A Theory of Collective Investment with Application to Venture Funding *

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Abstract

In many collective settings, early movers take extra risk or bear extra cost without benefiting more than late comers from the success of the cause. An example is the funding of an entrepreneurial venture. One investor may lead while others hold off to see evidence of investors before committing. What explains the actions of these different agents? If information is revealed over time, why doesn't everyone wait? Additionally, what is the pattern of investment in successfully funded ventures compared to those that fail?

A model of collective action with learning is proposed. It provides a rationale for some agents to jump in early while others wait. The implications of the theory on the likelihood of funding success, the dynamics of agents' actions, and on who moves early or later are borne out using data from Kickstarter, a crowd-funding investment platform.

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1 Introduction

Human history is full of enterprises for which payoffs were unknown when attempted.[1] In many contexts, the success of such undertakings requires collective action, such as political uprisings, funding a venture, or creating a market with a new technology. In these settings, early movers take extra risk or bear extra cost without necessarily benefiting more than their followers upon the success of the cause. If we believe the early movers are rational agents with potential desires to free-ride, this begs the question, why?

For instance, attempts to bring about a political change risk failure and personal danger when the movement cannot attain critical mass. The political movement starts when a group take early action. Frequently, the enthusiasm peters out, as they fail to attract enough followers to induce a change. Sometimes, however, an uprising of a few enjoys a large following and political change is effected. In some cases, early movers become leaders of the new regime if the revolution is successful, but only a few can receive special benefits and many may participate in early actions. Why are the vanguards willing to take such risks? [2]

Funding a new entrepreneurial venture bears many similarities to this example. In some situations, a critical level of capital is necessary for a venture to be viable. Developing the means to perform the intended function of the new business, such as building a factory or investing in engineering, may have strong scale effects. In some instances, spending a sufficient amount of capital to keep prices low and capture market share at an early stage in the hope of eventually turning a profit may be part of the business model. Often no investor is confident enough to want to act alone when others hold negative views of the venture, or no investor has enough funds to allocate to any one particular venture. One investor may take the lead, offering to provide some fraction of the necessary capital. In some cases, others may follow that lead and invest, generating enough funding to make the venture move forward. But as is the case with political uprisings, some leading investments may fail to attract followers and the aspiring entrepreneurial venture does not get

[1] As Hayek put it, "Contemporary events differ from history in that we do not know the results they will produce. Looking back, we can assess the significance of past occurrences and trace the consequences they have brought in their train. But while history runs its course, it is not history to us. It leads us into an unknown land and but rarely can we get a glimpse of what lies ahead" (Hayek (2014), P1).

[2] When the production of a team depends both on an unknown state and the collective effort taken by the members, sometimes the leader is worse off than her followers. This raises the question of why she would choose or agree to be the leader in such situations. This problem is investigated in Hermalin (1998) and Komai et al. (2007).

funded.

What determines the timing of agents' actions? What explains the investment patterns observed in such settings? What is the likelihood that a venture raises the critical mass of funding?

To get some intuition, consider a case in which three investors – A, B and C – examine a fund-raising entrepreneurial project, the payoff of which is uncertain but the same to all investors. The venture will be funded and executed if and only if at least two investors back it, in which case each backer receives one unit of output of the venture. Each investor has a private signal about the expected payoff. Signals can be good, moderate, or bad, with better signals implying a higher likelihood that the venture will generate positive returns. Suppose the inference is such that investors with moderate signals are not confident enough to invest unless they know at least one investor receives a good signal, and investors with bad signals need to know that at least two investors receive good signals to be willing to pledge. This environment gives rise to strategic calculus for investors.

Consider investor A. If he receives a good signal, he may find it optimal to pledge right away, even though he understands that his assessment is imperfect and the venture can turn out to be valueless. Investor B and C may not have received a good signal and thus are not sufficiently confident to invest absent a lead investor. To convey that he has a good signal, investor A is willing to pledge early, which may trigger the investors without good signals into making more informed decisions. This increases the likelihood that a project will be funded, from which the lead investor also benefits. For a venture to be funded, at least one investor must receive a good signal, in which case those with good signals pledge right away. One possibility is that one lead investor is joined by two investors with moderate signals, creating a back-loaded pattern. Ventures that are not funded either receive no pledges, or do not attract enough followers after the one lead. The key here is that those who receive good signals are willing to lead, even potentially at personal costs, because the project cannot succeed without collective action. Early movers understand that their behavior will influence others.

The basic logic is that individuals differ in their *ex ante* estimate of the prospects. When the success of one's investment hinges on the collective contributions from multiple investors, those who highly value a venture are most eager to influence others to participate to increase the likelihood that the critical mass will be reached. Agents self-select into early movers and followers on the basis of their signals. Those with lower signals find it optimal to wait and see what more confident agents do before committing resources. Under this rationale, some ventures will be unable to attract enough investment because the initial investment falls short of the amount needed to signal high expected returns. However, ventures with better, even if modest, openings can succeed when there is a large enough pool of investors willing to follow the lead investors. Information conveyed in the early investment makes other investors confident enough to follow suit.

I propose a model that combines learning with collective action. It has a number of features. Specifically, it yields a rationale for some to jump in early, while others wait, sometimes following and sometimes declining to take action. The two primary theoretical predictions are: (1) agents self-select into early movers and followers, with the most confident becoming early movers; and (2) when compared to failed ventures, a lead investment is more likely to be followed by a lag in investment in funded ventures, often as large or larger than the lead.

The model is applied to actual entrepreneurial project investment data from Kickstarter, the world's largest crowdfunding website. Prominent projects funded on Kickstarter include Pebble Watch (a smartwatch), Oculus (a virtual reality gaming goggle), the film Veronica Mars, and Coolest Cooler (a multi-function cooler) (e.g., Pebble Watch raised more than $20 million and Oculus raised $2.4 million, ten times the original goal of $250,000). The majority of projects on Kickstarter, however, are more modest, with a median funding goal of $5000: they are typically launched by designers, artists, makers and others. Backers pledge money for projects in exchange for in-kind rewards brought forth by successful execution of the project. On Kickstarter, projects are not funded unless a pre-specified monetary goal is reached by the end of the designated funding term, typically 30 days. Early investments can also be viewed by others who decide whether or not to pledge funds. I construct a unique date set that documents the investment dynamics of almost the entire universe of projects that were posted on Kickstarter between February 2012 and February 2016. A more comprehensive description of the data is in Section 3.

The predictions of the theory are tested empirically and are borne out by Kickstarter data. Specifically, funded projects have high lead investment and even higher follow-on investment than unfunded projects. When Lead and Lag periods are defined as the first and second halves of the funding term, respectively, an average funded project has a Lead pledge amount of $3,939, whereas an average unfunded project has a Lead pledge amount of $710. Moreover, the majority of funded projects are back-loaded, namely, the Lag pledge amount is more than the Lead pledge amount; 75% of the unfunded projects are front-loaded. The regression results show that for a funded project, the Lag pledge amount is expected to be 1.1 times its Lead pledge amount; for an unfunded project, the Lag pledge amount is only 0.4 times of the Lead pledge amount. The pattern that funded projects are more back-loaded than unfunded projects is robust to a number of controls and different durations of Lead and Lag periods. Allowing the definitions of the Lag period to vary from the last 90% of the funding term to the last 10% of the term does not change the fundamental result that the expected ratio of the Lag pledge amount to the Lead pledge amount is higher for funded projects than for the unfunded. There is also regression evidence that early investors have a higher willingness to pay for the same product than investors who pledge after the goal is met, consistent with the prediction that early movers are those who have higher expected payoffs from having the project funded. Additional implications that relate to factors that affect the incentives of early movers and the impact of early investment outcomes on followers, such as available public information and whether the opportunity to invest is limited, are also tested and found to hold.

An important ingredient in this investment setting is learning, but learning is insufficient to explain why some investors commit early when the opportunity to invest later remains open.[3] Absent a need for collective action, it does not pay to lead, because waiting provides investors with opportunities to learn. Therefore, it is never beneficial to be the first one to commit funds. In the light of this reasoning, a natural outcome is that interested investors would prefer to wait until the last minute to decide whether to pledge. Other than this learning scenario, another benchmark case has collective action but no informational value from others' actions. In this situation, investors' investment decisions should be independent of each other. If the investor likes the venture, she will pledge for it. She can make the pledge any time and there is no strategic advantage with regard to when she pledges. The dynamic investment pattern in this scenario hinges on the stochastic arrival of investors and ventures into the market. In this case, it is natural that when a venture first comes

[3] In social learning models with endogenous timing of actions, it is often assumed that there is asymmetric information and agents receive payoff whenever action is taken. The typical result is agents delay actions. For example, Gul and Lundholm (1995) presents a model where agents choose when to act, which gives the appearance of an information cascade – delayed and clustered action. Zhang (1997) and Grenadier (1999) both consider a model of continuous-time endogenous sequencing game with asymmetric private information and derive a unique, pure-strategy equilibrium where a *delayed* informational cascade always occurs – agents strategically delay investment, hoping to observe the actions of others in order to make a better decision, difference between the two being whether the precision of signal is common knowledge and whether the underlying uncertainty is static or a stochastic process.

into the market, a large stock of investors would see it immediately and decided whether to invest. The subsequent flow of new investors would then be smaller compared to the initial stock.[4] This implies in both funded and unfunded ventures, most investors should jump in early, with only a trickle of new market entrants investing later. In other words, this stochastic arrival theory always produces a front-loaded investment pattern, independent of final funding outcomes.

