |
| Campaign FE | Yes | Yes | Yes |

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

Notes: Robust standard errors, clustered by campaign. Each lagged pledge in the IV setting 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 6: The Effect of Prior Pledges and the Time Since the Most Recent Pledge: First Stages of the Alternative IV Regression

| | 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) | -0.657*** | -0.002 | -0.008 | -0.014 | 0.022 | -0.079*** |
| | (0.026) | (0.021) | (0.021) | (0.023) | (0.021) | (0.015) |
| Number of pledges (n-2) × Anonymous (n-2) | -0.022 | -0.673*** | -0.012 | -0.010 | -0.021 | -0.062*** |
| | (0.019) | (0.027) | (0.020) | (0.021) | (0.023) | (0.015) |
| Number of pledges (n-3) × Anonymous (n-3) | -0.037* | -0.048** | -0.683*** | -0.019 | -0.010 | -0.031** |
| | (0.020) | (0.020) | (0.027) | (0.020) | (0.022) | (0.015) |
| Number of pledges (n-4) × Anonymous (n-4) | -0.006 | -0.038* | -0.051** | -0.688*** | -0.030 | -0.041** |
| | (0.021) | (0.020) | (0.019) | (0.027) | (0.021) | (0.014) |
| Number of pledges (n-5) × Anonymous (n-5) | -0.011 | -0.018 | -0.061** | -0.071*** | -0.712*** | -0.016 |
| | (0.022) | (0.021) | (0.020) | (0.019) | (0.027) | (0.016) |
| Max amount invested (n-1) × Anonymous (n-1) | 0.563*** | 0.019 | 0.016 | -0.002 | -0.002 | -0.020** |
| | (0.082) | (0.016) | (0.011) | (0.015) | (0.017) | (0.010) |
| Max amount invested (n-2) × Anonymous (n-2) | 0.019 | 0.593*** | 0.045** | 0.019 | 0.008 | -0.007 |
| | (0.018) | (0.068) | (0.017) | (0.013) | (0.012) | (0.008) |
| Max amount invested (n-3) × Anonymous (n-3) | 0.024* | 0.036** | 0.592*** | 0.044** | 0.033** | -0.007 |
| | (0.013) | (0.017) | (0.083) | (0.021) | (0.011) | (0.009) |
| Max amount invested (n-4) × Anonymous (n-4) | 0.001 | 0.014 | 0.014 | 0.533*** | 0.062** | 0.002 |
| | (0.011) | (0.012) | (0.016) | (0.073) | (0.019) | (0.007) |
| Max amount invested (n-5) × Anonymous (n-5) | -0.016 | -0.002 | 0.021* | 0.029* | 0.526*** | -0.003 |
| | (0.019) | (0.012) | (0.011) | (0.018) | (0.083) | (0.008) |
| Log hours since 11am (n-1) | -0.068*** | -0.029** | -0.004 | 0.008 | 0.001 | 0.254*** |
| | (0.010) | (0.010) | (0.010) | (0.010) | (0.010) | (0.010) |
| Observations | 61,426 | 61,426 | 61,426 | 61,426 | 61,426 | 61,426 |
| 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 5 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 7: The Effect of Prior Pledges: Heterogeneous Effects by Investor Type