Neither of these two theories implies patterns consistent with the Kickstarter data. The model with learning and no collective action fails to account for commonly observed early actions. The other model without learning does not explain the differing investment dynamics for successfully and unsuccessfully funded ventures, or the back-loaded pattern commonly observed in the funded ventures. Only the combination of learning and collective action produces the observed empirical patterns. The need for collective action provides incentives for the investors with high enough valuations to convey their information to others by acting early, thereby motivating others to participate to increase the likelihood that a critical mass is reached.

My model also provides insights on the following phenomena:

1. In many documented cases, inventors freely shared knowledge with rivals, especially during the early stages of a new technology, even though this undermines the monopolistic position of the inventor.[5] For example, in 2014, Elon Musk of Tesla Motors opened up the electric car company's patents to all comers. This makes sense if the development of the technology or the market is conceived as a collective action problem.
2. People take political actions to influence the outcomes of a policy change.
3. Cooperation among financial institutions is a common feature of the equity issuance process, with syndicated underwritings in the U.S. dating back as far as an 1870 offering by Pennsylvania Railroad (Lerner (1994)). A successful early-round venture investment often involves multiple venture capitalists.
4. Threshold mechanism in fund-raising are common, especially when there is significant uncertainty or a need for community support. Some examples are:
   (a) Matching grants are popular funding mechanisms for social expenditures.
   (b) All-or-nothing funding schemes are commonly used on crowd-funding platforms (e.g.

[4] This is known as the stock-flow model in the search literature (McCall (1970); Diamond (1984); Mortensen (1986); Blanchard and Diamond (1992)).

[5] Refer to Bessen and Maskin (2009) and Bessen and Nuvolari (2014) for the documented cases.

Crowdpac, Kickstarter, Indiegogo, and many equity funding websites).

(c) Collective voting and consensual processes are often employed by angel groups in picking ventures.

The remainder of the paper is organized as follows: Section 2 presents the model. Section 3 describes the Kickstarter data and examines the predictions. Section 4 closes with concluding remarks. The Appendices provide a more elaborate version of the model, some proofs and additional empirical evidence.

2 The Model

A finite number of risk-neutral agents, $i = 1, 2 \cdots, N$, are interested in funding a venture that requires payment p from an individual investor. The unit value of the venture, V, can be high or low, $v \in \{v_L, v_H\}$, with a prior distribution $g(v)$ and $v_L < p < v_H$. Before the game, agents receive private signals, X, of the value of the venture. Conditional on V, X are distributed i.i.d. according to a conditional density $f(x|v)$ with the support $x \in [\underline{X}, \overline{X}]$. Suppose the likelihood ratio $\frac{f(x|v_H)}{f(x|v_L)}$ is non-degenerate, that is, $x \neq x' \Rightarrow \frac{f(x|v_H)}{f(x|v_L)} \neq \frac{f(x'|v_H)}{f(x'|v_L)}$. Without loss of generality, label the signals so that $x = \frac{f(x|v_H)}{f(x|v_L)}$.[6] Then, it follows that $f(X|V)$ has a monotone likelihood ratio property.

The venture is successfully funded if and only if at least $2 \leq M < N$ agents agree to fund it. [7]

Investment is open for two periods, $t = 1, 2$. In each period t, the actions of agents are denoted by $a_i^t \in \{0, 1\}$, with $a_i^t = 1$, meaning the agent commits to invest p upon successful funding of the venture. The action to pledge is irreversible: once an agent pledges, she cannot change her action, hence $a_i^2 \geq a_i^1$.[8] Actions are publicly observed. At the beginning of $t = 1$, all agents make the binary decisions, a_i^1, simultaneously. They either choose to pledge, $a_i^1 = 1$, or wait, $a_i^1 = 0$. At beginning of $t = 2$, those who have not pledged simultaneously choose whether or not to do so.

At the end of the game, all those who commit to a venture that is funded receive the same unit

[6]Other ways to label the signals include $x = E[v|x]$ or $x = \Pr[v = v_H|x]$.

[7]The coordination game setup is similar to the global game literature, with examples including Angeletos et al. (2007); Dasgupta (2007); Morris and Shin (2001); Carlsson and Van Damme (1993). The threshold mechanism is often used in settings of public good provision, where agents voluntarily contribute any non-negative amount of the private good they choose and the social decision is to provide the public good if and only if contributions are sufficient to pay for it. The contributions are refunded otherwise. See for example Bagnoli and Lipman (1989).

[8]An alternative to formulate this is to make it extremely costly to take back one's pledge. This assumption is not unrealistic in many of the investment settings where the involved agents care about their reputations as trust-worthy and consistent partners, especially when their investment decisions are made public.

value of the project, minus payment. Otherwise funding fails and no transaction takes place. The payoff from not pledging is always 0.[9] Agent i 's payoff, u_i, is thus given by

$$u_i(a_i^t, a_{-i}^t) = a_i^2(v-p)\mathbf{1}_{\Sigma a_i^2 \geq M}$$

Define $A^t = \Sigma a_i^t$ as the total number of agents that have pledged at the end of t. Because agents are symmetric, A^1 is a sufficient statistic of the first period action profile $\mathbf{a}^1 = (a_1^1, a_2^1, \ldots, a_n^1)$. In addition, because the individual investment amount, p, is assumed to be fixed, there is a one-to-one mapping from the number of agents who pledge to the amount of investment pledged.

Denote the information set of agent i at the beginning of period t as I_i^t, which consists only of her private signals at $t = 1$, combined with public information of the number of first-period actions at $t = 2$.[10] That is,

$$I_i^1 = \{x_i\} \in [\underline{X}, \overline{X}] \text{ and } I_i^2 = \{x_i, A^1\} \in [\underline{X}, \overline{X}] \times \{0, 1, \ldots n\}$$

A strategy for agent i, $\sigma_i^t : \mathcal{I}_i \to [0,1]$, maps his information set to a pledge probability, with the restriction that $\sigma_i^2(\cdot) = 1$ for an agent who has already pledged at $t = 1$.[11]

A strategy profile in the game is a vector $\sigma = (\sigma_1, \ldots, \sigma_n)$, in which $\sigma_i = (\sigma_i^1, \sigma_i^2)$.

Each agent maximizes her expected payoffs as estimated on the basis of her own signal, observations of the other agents' actions, and the initial prior probability assessment.

The setup attempts to capture a number of features that are common in crowdfunding, early-round venture investing and IPO underwriting. In these settings, information is aggregated from

[9] By doing so, I abstract away from various other sorts of utility gains such as helping a venture succeed. Instead, the only return comes from the proceeds generated from execution of the project for the investor. It is a pure common value setting and sources of uncertainty come from both the expected value of the venture, as well as whether the venture can be successfully funded. A contrasting problem with pure private value is presented in Liu (2015). In that paper, there is lump-sum cost associated with taking an action. Uncertainty comes from whether the collective action will be successful, while every agent knows with certainty his payoff upon the success of the collective action.

[10] I assume that the information available to an agent is his own private signal, plus the observed actions (investment decision) of other agents. The assumption that information transmission is accomplished entirely through actions, and not words, is based on the belief that only (irreversible or costly) actions are truly believable, and that communication mechanisms such as social media, media coverage and information disclosures are not credible. The assumption is also quite common in the literature, see for instance Banerjee (1992); Bikhchandani et al. (1992); Grenadier (1999); Kricheli et al. (2011); Murto and Välimäki (2011).

[11] Murto and Välimäki (2011) studies information aggregation in a stopping game with uncertain payoffs, in which agents' strategies are a mapping from their own private experiences as well as publicly observed history. The context is similar whereas there are many crucial distinctions: foremost, there is no collective action in their game – the types of other agents are payoff relevant to mine only through correlated types, thus they are merely informational.

diverse investors, moves are often sequential, learning occurs and it is common for success to be contingent upon achieving certain fundraising targets.[12]

In what follows, the equilibrium concept used is symmetric pure-strategy monotone equilibria, that is, symmetric perfect Bayesian equilibria in pure strategies in which conditional on having not pledged, the action an agent takes at t, denoted by $a_i(x_i) \in \{0, 1\}$, is nondecreasing in his private signals x_i. It is natural to look at monotone equilibria because by the choice of labels, the posterior probability that the venture is a worthy investment is increasing in x. The focus is on the interesting equilibrium wherein there is a positive probability that some agents make an early move.[13] From now on, for brevity, call those the *Coordinated Equilibria.* A formal definition is given in the next section 2.1.

In the *Coordinated Equilibrium*, all actions in the support of $\sigma_i^t(I_i^t)$ are the best responses to σ_{-i} for all i, for all I_i and t. Sequential rationality restricts individuals to use Bayes' rule to update based on the value of the venture, taking into account the other agents' strategies, their beliefs at different stages of the game, and the common priors on nature's actions.

As observed earlier, $f(X|V)$ satisfy monotone likelihood ratio property (MLRP). The implications of this condition have been developed extensively in the literature. In particular, monotone likelihood ratio and i.i.d draws of signals imply that the value V, and the signals $X_1, \dots X_n$ are *affiliated*, a concept used often in settings with interdependent values.[14] The following theorems from Milgrom and Weber (1982) on properties of affiliated variables are used later.

Let $X_{(1)} > \cdots > X_{(N)}$ be the order statistics of the agents' signals ranked by their likelihood ratio. Of central importance to any given agent is the distribution of the signals of the others. Without loss of generality, the argument is focused on agent 1, with $Y_1 > \cdots > Y_{N-1}$ denoting the

[12]Interactions of information, collective action and sequential move are also explored in Ali and Kartik (2012), Cong and Xiao (2018), and Deb et al. (2019), where the timing of the move is exogenous. Brown and Davies (2019) analyzes financing Efficiency with all-or-nothing financing mechanism in a static setting. Akerlof and Holden (2016) and Akerlof and Holden (2019) focus on how social connections of the entrepreneur and investors matter for venture's funding success, respectively.

[13]There are some uninteresting pure-strategy monotone equilibria due to the nature of coordination games, such as the one in which no one invests on the equilibrium path at any time and each player believes that no one would. A different way to rule out equilibria of this sort is to evoke intuitive criterion or restrict strategies to be weakly undominated. But essentially, the purpose is to restrict attention to only equilibria where early action is possible on the equilibrium path.

[14]A definition for affiliation is, for all $\boldsymbol{x}, \boldsymbol{x}' \in [\underline{X}, \bar{X}]^n$, and for all $v, v' \in \{v_L, v_H\}$,

$$f((v, \boldsymbol{x}) \vee (v', \boldsymbol{x}'))\, f((v, \boldsymbol{x}) \wedge (v', \boldsymbol{x}')) \geq f(v, \boldsymbol{x}) f(v', \boldsymbol{x}'),$$

where $\vee$denotes the component-wise maximum, while $\wedge$ denotes the component-wise minimum.

order statistics of $X_2, \dots X_N$.

Theorem 1. *If $V, X_1, \dots X_n$ are affiliated, and X_i are exchangeable,*[15] *then $V, X_1, Y_1 \dots, Y_{n-1}$ are affiliated.*

This theorem provides a property of the distribution of order statistics of affiliated variables.

Theorem 2. *If $Z_1, \dots, Z_k$ are affiliated, then $Z_1, \dots, Z_{k-1}$ are affiliated.*

Affiliation holds for any subset of variables.

Theorem 3. *Let $Z_1, \dots, Z_k$ be affiliated and let H be any nondecreasing function. Then the function h defined by*

$$h(a_1, b_1; \dots, a_k, b_k) = E[H(Z_1, \dots, Z_k) \,|\, a_1 \leq Z_1 \leq b_1, \dots, a_k \leq Z_k \leq b_k]$$

is nondecreasing in all of its arguments. In particular,

$$h_l(z_1, \dots, z_l) = E[H(Z_1, \dots, Z_k) \,|\, z_1, \dots, z_l]$$

for $l = 1, \dots k$ are all nondecreasing.

Theorem 3 shows that *affiliation* is a way of strengthening positive correlation to fine details. There is positive dependence not just on average but also locally.

2.1 Equilibrium Analysis

In the model, each agent has only an imperfect signal of the venture's value and thus will benefit from knowing others' signals before making the investment decision. The primary question is: in equilibrium, will some agents be willing to commit early? And if so, why? In this subsection, I derive the equilibrium for the collective investment game.

First and foremost, note that the *Coordinated Equilibrium* requires monotone pure strategies, which is equivalent to agents using cutoff strategies with respect to their private signals. We thus have the following definition,

[15] The joint distribution of $V, X_1, \dots X_n$ is invariant under permutation of the indices of the sequence $X_1, \dots X_n$.

Definition. Any *Coordinated Equilibrium* of the game is characterized by a first period cutoff x^1 and a vector of second period cutoffs $\mathbf{x}^2$ with $x^1 \in [\underline{X}, \overline{X}]$ and $\mathbf{x}^2 = (x^2(0), x^2(1), \ldots, x^2(N)) \in \{-\infty\} \cup [\underline{X}, \overline{X}]^{N+1} \cup \{+\infty\}$, such that

- At $t = 1$, an agent invests if $x_i > x^1$ and waits if $x_i < x^1$;
- And suppose A^1 agents invest at $t = 1$, then at $t = 2$, the rest of agents invest if $x_i > x^2(A^1)$ and do not invest if $x_i < x^2(A^1)$.

The following regularity conditions on the payoffs are imposed.

Assumption 1. *Regularity Conditions on the Payoffs:*

1. $E[v|X_i = \bar{X}] < p$;
2. $E[v|X_{(M)} = \bar{X}] > p$;
3. $E[v|X_i, \{X_j\}_{j \neq i}]$ *is continuous in* X_i *and* X_j, $\forall j \neq i$.

These conditions are innocuous. Recall M is the number of investors needed for the venture to be funded. Condition 1 says the expected net payoff of the venture estimated with the best possible private signal is negative and thus no investor is confident enough to act alone. Condition 2 says that if at least M agents have received the best possible signals, the expected net return of the venture is positive. Otherwise, the venture can never be funded. Condition 3 is a continuity assumption. These regularity conditions ensure the existence of a *Coordinated Equilibrium.*

The first lemma shows that if in the first period, agents follow cutoff strategy with a signal threshold x^1, then in the second period, there is a unique subgame equilibrium.

Before deriving this formally, here is the intuition. With the public information and common knowledge of first period strategy, agents update their beliefs, which are strictly increasing in their private signals. Given any symmetric strategy profile in this subgame, the agents' belief of funding success is also increasing. Hence agents' incentive to invest is higher with higher private signals.

To capture this, define:

$$v(x; x^1, A^1) = \begin{cases} E[V|X = x, Y_{A^1} \geq x^1, Y_{M-1} \geq x] & A^1 \leq M-2 \\ E[V|X = x, Y_{A^1} \geq x^1] & A^1 \geq M-1 \end{cases}$$

Lemma 1. *The unique Coordinated Equilibrium of the subgame in which it is public information that* A^1 *agents have signals* $x \geq x^1$, *is characterized by a cutoff* $x^\star(x^1, A^1)$ *such that:*

1. *For all x, $a(x) = 1$ if $x > x^\star$ and $a(x) = 0$ if $x < x^\star$;*
2. *$x^\star$ is one of the following:*
   (a) *$x^\star(x^1, A^1) = \{+\infty\}$, namely, for all x, $a(x) = 0$, if $v(\bar{x}^1; x^1, A^1) < 0$;*
   (b) *$x^\star(x^1, A^1) = \{-\infty\}$, namely, for all x, $a(x) = 1$, if $v(\underline{X}; x^1, A^1) > 0$; and*
   (c) *Otherwise, $x^\star(x^1, A^1)$ satisfies $v(x^\star; x^1, A^1) = 0$.*

Proof. A key step in the proof is to show that $v(x; x^1, A^1)$ is strictly increasing in x. It follows from MLRP and Theorem 1, 2 and 3. The essential idea is that $E[V|X_1, \ldots, X_N]$ strictly increases in each X_i, due to the strictly affiliation of (V, X_i) conditional on any subset of $\{X_j\}_{j \neq i}$. The rest of the proof is straightforward and thus omitted. The uniqueness of this subgame may be surprising given the setting of collective action. □

Next, use backward induction to determine the first period cutoff. Let $\pi^1(I_i, a^1; \{x^1, \mathbf{x}^2\})$ denote the expected payoff at $t = 1$ of an agent with information set of I_i taking action $a^1 \in \{0, 1\}$ given the cutoffs $\{x^1, \mathbf{x}^2\}$ and corresponding beliefs induced by the strategy profile σ_{-i} . Let $\Delta\pi^1(x_i; \{x^1, \mathbf{x}^2\}) = \pi^1(I_i, 1; \{x^1, \mathbf{x}^2\}) - \pi^1(I_i, 0; \{x^1, \mathbf{x}^2\})$ denote the expected payoff difference of investing rather than wait at $t = 1$. The following result characterizes the set of *Coordinated Equilibrium* for the entire game.

Lemma 2. *The strategy $\{\sigma(\cdot)\}$ is a Coordinated Equilibrium if and only if there exists a set of cutoffs $\{x^1, \mathbf{x}^2\}$ such that:*

1. *At $t = 1$, $a^1(x_i) = 1$ if $x_i > x^1$ and $a^1(x_i) = 0$ if $x_i < x^1$, in which x^1 solves $\Delta\pi^1(x^1; \{x^1, \mathbf{x}^2\}) = 0$;*
2. *$x^2(A^1) = x^\star(x^1, A^1)$ as given by Lemma 1 ;*
3. *Beliefs are pinned down by Bayes' rule.*

Proof. Given Lemma 1, one only need to demonstrate that given the strategy profile, agent's first-period strategy is optimal. It is equivalent to show that when the cutoff agent is indifferent between pledging now and waiting, those above have strict preference to pledge while those below would rather wait. This is assured by the fact that $\Delta\pi^1(x; \{x^1, \mathbf{x}^2\})$ is strictly increasing in x, which is a result of MLRP and Theorem 1, 2 and 3. □

This result provides the main rationale that differentiates leaders from followers. It is the formal demonstration of the intuition given in the introduction. Note that both collective action and learning are required.