| | *Dependent Var*: log amount pledged (£) | | | | | |
|---|---|---|---|---|---|---|
| | All | High-Net-Worth | Sophisticated | Authorized | Recurrent | Single Campaign |
| **Prior pledges** | | | | | | |
| Log amount pledged (n-1) | 0.120*** | 0.126** | -0.028 | 0.135*** | 0.089*** | 0.212*** |
| | (0.018) | (0.045) | (0.064) | (0.024) | (0.018) | (0.062) |
| Log amount pledged (n-2) | 0.042** | 0.059 | 0.159 | 0.031 | 0.046** | 0.035 |
| | (0.019) | (0.055) | (0.132) | (0.022) | (0.018) | (0.052) |
| Log amount pledged (n-3) | 0.022 | 0.061 | 0.037 | 0.017 | 0.022 | 0.009 |
| | (0.017) | (0.077) | (0.055) | (0.018) | (0.019) | (0.067) |
| Log amount pledged (n-4) | -0.011 | 0.083 | -0.055 | -0.025 | -0.010 | -0.009 |
| | (0.018) | (0.055) | (0.073) | (0.019) | (0.019) | (0.048) |
| Log amount pledged (n-5) | 0.016 | -0.057 | -0.038 | 0.040 | 0.028* | -0.089 |
| | (0.017) | (0.063) | (0.064) | (0.038) | (0.017) | (0.074) |
| Log time (hours) since most recent pledge | -0.097** | -0.010 | -0.203* | -0.095** | -0.072** | 0.010 |
| | (0.036) | (0.086) | (0.116) | (0.042) | (0.036) | (0.089) |
| Observations | 61,426 | 8,121 | 5,036 | 48,130 | 45,476 | 15,889 |
| Average pledge (£) | 1,244 | 3,169 | 1,719 | 867 | 814 | 2,472 |
| SD pledge (£) | 11,859 | 13,130 | 11,545 | 11,629 | 10,741 | 14,516 |
| Average time (hours) since most recent pledge | 11.4 | 11.6 | 10.2 | 11.5 | 12.1 | 9.6 |
| S.D. time (hours) since most recent pledge | 40.2 | 46.0 | 35.3 | 39.6 | 40.6 | 39.0 |
| 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 5 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 1 for the definitions used to classify investors.

Table 8: Probability of Observing a Pledge at Any Given Hour and Size of Last Pledge

| | *Dependent Var*: Dummy Investment in the Period (Hour) | | | |
|---|---|---|---|---|
| | Full Sample | Full Sample | Weeks 1-2 | Weeks > 2 |
| **Prior pledges** | | | | |
| IHST amount pledged (t-1) | 0.019*** | 0.018*** | 0.021*** | 0.014*** |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| IHST amount pledged (t-2) | 0.015*** | 0.013*** | 0.015*** | 0.011*** |
| | (0.000) | (0.000) | (0.001) | (0.001) |
| IHST amount pledged (t-3) | 0.011*** | 0.010*** | 0.010*** | 0.009*** |
| | (0.000) | (0.000) | (0.001) | (0.001) |
| IHST amount pledged (t-4) | 0.010*** | 0.008*** | 0.008*** | 0.007*** |
| | (0.000) | (0.000) | (0.001) | (0.000) |
| IHST amount pledged (t-5) | 0.008*** | 0.006*** | 0.007*** | 0.005*** |
| | (0.000) | (0.000) | (0.001) | (0.000) |
| **Controls** | | | | |
| Log amount funded (t-1) | | -0.001 | -0.010* | 0.001 |
| | | (0.004) | (0.005) | (0.009) |
| Log amount funded squared (t-1) | | 0.000 | 0.001 | 0.000 |
| | | (0.000) | (0.000) | (0.001) |
| Campaign hotness at start of the day | | 0.002*** | 0.002*** | 0.002*** |
| | | (0.000) | (0.000) | (0.000) |
| Dummy campaign hotness intraday rise | | 0.007*** | 0.016*** | 0.005*** |
| | | (0.001) | (0.002) | (0.001) |
| Total pledges (/100) (t-1) | | -0.015*** | -0.019** | -0.008 |
| | | (0.004) | (0.008) | (0.005) |
| Days from start of campaign | | -0.000 | -0.000 | -0.000** |
| | | (0.000) | (0.000) | (0.000) |
| FTSE 100 index | | -0.000 | 0.000 | -0.000 |
| | | (0.000) | (0.000) | (0.000) |
| Google trend index | | 0.000*** | 0.000*** | 0.000** |
| | | (0.000) | (0.000) | (0.000) |
| Observations | 866,912 | 866,912 | 209,363 | 657,549 |
| R2 | 0.067 | 0.075 | 0.095 | 0.050 |
| Frequency of Investments per Hour | 0.055 | 0.055 | 0.088 | 0.044 |
| SD of Frequency of Investments per Hour | 0.227 | 0.227 | 0.284 | 0.205 |
| Campaign FE | Yes | Yes | Yes | Yes |
| Hour of Day 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. 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, which can be interpreted in the same way as the standard logarithmic transformation but is defined at zero.

Table 9: Probability of Observing a Pledge at Any Given Hour and Time Since Last Pledge

| | *Dependent Var*: Dummy Investment in the Period (Hour) | | | |
|---|---|---|---|---|
| | Full Sample | Full Sample | Weeks 1-2 | Weeks > 2 |
| Log hours since most recent activity in bin | -0.023*** | -0.020*** | -0.033*** | -0.014*** |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| **Controls** | | | | |
| Log amount funded (t-1) | | 0.001 | -0.007 | -0.010 |
| | | (0.005) | (0.008) | (0.009) |
| Log amount funded squared (t-1) | | -0.000 | 0.000 | 0.001 |
| | | (0.000) | (0.001) | (0.001) |
| Campaign hotness at start of the day | | 0.003*** | 0.003*** | 0.003*** |
| | | (0.000) | (0.000) | (0.000) |
| Dummy campaign hotness intraday rise | | 0.011*** | 0.025*** | 0.008*** |
| | | (0.001) | (0.003) | (0.001) |
| Total pledges (/100) (t-1) | | -0.024*** | -0.049** | -0.009 |
| | | (0.006) | (0.017) | (0.008) |
| Days from start of campaign | | 0.000*** | 0.002*** | -0.000 |
| | | (0.000) | (0.001) | (0.000) |
| FTSE 100 index | | 0.000 | 0.000 | -0.000 |
| | | (0.000) | (0.000) | (0.000) |
| Google trend index | | 0.000*** | 0.000*** | 0.000*** |
| | | (0.000) | (0.000) | (0.000) |
| Observations | 825,761 | 825,761 | 212,083 | 613,678 |
| R2 | 0.038 | 0.052 | 0.063 | 0.036 |
| Frequency of Investments per Hour | 0.058 | 0.058 | 0.090 | 0.047 |
| SD of Frequency of Investments per Hour | 0.234 | 0.234 | 0.286 | 0.212 |
| Campaign FE | Yes | Yes | Yes | Yes |
| Hour of Day 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.

Table 10: Variables Associated with the Probability that a Campaign is Successful

| | Average Marginal Effects after Probit | | |
|---|---|---|---|
| | I | II | III |
| **Early Campaign Dynamics** | | | |
| Number of backers in week 1 | 0.000 | 0.000 | -0.001*** |
| | (0.001) | (0.001) | (0.000) |
| % Covered in week 1 | 0.008*** | 0.007*** | 0.001*** |
| | (0.001) | (0.001) | (0.000) |
| **Predetermined Campaign Controls** | | | |
| Log pre-money valuation (£) | | 0.085*** | 0.016 |
| | | (0.022) | (0.015) |
| Log campaign goal (£) | | -0.093*** | -0.219*** |
| | | (0.024) | (0.017) |
| # Entrepreneurs | | 0.015* | 0.004 |
| | | (0.008) | (0.005) |
| % EIS tax relief | | 0.000 | -0.000 |
| | | (0.000) | (0.000) |
| % SEIS tax relief | | 0.000 | 0.000 |
| | | (0.000) | (0.000) |
| **Campaign Variable Controls** | | | |
| % Recurrent investors | | | 0.001 |
| | | | (0.001) |
| % Authorized | | | -0.000 |
| | | | (0.001) |
| % High-net-worth | | | -0.000 |
| | | | (0.002) |
| Total # Pledges | | | 0.002*** |
| | | | (0.000) |
| Log mean pledge (£) | | | 0.113*** |
| | | | (0.023) |
| Log max pledge (£) | | | 0.059*** |
| | | | (0.014) |
| Observations | 710 | 710 | 710 |
| **Standardized Effect** | | | |
| Number of backers in week 1 | 0.01 | 0.01 | -0.04 |
| % Covered in week 1 | 1.31 | 1.14 | 0.24 |
| Log pre-money valuation | | 0.09 | 0.02 |
| Log campaign goal | | -0.10 | -0.24 |
| # Entrepreneurs | | 0.03 | 0.01 |
| % EIS tax relief | | 0.02 | -0.00 |
| % SEIS tax relief | | 0.00 | 0.01 |
| % Recurrent investors | | | 0.02 |
| % Authorized | | | -0.00 |
| % High-net-worth | | | -0.00 |
| Total # Pledges | | | 0.28 |
| Log mean pledge | | | 0.16 |
| Log max pledge | | | 0.14 |