Proposition 1. *A Coordinated Equilibrium always exists.*

Proof. The existence of a Coordinated Equilibrium follows from the fact that at least one such equilibrium that is characterized as in Lemma 2 can always be constructed. Let $\hat{x} \in (\underline{X}, \overline{X})$ be the solution to $E[v|X_{(M)} = \hat{x}] = p$, and $\hat{\mathbf{x}}^{\mathbf{2}}$ calculated by Lemma 1.[16] To prove this is an equilibrium, I just need to establish that $\Delta\pi^1(\hat{x}; \{\hat{x}, \hat{\mathbf{x}}^{\mathbf{2}}\}) = 0$, namely, $\hat{x}$ is indifferent between pledging early or waiting. The proof is as follows:

Suppose agent i's private signal is $\hat{x}$, and she chooses to wait. Let A' denote the number of other agents $j \neq i$ with $x_j \geq \hat{x}$ (from i's perspective this is a random variable). There are three possible first period outcomes from i's perspective: (i) $A' < M-1$; (ii) $A' = M-1$; or (iii) $A' \geq M$. In the event of the first or third outcome, i 's action does not affect the final funding outcome, so i would have done equally well to pledge early. In (i) the funding will not be successful because no one would follow, so it doesn't matter that i pledged for the venture, and in (iii) funding will be successful and rightly so, regardless of when agent i pledge. However, in case (ii), agent i is pivotal in determining the final funding outcome. Yet meanwhile, he is indifferent whether the funding is successful or not, because his expected payoff of this venture conditional on being the pivotal investor is exactly 0. □

The *Coordinated Equilibrium* has a simple structure. Agents who receive $x_i > x^1$ pledge at $t = 1$, whereas the remaining wait until $t = 2$ to make the decision. In the second period, those less enthusiastic agents base their investment decision on first period outcome A^1, and there is a path-dependent threshold only above which certain agents are willing to follow suit. As a signaling game, it may have multiple equilibria.[17]

This simple model illustrates several general principles.

[16] A solution to $E[v|X_{(M)} = \hat{x}] = p$ is assured by the three regularity conditions given in Assumption 1.

[17] By definition, on the equilibrium path of a coordinated equilibrium, early action happens with positive probability. One may ask: Is there a perfect Bayesian Nash equilibrium where everyone wait and invest in the second period, making it essentially a one-shot investment game? The answer is a yes, if somewhat unreasonable off-path beliefs are allowed. For example, the strategy profile that no one moves in the first period, and in the second period, those and only those with signals higher than $\hat{x}$, the solution to $E[v|X_{(M)} = \hat{x}] = p$, pledge, with the belief that any early action is a mistake and no information should be inferred from it is such an equilibrium. It can be shown that no one wants to deviate from the equilibrium strategy, in particular, no one will want to go in early when the early action is not informational.

First and foremost, agents self-select into leaders and followers, with the most optimistic agents endorsing the ventures early.[18] Particularly, the early investment plays two roles. First, early investment pushes the total toward the critical mass. Second, early investment provides the informational public good on the quality of the venture.[19]

Moreover, different from the conventional wisdom that collective action leads to free-riding and under-provision, the analysis here reverses that intuition. The need for collective action provides enhanced, rather than reduced incentives to initiate a move. The logic is this. Collective action creates the signaling incentive highlighted before: First movers are essentially saying, "I like the venture and I want you to know it." An agent with good private information wants to convey that information to influence others who will not invest unless someone else leads. Furthermore, in equilibrium, once it is expected that agents with good signals go in, they must go in early. However, there is another subtler effect. Notice the agents who go in early do not know with certainty that the venture is a good one. They have a private estimate, but the estimates are not required to be positive. The fact that funding is successful only when a sufficient number of agents invest emboldens an individual to participate because consensus among many agents is a testament to the quality of the investment. This threshold mechanism motivates agents to pledge, even if individually agents may have concerns about the payoff.

Obviously, the strength of this second effect is governed by parameters of the problem, notably, the level of funding goal. Here, the entrepreneur's strategic actions are not modeled. The funding goals are taken as exogenous, thus are independent of the quality of the venture. Otherwise, the level of the funding goal may be a signal of the expected payoff. Still, somewhat surprisingly, a higher goal makes investors more inclined to pledge because success only contingent on consensus of interest serves as "insurance" and reduces individual investor's concern of funding a venture as a result of overestimating its value. This is not to say a higher goal necessarily leads to higher probability of funding success, which suggests a tradeoff in choice of funding goal and is for future investigation.

In this model, the need for collective action is built in. It can be interpreted as individual investors having budget constraints or diversification concerns such that they cannot afford all the

[18] Unlike Lohmann (1994), Grenadier (1999) or Kricheli et al. (2011), sorting is not through variation in information informedness.

[19] A similar discussion can be found in Andreoni (2006).

required financing. However, the analysis suggests that there could be informational reasons as to why no investor wants to act alone, thus the institution of collective investment plays an economic role. In reality, acting alone could be even worse due to adverse selection and winner's curse. Indeed, the existence of *Coordinated Equilibrium* under the condition $E[v|\bar{X}] < p$ speaks to why funding is collective in the first place. If funding does not allow for cooperation among M investors, with more precise assessment made possible by pooling many private signals, the venture will never be funded. Note this is a result of imperfect information, not of risk aversion. The implication is that in a decentralized funding setting, threshold funding mechanism should be common.

Summarizing, there are two aspects to the agents' decisions: The first is whether to pledge or not and the second is when should the pledge be made – early or later. Those who receive positive signals have an incentive to pledge. The fact that pledges only turn into actual payments only when a sufficient number of investors hold positive views increases the incentives to pledge. The reason that some pledge early rather than waiting is that this will influence others to follow.

There is a continuous-time analog of this collective investment game included in the Appendix A for interested reader. In the equilibrium, agents with higher signals pledge early. As a result, agents know that by pledging at the equilibrium specified time, they disclose their signals perfectly to the other agents and are willing to do so to affect the final outcome. Consequently, the continuous time version of the model provides similar results and intuition to the one exposited above.

2.2 The Likely Pattern of Investment

In what follows, I derive some properties of the *Coordinated Equilibrium* that speaks to the likely pattern of investment, which will be examined empirically.

The existence of the *Coordinated Equilibrium* indicates that leaders are common given the need of collective action, even without any direct payment to acting early. The impact of the early movers on followers is characterized by,

Corollary 1. *In any Coordinated Equilibrium characterized by* $\{x^1, \mathbf{x}^2\}$, $x^2(A^1)$ *is non-increasing in* A^1.

Early pledges make agents more likely to follow. The proof is omitted. Mathematically, this is guaranteed by the fact that binomial distribution $B(N; p)$ has MLRP in p. Intuitively, when many jump in early, potential investors infer that others have received good signals about the venture, which boosts their confidence about the venture. Some of the dispersed private information is pooled and partially revealed through the number of lead investors or the level of lead investment. Since the private information is correlated with the true value of the venture, this yields more probable financing of good ventures and weeds out bad ones, especially when there is a large crowd of investors.

Under this rationale, some ventures will not attract any followers because the initial investment falls short of the amount needed to signal high expected return, and thus fail to be funded. However, ventures with better, but still modest openings can succeed when there is a large enough pool of agents willing to invest. The investment patterns of successful and unsuccessful ventures are different. This result is formalized in Proposition 2.

Proposition 2. *Timing pattern varies with whether the venture is eventually funded:*

- *There exists an equilibrium with the property that* $E[\frac{A^2-A^1}{A^2}|A^2 \geq M] > E[\frac{A^2-A^1}{A^2}|A^2 < M] = 0$.
- *A sufficient condition for all equilibria to have the property that* $E[\frac{A^2-A^1}{A^2}|A^2 \geq M] > E[\frac{A^2-A^1}{A^2}|A^2 < M]$ *is* $Prob[A_1 = A_2|A_2 < M] + \frac{1}{2}Prob[A_1 < \frac{1}{2}A_2|A_2 \geq M] > 1$.

Proof. In the Appendix. □

Recall A^1 is the number of lead investors, and A^2 is the number of total investors. The ratio of followers to the sum of all investors for the venture, $\frac{A^2-A^1}{A^2}$, measures the degrees of back-loading. If many investors have positive assessments of the venture, then there is a large amount of lead investment, and even more following, as many investors become confident and willing to pledge. Conversely, if there are few investors with positive assessments of the venture, then there is a small amount of lead investment and even less following. Proposition 2 states that the investment pattern for compared to unfunded ventures, successfully funded ventures in general have a bigger fraction of lag investment. The condition required is (a) effective signaling: a large fraction of ventures fail because the first period investment outcome falls below the level that makes the stand-by investors confident to follow, and (b) the prior is low enough that only investors who have sufficiently high signals jumps in first, and thus the number of early movers are usually small.[20]

[20] Because the total number of investors are fixed, at certain point, the first period and the second period investment become substitutes. For example, suppose $\exists \overline{A} < n$, s.t. $x^2(\overline{A}) = \underline{X}$, namely, if the early investment is equal or

This result is non-trivial. It is true that conditional on the first period, successfully funded ventures will always have larger follow-on investments, even if there is no learning in the second period. But unconditionally, this does not always hold. For example, if investors have private value and do not learn from others' action, they are indifferent between pledging early or later. Then the two periods are completely symmetric and thus the fraction of lag investment is half in either funded or unfunded ventures.