*** 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 11: The Effect of Prior Pledges: Private and Public Stages of a Campaign

| | *Dependent Var*: log amount pledged (£) | | |
|---|---|---|---|
| | All | Weeks 1-2 | Weeks > 2 |
| **Prior pledges** | | | |
| Log amount pledged (n-1) | 0.120*** | 0.126*** | 0.104*** |
| | (0.018) | (0.034) | (0.023) |
| Log amount pledged (n-2) | 0.042** | 0.031 | 0.038* |
| | (0.019) | (0.029) | (0.021) |
| Log amount pledged (n-3) | 0.022 | 0.037 | 0.002 |
| | (0.017) | (0.026) | (0.025) |
| Log amount pledged (n-4) | -0.011 | -0.028 | -0.004 |
| | (0.018) | (0.028) | (0.025) |
| Log amount pledged (n-5) | 0.016 | 0.023 | 0.008 |
| | (0.017) | (0.025) | (0.022) |
| Log time (hours) since most recent pledge | -0.097** | -0.114** | -0.054 |
| | (0.036) | (0.045) | (0.046) |
| Observations | 61,426 | 28,593 | 32,796 |
| Average pledge (£) | 1,244 | 1,255 | 1,235 |
| SD pledge (£) | 11,859 | 14,429 | 9,041 |
| Average time (hours) since most recent pledge | 11.4 | 4.3 | 17.6 |
| S.D. time (hours) since most recent pledge | 40.2 | 11.6 | 53.1 |
| Kleibergen and Paap rk statistic | 207.66 | 180.58 | 143.69 |
| Hansen J statistic P-Val | 0.64 | 0.79 | 0.48 |
| Campaign FE | Yes | Yes | Yes |

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

Notes: Robust standard errors, clustered by campaign. All the controls from Table 5 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 12: The Effect of Prior Pledges, Underfunding and Overfunding Stages of a Campaign

| | *Dependent Var*: log amount pledged (£) | | |
|---|---|---|---|
| | All | Underfunding | Overfunding |
| **Prior pledges** | | | |
| Log amount pledged (n-1) | 0.120*** | 0.114*** | 0.129*** |
| | (0.018) | (0.024) | (0.033) |
| Log amount pledged (n-2) | 0.042** | 0.032 | 0.051 |
| | (0.019) | (0.021) | (0.036) |
| Log amount pledged (n-3) | 0.022 | 0.030 | 0.005 |
| | (0.017) | (0.022) | (0.029) |
| Log amount pledged (n-4) | -0.011 | 0.000 | -0.039 |
| | (0.018) | (0.019) | (0.046) |
| Log amount pledged (n-5) | 0.015 | 0.011 | 0.023 |
| | (0.017) | (0.019) | (0.030) |
| Log time (hours) since most recent pledge | -0.096** | -0.130*** | 0.014 |
| | (0.036) | (0.039) | (0.080) |
| Observations | 61,426 | 45,384 | 16,027 |
| Average pledge (£) | 1,244 | 1,129 | 1,571 |
| SD pledge (£) | 11,859 | 7,145 | 19,851 |
| Average time (hours) since most recent pledge | 11.4 | 13.0 | 6.8 |
| S.D. time (hours) since most recent pledge | 40.2 | 43.7 | 27.1 |
| Kleibergen and Paap rk statistic | 207.15 | 193.32 | 66.37 |
| Hansen J statistic P-Val | 0.64 | 0.85 | 0.44 |
| Campaign FE | Yes | Yes | Yes |

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

Notes: Robust standard errors, clustered by campaign. All the controls from Table 5 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.

## 6.2 Proofs

### 6.2.1 Proof of Proposition 2.1

**1** Observe that during the overfunding phase $S_\rho(x, h_t) = 1$ for all $x$ and all $\rho\{0, \alpha\}$. Substituting this expression in (2.4), we can take first-order conditions with respect to $x$ 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 (2.7).