To summarize, funded projects tend to have high lead investment and a bigger fraction of lag investment than unfunded ones. This is the main prediction to be tested in the next section. This prediction is in sharp contrast with models with only learning or only collective action. Specifically, absent the need for collective action, no agent pledges early. It is better to wait for information to be revealed by others' actions. On the other hand, if there is no benefit to learn from others' actions, then there is no incentive to wait, no causal relationship between the lead investment and the lag investment and thus no differing pattern between funded and unfunded ventures. Both collective action and learning are the essential ingredients of the model.

Lastly, because the information conveyed by the early action is interpreted taking into account the equilibrium strategies, it is the number of early movers relative to the expectation that affects followers. A given number of pledges has a greater impact on followers when the expected number of lead investors is low than when the expected number is high. This result is summarized in Proposition 3.

Proposition 3. *For any two Coordinated Equilibria, characterized by* $\{x^1, \mathbf{x}^2\}$ *and* $\{\tilde{x}^1, \widetilde{\mathbf{x}}^2\}$ *respectively, if* $x^1 < \tilde{x}^1$*, then either* $x^2(A^1) > \tilde{x}^2(A^1)$ *or* $x^2(A^1) = \tilde{x}^2(A^1) \in \{-\infty, +\infty\}$, $\forall A^1$.

Proof. In the Appendix. □

The result will not be tested directly, but the same reasoning will be used in the additional empirical tests on factors that affect the relative size of induced follow-on investment.

greater than $\overline{A}$, everyone follows in the second period. Hence $A^2 \equiv n$ for $A^1 \geq \overline{A}$. It is clear that in this region, as A^1 increases, $A^2 - A^1$ decreases (by the same units). The regularity condition essentially restricts the probability of realizations falling into this region.

2.3 Discussion

There are a number of implications that have been suggested by this model. The basic prediction is that even when there is no benefit of pledging early, lead investment is common. More early investors, and thus more early investments, draw in more investments in the later stage, making the funding more likely to succeed. The model predicts that projects that start weak, with low initial investment, typically have less follow-on action than those that begin strong. Therefore, as compared to projects that fail to meet the funding goal, successfully funded projects tend to have more early investors, higher levels of total lead investment and are also more likely to be back-loaded. It is also implied that lead investors are those with good private signals and are most eager to have the project funded. Additionally, a given early investment outcome has a greater positive impact on followers when the expected number of lead investors is low than when the expected number is high.

The motivation for investing early comes from the fact that those with positive signals want to influence others to follow. Those who follow do so because the inference that they draw from early pledges is relevant to them as well since the project's value to one agent is not independent of that to another agent. Early moves do not result from differences in risk aversion (which are assumed away), nor do they result from different amounts of information. All agents receive a signal initially, albeit varying across agents. Even if risk aversion and different amounts of information are introduced, agents will still wait as long as they can, so they can learn from others. The need for collective action is a necessary ingredient to induce individuals to move early.

3 Empirical Analysis

A unique data set from the crowdfunding website, Kickstarter, is used to examine the theoretical predictions discussed above. This section proceeds as follows. First, I describe the Kickstarter settings and the data set. Then, I test the main prediction that successfully funded projects are more back-loaded. Lastly, I present evidence consistent with the implications on who moves early and the impact of early investment outcomes on followers, as suggested by the model.

3.1 Kickstarter

Based in the U.S., Kickstarter is the world's largest reward-based crowdfunding platform. The company was launched on April 28, 2009; as of September 24, 2017, more than 373,000 projects have been launched on the platform, receiving $3.3 billion pledged funds from 13 million backers. Currently, Kickstarter is open to entrepreneurs from 22 countries and backers from all over the world.

To raise a fund for a project on Kickstarter, an entrepreneur (the "creator") creates a webpage on the platform that typically contains information on the product, the entrepreneur, the use of funds, the relevant risk, and a list of rewards options that correspond to different contributing amounts.[21] The creator also sets a monetary funding goal and a funding deadline. Within the project's launch and end date, a "backer" can choose a reward to his liking and pledge money in exchange for that particular reward upon successful funding of the project. The creator specifies the minimum amount of pledge for a particular reward, but backers can contribute more if he or she pleases. Rewards vary across projects, ranging from project partials, such as gifts, early samples, product parts, to the full final product eventually brought forth by the creator. Backers do not receive equity in the project. As funding proceeds, all those who visit an active project's webpage can also see the current funding status (e.g. funds raised, total number of backers, and the numbers of backers that have pledged for each type of reward), and the number of days remaining until the funding term expires (see Figure 1).[22] On Kickstarter, projects are grouped into 15 categories: Art, Comics, Dance, Design, Fashion, Food, Film and Video, Games, Journalism, Music, Photography, Publishing, Technology, Theater and Crafts. There is a great diversity as to what the projects are about, but the common thread is that they are creating something that can be shared with the backers. More characteristics of the projects are provided in the descriptions of the data set in the next subsection.

Two important features of Kickstarter render it an ideal testing ground for the theory. The first is the threshold mechanism, called the "all-or-nothing" funding scheme on Kickstarter. Only if the total pledges reach or surpass the funding goal by the end of the project's funding term, the backers

[21] For instance, a book project may have two rewards options upon completion of the project: a of $25 minimum for an electronic copy and a $50 minimum for a hard copy. A project can also offer just one reward option.

[22] To help potential backers discover projects they want to support, Kickstarter also has a number of search options. In particular, projects can be sorted based on the first week after their initial launch ("Recently Launched"), last week before the project funding closes ("Ending Soon"), or popularity (based on the number of backers recently added to a project).

are charged and the entrepreneur gets all the pledged money minus Kickstarter's commission (5%) and payment processing fees. Otherwise no money pledged by any backer is transferred to the project creator. Second, a project can receive contributions after the funding goal is met, up until the project's funding deadline.[23]

In addition, the payoff of investing on Kickstarter is uncertain. The uncertainty lies in the lack of knowledge about a project's value, including the quality of the product and whether the creator can deliver the promised rewards. Unlike traditional entrepreneurial finance, where the high level of information asymmetry is mitigated by close relationships between investors and entrepreneurs, a crowdfunding website such as Kickstarter mainly provides a platform for funders and entrepreneurs to match. Kickstarter does not engage in the screening, pricing, or monitoring of entrepreneurs' projects. The site also makes clear that an estimated 9.95% of successfully funded projects fail to deliver the promised rewards (Mollick (2015)). This highlights the intrinsic nature of crowdfunding that leverages the collective information produced by the crowd (see for example Agrawal et al. (2013), Kim and Viswanathan (2013) and Schwienbacher and Larralde (2010)).[24]

3.2 Project Funding Data

Data for this study come from publicly available information on the Kickstarter website and Kicktraq, the website that tracks the funding dynamics of Kickstarter projects.[25] The dataset that I developed for this paper contains both project characteristics and daily aggregate investment information throughout the funding term of almost the entire universe of projects that were posted

[23]Pledges are only charged at the end of the project's funding term if the goal is met. In theory, backers can cancel their pledges as long as it's not within the last 48 hours and won't make it below funding. In practice, anecdotal evidence suggests that the cancelation rate is around 5%.

[24]Even though Kickstarter makes it clear that it is not a store and added the "Risks and Challenges" section in Sep 2012 to reinforce that creators' projects are in development, some use Kickstarter partially as a trial marketing program. The interest shown on Kickstarter is sometimes used by entrepreneurs as evidence of market success when they seek funding later elsewhere.

[25]The web pages of projects launched on Kickstarter are permanently archived and are accessible to the public. After funding term is completed, projects and uploaded contents cannot be edited or removed from the site. Hence the project characteristics data can be collected directly from Kickstarter website. Figure A.1 provides a sample page of an archived project. However, because Kickstarter does not show the full list of finished projects from its search results and discover interface, the collection of projects is retrieved from Kicktraq.com. Kicktraq is a crowdfunding analytics and discovery platform, and tracks projects that are launched on Kickstarter, even after they fail. It goes through all the active projects on Kickstarter, turns the updated data to a visualization of the funding progress of any campaign on the site, with a graphic illustration as presented in Figure A.2. The illustrations were extracted from Kicktraq and the text are recognized from them using a script. Once the list of projects and their dynamics are gathered from Kicktraq, a second scraper is deployed to collect detailed data from individual projects on Kickstarter website. The final data set contains only projects from two sources with matched duration.

on Kickstarter between Feb 2012 and Feb 2016. To the knowledge of the author, this is the most comprehensive reward-based crowdfunding panel data compiled so far.

For the purpose of the empirical analysis, cancelled and suspended projects are ignored; only projects that have completed their full funding term are considered. Also deleted are projects with fewer than two backers.[26] That leads to a data set of a total of 83,621 projects, 2.5 million project-day observations. However, some projects on Kickstarter have a limited number of rewards, therefore a quota on the number of backers that can be accepted. A quantity limit creates a rationale for early moves. These 50,319 projects with limited number of rewards are excluded from the main analysis, which focuses on the subset of all the projects that provide no direct payment to early movers. The goal of using this reduced dataset, the main sample of the empirical analyses, is to focus on those projects that, absent incentives for collective action, would provide no rationale for early moves. The main sample contains 33,302 projects, with 17,165 funded and 16,133 unfunded.[27]

Descriptive statistics for the main sample are reported in Table 1. Panel A presents the summary statistics of the time-invariant characteristics of the projects. There is a considerable amount of variance in the funding goals of Kickstarter projects. For the whole subset, the average funding goal is \$32,712, and the median is \$4,500. The distribution of funding goals is rather skewed with a long right tail. The duration of a funding term is typically around one month. Comparing the time-invariant characteristics of the funded with those of the unfunded projects gives a rough idea of which characteristics may be associated with funding success. Funded projects have on average much lower funding goals than unfunded ones.[28] Somewhat surprisingly, conditional on having a Facebook profile linked to Kickstarter, funded entrepreneurs tend to have fewer Facebook friends.[29] Characteristics that are similar to both funded and unfunded projects include the duration of the funding term, the length of project description, the number of reward options, the choice of whether

[26] The preliminary matched data set from two sources contains 120,157 projects. Removing 11,990 projects that have canceled or suspended the fundraising, 12,155 projects that end with no backer or pledge, and 12,391 projects that have either one or two backers, leaves us with 83,621 projects. Since the dynamics of backer behavior is the primary interest, projects with zero backers will not contribute any information to the analyses. To reduce the idiosyncrasy of backer behavior, only projects with at least three backers are considered.

[27] Projects in this subset are largely similar in terms of project and entrepreneur characteristics to those that provide benefit for pledging early, even though the funding dynamics and outcomes of the two samples are quite different. This difference in funding dynamics will be explored in one of the empirical tests in the next section.

[28] The mean funding goal of a funded project is \$5,490 whereas that of an unfunded project is \$56,582. The difference in median funding goals of the two groups is smaller, with the funded projects having a median of \$2,500 and the unfunded projects \$10,000.

[29] On average, an entrepreneur who project is funded has 352 Facebook friends and entrepreneur whose project fails to be funded has 483 Facebook friends.

to use videos, the number of projects the entrepreneur has created, the length of entrepreneur biography, and the number of projects the entrepreneur has backed on Kickstarter.[30] Overall, the statistics suggest that *ex ante*, the funded and unfunded projects look similar, except that some entrepreneurs are too ambitious in setting a funding goal that may result in the failure to be funded. The final funding outcomes of the two groups, however, are very different, as reported in Panel B. On average, a funded project attracts 118 backers, whereas an unfunded has merely 17 backers. The mean pledged dollar amount is also much higher for a funded project than for one that fails to be funded ($9,026 compared to $1,165). Defined by total pledged amount divided by funding goal, the mean pledge ratio for a funded project is 7.1 and the median is 1.12, suggesting a small number of projects are extremely successful and vastly over-subscribed. For unfunded projects, many received little investment, with a mean pledge ratio of 0.11 and a median of 0.05. The average pledged amount per backer is $70; the amount pledged is also higher for funded projects ($84) than for unfunded projects ($55).

To characterize the funding dynamics of the projects, Lead and Lag periods are thus defined as the first and second halves of the funding term, respectively. The Lead pledge corresponds to the total dollar amount pledged in the Lead period, and the Lag pledge corresponds to the total dollar amount pledged in the Lag period. Table 2 presents the summary statistics of the funding outcomes of the Lead period, including the Lead pledge, the number of backers, and the proportion of funding goal achieved. Also included is the variable "Lead ratio", defined as the ratio of the Lead pledge to the total pledge. It is clear even by halfway through the funding campaign that the eventually funded projects on average perform much better in every respect than the unfunded ones. They have more backers, more pledge amount and attain a larger proportion of the goal.[31] It is also evident that the funded projects on average have more Lag pledge than Lead pledge (the Lead ratio is 0.47), whereas the unfunded projects typically have less (the Lead ratio is 0.69). The Lead and Lag pledges of the average funded and unfunded projects are compared in Figure 2, the number

[30] A funded project typically has a funding term of 31 days, 521 words in the project pitch, 7 types of rewards, 78% chance of using videos and displays a biography of 63 words. Funded entrepreneurs on average have backed 3.37 projects on Kickstarter and have previously created 1 projects. Very similarly, an unfunded project typically has a funding term of 35 days, 554 words in the project pitch, 7.5 types of rewards, 74% chance of using videos and displays a biography of 65 words. Unfunded entrepreneurs on average have backed 1.82 projects on Kickstarter, have previously created 0.42 projects.

[31] A funded project typically has 61 backers pledging $3939 and achieves more than half of the funding goal, whereas an unfunded project on average has 12 backers pledging $710 and barely accomplish 6.8% of the goal.

above the bar being the ratio of the Lag pledge to the Lead pledge. An average funded project receives a Lag pledge 1.2 times of its Lead pledge. An average unfunded project's Lag pledge, however, is barely half as much as its Lead pledge. To have a better sense of the variance within groups, Figure 3 compares the distributions of proportion of the Lag pledge to the total pledge of funded and unfunded projects. The distinction is pronounced, with the majority of unfunded projects having little or no pledge in the Lag period.

Figure 4 provides some evidence on the relationship between the Lead pledge and the expected Lag pledge by the level of the Lead pledge, using the same specification of Lead and Lag periods. It reports the average Lag pledge, broken down by the level of the Lead pledge in each $500 interval, up until $10,000. The conditional expectation curve has a slope slightly above 1, indicating there is a consistent positive relation of the Lag to Lead pledge, and that the more earlier endorsement a project has, the proportionately more follow-on investment it will likely create.

To examine the general pattern of funding dynamics through the entire funding term, Figure 5 plots the empirical cumulative density function both in terms of the number of backers and the pledged amount of an average funded and unfunded project. Because different projects may have different durations, instead of using the unit of time, the unit of observation in this figure is standardized to 5% of the funding term, equivalent to one to two days depending on the funding duration. The empirical cumulative density function of number of backers and pledged amount of unfunded projects are almost exactly the same, indicating that the average individual backer pledge for unfunded projects is constant over time. For funded projects, there is evidence that the average pledge rises as the funding progresses and then eventually declines. These varying willingnesses to pay will be further explored using more rigorous empirical tests later. The shape of the empirical cumulative density function also suggests that the daily investment data shows a U-shaped pattern: namely, there are a lot of activities in the beginning and end of the funding campaign (as evidenced by steeper slope of the density function closer to 0 and 1), and relatively calm in the middle.[32] The empirical cumulative density function of the funded projects first order stochastic dominates the unfunded, implying that for any elapsed percentage of funding term, both the ratio of cumulative

[32]This pattern of backer support is well-associated with reward-based crowdfunding pundits (Kuppuswamy and Bayus (2015); De Witt (2012); Mollick (2014); Steinberg (2012)) and is sharply different from the generally increasing pattern associated with herding observed with some equity or lending-based crowdfunding (for instance, Zhang and Liu (2012)) and P2P lending (for instance, Herzenstein et al. (2011)) or the decreasing pattern found with donation-based crowdfunding (for instance, Burtch et al. (2013)).

number of backers to total number of backers and the ratio of cumulative pledges to total pledges are smaller for a funded project than an unfunded project.

Table 3 compares the final funding outcomes of projects in different categories. Among the 15 categories, a large proportion of projects are in Games, Film & Video, Music and Design, with another sizable share in Publishing, Technology, and Food. Technology projects typically have the largest funding amounts, while Crafts has the smallest. Success rates also differ across project categories. Fashion, Comics, Technology and Games have the lowest success rates, while Dance, Theater, and Music have the highest.

3.3 A Deeper Analysis

This section presents and discusses the reduced-form empirical analyses of some implications derived in Section 2. First, the key hypothesis tested is the main prediction that successfully funded projects have a more back-loaded funding pattern than unfunded projects. A second hypothesis testes is that pledges made before the total pledged amount reaches the funding goal will be higher than pledges made after the goal is met. Lastly, institutional factors that are expected to affect the incentives to pledge early are added to evaluate the impact of the early investment on follow-on investment.

3.3.1 Funding Success is Associated with Back-loaded Pattern

The main prediction of the theory is that successfully funded projects tend to have a more back-loaded funding pattern relative to projects that fail to be funded. For the initial empirical test of this prediction, the specification of Proposition 2 suggests a dependent variable of the Lag pledge divided by the total pledge as a measure of back-loadedness. The full specification of the regression is:

$$LagRatio_i = \alpha_0 + \alpha_1 Funded_i + AX_i + \nu_{\text{category}} + \eta_t + \epsilon_i \tag{1}$$

$LagRatio_i$ is the ratio of the Lag pledge to the total pledge of project i. $Funded_i$ is an indicator of whether a project is successfully funded. The matrix X_i contains project characteristics including the funding goal, funding duration (in days), project pitch length, number of reward tiers, whether the project pitch contains videos, and entrepreneur characteristics including the number of projects created and the number of projects backed (detailed definitions of these variables are in Appendix A.1). As observed earlier, there are big differences in final funding outcomes between categories, and hence category fixed effects, ν_{category}, are included to account for the heterogeneity across projects of different nature. Also included are dummy variables η_t representing the exact day when a project launches and when the funding term ends.[33] The standard errors, ϵ_i are clustered at the category level.[34] Hence α_1 identifies the average difference between the ratio of the Lag pledge to the total pledge between projects that are eventually funded and those that fail. The hypothesis is that the coefficient α_1 is positive.

Equation (1) is estimated with and without the matrix X_i of project and entrepreneur characteristics, day fixed effects and category fixed effects. The X_i are added because variables such as the funding goal will be correlated with the funding outcome so the estimated α_1 without X_i will pick up these funding goal effects. These variables aim to control for observables that may affect investors' decisions on when and whether to pledge, and thus the funding pattern.