**2.a** Because of the monotonicity of pledges with respect to beliefs and because signals are informative, the optimal size of pledges differ across backers type. Hence the public can deduce the backer type from the size of her pledge.

**2.b** When $\pi_t > \underline{\pi}^b$ a backer pledge a positive amount no matter his 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 pledge, hence observing no pledge provides no information about backer's signals and the project's quality. For $\underline{\pi}^g < \pi_t \leq \underline{\pi}^u$ only positively informed backer pledge. The probability of observing no pledge between $t$ and $t'$ is $e^{-\lambda q(t-t')}$ if the project is good, and $e^{-\lambda(1-q)(t-t')}$ if the project is bad. Applying Bayes' rule one gets

$$\pi_{t'} = \frac{\pi_t e^{-\lambda q(t-t')}}{\pi_t e^{-\lambda q(t-t')} + (1-\pi_t) e^{-\lambda(1-q)(t-t')}}.$$

Simplifying one gets expression (2.6). For $\underline{\pi}^u < \pi_t \leq \underline{\pi}^b$ only uninformed backer and positively informed backer 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 and $e^{-(\lambda(1-q)+1-\lambda)(t-t')}$ if the project is bad. Applying Bayes' rule and simplifying one gets expression (2.6).

**3** Because of the monotonicity of pledges with respect to beliefs, when $\pi_t \leq \underline{\pi}^g$ no backer ever invests, beliefs do not change and hence an abstention cascade occurs. To see that an information cascade is impossible if $\pi_t > \underline{\pi}^g$, it is sufficient to note that when the public belief is above $\underline{\pi}^g$, informed backers invest strictly positive amounts that differ from those of uniformed or negatively informed backers. HEnce with strictly positive probability a pledge from positively informed backers arrive, disclose their signal and move the public belief. Q.E.D.

### 6.2.2 Proof of Proposition 2.3

Where first 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 start with some preliminaries. Take any finite history $s$ of backers arrivals, that is $s := \{(t_1, s_1), \dots, (t_n, s_n), \dots\}$, 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

$$\begin{aligned} \mathbb{P}(S|\text{bad project}) \in (0,1) &\Leftrightarrow \mathbb{P}(S|\text{good project}) \in (0,1) \Rightarrow \\ \mathbb{P}(S|\text{bad project}) &\neq \mathbb{P}(S|\text{good project}). \end{aligned} \tag{6.1}$$

In particular the following property applies:

**Property 1:** *There is a positive and bounded $M$ such that for any $S \subseteq \mathcal{S}$ such that $\mathbb{P}(S|\text{good project}) > 0$ one has:*

$$0 < \frac{\mathbb{P}(S|\text{good project})}{\mathbb{P}(S|\text{bad project})} < M. \tag{6.2}$$

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 histories that start with $h_t, x_t$, and 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 $s(h) \in \mathcal{S}$ 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 $\rho$ can be written as

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

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. Namely for a backer arriving with belief $\pi$ the optimal pledge solves

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

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 (6.1) 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 $\pi$ 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:

$$S_0(x, h_t) \leq S_\alpha(x, h_t). \tag{6.3}$$

**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 his pledge.

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

**3.** Because pledges are non-decreasing in the backer's belief 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. Consider 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 (6.1) 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 $\pi_t$ 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 and bounded by $M$ because of (6.1) and (6.2). But this implies that

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

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. Q.E.D.

### 6.2.3 Proof of Proposition 2.6

**1.** The proof is identical to the proof of Proposition 2.1.

**2.a** Let's denote with $\theta^*(\pi) > 0$ backers of type $\theta$ 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 $\pi$. If the public belif is $\pi$, then a backer pledge only if his 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, $\lambda$, 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 $\rho$ is $F(\theta^*(\pi_t)|\rho)$. Applying Bayes' rule one has 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 backers 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 $x > 0$, $\pi_t$ and $W \in [0, 1]$, let $\theta(x, W, \pi_t)$ be the $\theta$ such that $x = \max\left\{0, \frac{\pi_t^\theta \alpha - 1}{\alpha - 1} W\right\}$ and if no such $\theta$ 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 $\pi_t$. 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 $\theta$ 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 belief 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 2.1. Q.E.D.