Table 4 contains the estimation results of equation (1). Columns (1) and (2) present the basic OLS results with and without controls, with the Lag period defined as the second half of the funding term. The coefficients on $Funded_i$ are positive and significant. To interpret the economic size of the α_1 coefficient, recall that funded projects on average accrue pledges that are five times larger than unfunded projects in the Lead period (\$3939 compared with \$710), as reported in Table 2. Coupled with the results in columns (1) and (2), this implies even larger differences in the amount of pledges between the two groups in the Lag period. Comparing the estimation result in column (2) with that in column (1), unsurprisingly, adding controls significantly improves the R^2 fit of the model. The coefficient on $Funded_i$ almost remains unchanged after controlling for observables and unobservables, suggesting that the investment pattern is largely related to whether a project is funded and not driven by time-invariant characteristics.

[33] As observed earlier, most pledges come on the first and last few days of the funding term. Day fixed effects are included to account for possible exogenous reasons that affect the amount of pledges received on that day. For example, projects may get more pledges on rainy days when everyone has to stay indoors.

[34] I assume here that regression errors are independent across categories of projects but correlated within categories. This is more likely to be true if the project creators and backers are completely different across the categories. There are several reasons why this may be a valid assumption. First of all, serial creators on Kickstarter often create projects of the same category (See `https://www.kickstarter.com/blog/by-the-numbers-when-creators-return-to-kickstarter` for reference). Second, on Kickstarter, around 32% are repeat backers and the rest are one-time backers. One-time backers only pledge in one project. For the repeat backers, because the recommendation algorithm used by Kickstarter is based on a backer's previous interest and a large part of Kickstarter's search is through the category, it is likely many of them browse regularly within the same category.

In the regressions for the results in columns (3) to (10), I allow the definitions of the Lag period to vary from the last 90% of the funding duration to the last 10% of the duration. For example, if the Lag period is the last 90% of the funding term, this means that the initial Lead period averages 3 days, compared to an initial Lead period of 15 days when the Lag period is the last 50% of the funding term. These variations do not affect the fundamental results. Specifically, α_1 remains positive and significant. This is re-assuring but not surprising. In the model, the first and second periods are only informational. Nothing restricts them to be of equal length in the unit of time.[35] For robustness, Table **??** reports the estimation results using the ratio of the number of backers in the Lag period divided by the total number of backers as the dependent variable. The coefficients on $Funded_i$ are positive and significant. For the same definitions of Lead and Lag periods as in Table 4, the estimates are also generally of similar magnitude as in Table 4. In the remaining body of the paper, only the pledge amount will be used as the variable of interest.

In an alternative specification, I regresses the total dollar value of the Lag pledge on that of the Lead pledge, directly testing whether the Lag pledge exceeds the Lead pledge. Thus,

$$\begin{aligned} LagPledge_i = & \beta_0 + \beta_1 LeadPledge_i + \beta_2 Funded_i + \beta_3 LeadPledge_i \cdot Funded_i \\ & + BX_i + \nu_{\text{category}} + \eta_t + u_i \end{aligned} \tag{2}$$

in which $LeadPledge_i$ and $LagPledge_i$ are the total amount pledged in the Lead and Lag periods, respectively. The other variables are as previously defined. The β_3 identifies the expected difference in the slope estimate for the predictor $LeadPledge_i$ between the funded and unfunded projects. The hypothesis is that the coefficient β_3 is positive.[36]

[35] From columns (2), (4), (6), (8) and (10), as the length of the Lag period increases from 10% of the funding term to 90%, the estimates are 0.132, 0.186, 0.217, 0.196, and 0.138, respectively. Perhaps surprising is that the coefficient estimates are not monotonic in the length of Lag period. While the intuition is the longer the Lag period, the more dramatic the learning effect ought to be, this is a logical outcome given the specification of this dependent variable. The key is that the longer the Lag period, the Lag Ratios (ratios of Lag pledge to total pledge) for both groups of projects are also bigger. In particular, the Lag Ratio of unfunded projects is higher. For example, as in columns (1), (3), (5), (7) and (9), when the lengths of Lag period increases from 10% of funding term to 90%, the estimated average Lag Ratios among unfunded projects are 0.137, 0.202, 0.315, 0.481, and 0.664. Because the Lag Ratio can at most be 1, when the Lag Ratio of unfunded projects increases, the maximum possible difference between the two Lag Ratios decrease. This offsets the learning effect that implies larger difference over time.

[36] In the following, 1,278 projects, 3.8% of the entire sample, that have Lead pledges more than $10,000 are excluded from the analysis. Many of these extremely successful or oversubscribed projects, the largest one accruing more than $2 million of pledges, have either received media coverage at some point during the campaign, or have created a fad on social media. Their dynamic patterns may be driven by forces outside of the model, even though results with them included, reported in Table **??**, are consistent with the hypothesis. Table **??** reports the estimation results from equation (2) on the entire sample. The coefficients are positive and significant, but the magnitudes are smaller than those in Table 5. The result, that the coefficient estimate is smaller compared to more modest projects, is consistent

Again, the definitions of the duration of Lead and Lag periods are varied and results both with and without controls as specified in equation (2) are reported. The results in Table 5 provide further evidence supporting the same hypothesis tested in Table 4. Regardless of which specification of the length of Lag period is used, in columns (1) to (10), the β_3 coefficient on the interaction term $LeadPledge_i \cdot Funded_i$ is positive and both statistically and economically significant. For example, in column (2), it is estimated that the Lag pledge is 0.396 times of the Lead pledge of an unfunded project. With a coefficient estimate of 0.702 on $LeadPledge_i \cdot Funded_i$, this implies that for a funded project, the Lag pledge is expected to be 1.098 times its Lead pledge. To provide a sense of scale, using the coefficient estimates in column (2), an average unfunded project which has total Lead pledge of \$710, expects to have \$281 follow-on investment, whereas an average funded project with initial pledges of \$3,939, is predicted to draw in \$4,325 additional funding.

Comparing results between different specifications of Lead and Lag periods, the variation in estimations are by-and-large consistent with the intuition that the early advantage is magnified by learning throughout the funding campaign. Suppose funding lasts 30 days. The results in column (4) imply that at the end of the third day, a project that eventually succeeds on average receives follow-on investments of size more than 2.23 times the total amount pledged in the first three days. A project that fails to be funded only receives roughly 80% of the Lead pledge. The difference in the ratio of Lag to Lead pledge decreases as the length of the Lag period decreases. When the Lag period is defined to be the last three days, on average, the Lag pledge is 33.5% of the Lead pledge for a unfunded project and 14.4% for the unfunded. The key result is that the coefficient of $LeadPledge_i \cdot Funded_i$ is always positive and significant.

Alternative Explanations There are two obvious alternative explanations for the strong association between funding success and the back-loaded investment pattern observed in the data. First, projects with good early outcomes may simply receive more exposure on the website as a result of Kickstarter's search algorithm. Second, in the model, ignored in this model is the entrepreneur's ability to direct traffic to the project's website. One may argue that if the entrepreneurs

with the theory. The logic is the following: because the total number of investors is limited, for a really good project from which everyone receives good signals, the first period and the second period pledges become substitutes. So for the most popular projects, the Lag pledge may be smaller. Note that even though the subset of projects takes up only 3.8% of the main sample, they clearly have a disproportionately large impact on the estimates due to the scale. Hence, from this point forward, these projects are excluded. The summary statistics of the rest of main sample are reported in Table **??**.

of successfully-funded projects are systematically different from those of unfunded projects in terms of mobilizing new potential investors, then this back-loaded pattern is an outcome of differential effort or the effectiveness of the fund-raising, not of learning by those who lag.

To refute the first alternative, a supplemental dataset is used to check whether the position of the project on the website has a significant impact on the amount of investment. Table **??** reports the regression results where the dependent variable is the daily pledges, as measured by either the daily pledge amount or the daily number of backers. Included in the regressions are variables that correspond to the projects' position on the web page, including whether the project is chosen to be the project of the day, whether it is featured, and which position on the category webpage the project is shown. The inclusion of these variables does not affect the coefficients on the model's key variables, namely the day-of-funding indicator variables.[37] In fact, somewhat surprisingly, the position on the web page has little effect on the size of the pledge.

For the second alternative explanation, there are two possible arguments that explain a successful entrepreneur's more (or better) direct fundraising efforts. The first is that the entrepreneurs of successful projects are more connected than those of unsuccessful. However, there is at least one piece of contradictory evidence. Recall, conditional on having a Facebook profile linked to the account, the creators behind unfunded projects tend to have more friends on social media than those behind funded projects – the opposite of what would be expected if friends were activated to make pledges. In addition, even if creators of successful projects do have more friends than others, and further if many backers are their friends, there is no natural reason why unfunded projects are front-loaded whereas those successfully funded are back-loaded. Another rationale is then needed to explain the different patterns between funded and unfunded projects. Whether it is the friends of the creator influencing other friends of the creator, or more confident investors motivating less confident investors, either scenario is compatible with the theory.

A final possibility is that the creator whose project has low initial pledge amount may not promote the project as actively as creators whose projects start strong. The creator may make little or no effort to attract potential backers while funding is open, thinking the project is unlikely to succeed. This explanation unlikely holds for several reasons. To begin with, Kickstarter gives creators

[37]The key variables are the first three and last three day-of-funding indicator variables, the days when investors are most active. As observed earlier, most activities are in the beginning and end of the funding term, as implied in Figure 5. The U-shaped dynamics are also demonstrated in Figure A.2.

the option to cancel or suspend a funding campaign at any time before the funding deadline. If, after seeing the early pledges, the creator believes the project's success is improbable, she can cancel or suspend the funding campaign. Indeed, more than 10% of projects in the preliminary dataset were canceled or suspended. Additionally, conditional on running the campaign and endeavoring to achieve funding success, the creator whose project has low initial pledge amount has no reason to advocate less hard than those whose projects receive strong early pledges.

3.3.2 Evidence that Early Investors Have Higher Willingness to Pay

In the equilibrium derived in Section 2, agents that have good private signals and thus are more confident jump in early, while those who are less confident wait to learn from the actions of others. In the model, all agents who pledge early have only private signals. In reality, only those who are among the first few to pledge act entirely upon their private information. Those who move after the first few days have both private and public signals. If both private and public signals are good, some agents will follow soon rather than waiting until the deadline. This occurs for the same reason that some agents act early in the model – namely, they act to motivate others to invest and thus increase the project's likelihood of achieving the funding goal. This implies that those who pledge immediately following the very first lead investors should have a higher willingness to pay than those who wait to pledge until after the project reaches its goal. In this subsection, I investigate whether or not the evidence is consistent with the implication that early backers have a higher willingness to pay.

Recall that a backer can pledge an amount greater than or equal to the minimum specified for a particular reward on Kickstarter. Before the total pledge reach the funding goal, an investor may find it beneficial to pledge more than required, because the higher pledge makes achieving the funding goal more likely. A higher pledge can also signal greater confidence to those who may follow, especially when the funding goal is modest. This "pay-what-you-want-as-long-as-it-is-above-the-price" feature allows an analysis of the willingness-to-pay of agents at different stages of the funding campaign.

The ideal setting for testing whether early backers have a higher willingness to pay is to compare individual backers' contributions pledged at different times within the funding term for the same reward. However, only the daily aggregate pledge and the number of backers are observed in the data set; the individual pledges and which reward the pledges are for are not observed. To make sure the differences in the average daily pledges represent the differences in the willingness to pay for the same reward, a subset of Kickstarter projects is selected that offer only one type of reward and one minimum pledge amount to receive it if the project is funded.[38]

The empirical strategy is to estimate the following:

$$WTP_{it} = \phi_0 + \phi_1 BeforeSuccess_{it} + \phi_2 Early_{it} + \nu_i + \epsilon_i \tag{3}$$

WTP_{it}, willingness to pay, is defined as the daily total dollar pledge amount divided by the daily number of backers. It captures investors' average willingness-to-pay for the single reward offered by the project on a particular day during the funding term. $BeforeSuccess_{it}$ is an indicator variable that takes the value 1 if it is more than three days into the funding term and the goal has not been reached that day. $Early_{it}$ is an indicator variable that takes the value 1 if that day is in the first three days of the project's funding term. The ϕ_1 thus identifies the difference in average daily pledges of days after the first three days but before funding succeeds as compared to days after the funding goal is reached. Included are project fixed effects to account for the heterogeneity of rewards across projects. The standard errors are clustered by project. The hypothesis is that ϕ_1 is positive.

The results are reported in Table 6. In column (1), the project-day observations of all projects that have only one reward category are included. The ϕ_1 coefficient on $BeforeSuccess_{it}$ is positive (32) and statistically significant, indicating an average pledge made before the project reaches the funding goal is \$32 more than an average pledge made after the goal is met. This is equivalent to 33% of the mean reward price (\$95) of this subsample. A concern is that the evidence that early backers are willing to pay more might be driven primarily by agents who, seeing the goal is almost attained, pledge more to tip the funding to success. To address this concern, in the regression for the results in column (2), I exclude project-day observations in which the funding goal is reached on that day. The coefficient estimate on $BeforeSuccess_{it}$ is smaller (19 compared to 32) but still statistically and economically significant. In columns (3) and (4), projects where backers are

[38] This subset has 1,656 projects, a small proportion of the whole sample. Summary statistics of the key descriptive variables are provided in Table **??**. The key is that the project and entrepreneur characteristics of this subset are largely similar to those of the whole sample. The average success rate in this subset is around 50%, roughly the same as the whole sample. The distribution of reward prices has a median of \$20 and mean of \$95.

believed to purchase a product are selected (projects for which the description of reward contains the keywords including "product", "purchase", "shipping", "copy" or "copies"). The coefficient estimate on $BeforeSuccess_{it}$ remains significant, although the strength is weaker and the economic size is smaller, implying the differences in willingness to pay between early movers and later backers tend to be bigger when backers are funding a project rather than just pre-ordering a product.

The key finding is that backers who pledge before the project reaches its funding goal voluntarily contribute more for the same reward than those who wait after the goal is met, indicating these backers have a higher willingness to pay. This finding can be viewed as consistent with the prediction that agents who jump in early are those who have higher expected payoffs of successful funding and thus most eager to have the project funded.

3.3.3 Impact of Early Pledges on Follow-on Investment

An implication from Proposition 3 is that the impact of the Lead pledge on follow-on investment is affected by agents' understanding of the incentives of the early movers and their assumptions about the information that early movers have. A possible way to test this prediction is to construct comparison groups that differ in aspects that affect the incentives of early movers and compare the impact of a given amount of Lead pledge on follow-on investment. Two characteristics are suited for this purpose.

One such attribute is the amount of credible public information potential investors have about the project's creator. As discussed above, an important distinction of crowdfunding from traditional entrepreneurial financing is the lack of intermediation: Kickstarter does not screen projects. Because there is no project screening, the high information asymmetry makes investors cautious in backing projects. Backers worry about moral hazard by the project's creator, which reduces the chances that investors receive the promised rewards, especially given their inability to monitor the creator. Recall that 9.95% of successfully funded projects are not completed by the creator, and thus fail to deliver the promised rewards. It is natural that investors would pay close attention to signals of credibility. A new creator without any track record or verification of identity by Kickstarter is *ex ante* risky.[39] Intuitively, someone will only pledge early for a risky creator if the individual has

[39]For projects that have launched since May 19, 2014, all creators of projects have to go through the process of identity verification by Kickstarter, usually through government-issued ID or banking information.

sufficiently high private information that offsets the concern. Therefore investors who pledge early for an unverified new creator must be truly confident in their expected payoff. Hence the signal associated with early pledges is more positive for projects created by unverified new creators with many early pledges. The implication is that if a project developed by a risky creator and a project created by one who is more credible (either a serial creator or someone whose identity is verified by Kickstarter) have the same amount of the early pledges, the project created by the risky creator should have a larger induced following due to the strong signal conveyed by the early movers.

To test this, the empirical strategy is to estimate the following regression:

$$\begin{aligned} LagPledge_i =& \delta_0 + \delta_1 LeadPledge_i + \delta_2 Risky_i + \delta_3 LeadPledge_i \cdot Risky_i \\ &+ DX_i + \nu_{\text{category}} + \eta_t + u_i \end{aligned} \tag{4}$$

Again, the Lead and Lag periods are defined as the first and second halves of the funding term, respectively. $LeadPledge_i$ and $LagPledge_i$ are the total amount pledged in the Lead and Lag periods, respectively, and the other variables are as previously defined. $Risky_i$ is an indicator variable that takes a value of 1 if project i is created by someone who has never created a project previously nor been verified by Kickstarter. Therefore, the hypothesis is that δ_3 is positive.

The results in columns (1) and (2) of Table 7 support this hypothesis. The δ_3 coefficient on $LeadPledge_i \cdot Risky_i$ indicates that the signaling effect of the Lead pledge depends on whether the creator of the project is deemed risky. The projects by creators deemed to be risky tend to have larger induced follow-on pledges (1.2 times the Lead pledge), relative to the other projects (the same as the Lead pledge). Using coefficients from column (2), with a funding goal larger than \$3,000, a project of a risky creator that achieves 48% of the funding goal in the Lead period will, on average, attract enough following and eventually succeed, whereas a project created by an *ex ante* less risky entrepreneur with the same percentage of goal reached will fail to achieve the funding goal.

Another attribute is that a project may have a limited number of rewards, therefore there is a quota on the number of backers that can be accepted. This limits the opportunity to pledge. When the opportunities to invest are limited, the early actions for the purpose of signaling and motivating followers are confounded by the early actions taken to increase the probability of participating before the opportunity closes out. Hence the signal associated with early pledges is more positive for projects with unlimited opportunities to pledge, as in those cases in which the only incentive to back early is to endorse the project. The implication is that, for the same amount of early pledges, a project with unlimited offerings should have a larger induced follow-on investment than one with limited reward offerings.

To test this prediction, projects that have limited offerings of rewards but have not filled the quota before funding ends are selected from the 50,319 projects, and are compared to projects with unlimited offerings. Thus,

$$\begin{aligned} LagPledge_i = &\gamma_0 + \gamma_1 LeadPledge_i + \gamma_2 Unlimited_i + \gamma_3 LeadPledge_i \cdot Unlimited_i \\ &+ GX_i + \nu_{\text{category}} + \eta_t + \epsilon_i \end{aligned} \tag{5}$$

$Unlimited_i$ is an indicator variable of whether the provision of investment opportunities is unlimited. The hypothesis is that the coefficient γ_3 is positive.

The results are reported in columns (3) and (4) of Table 7. The positive and statistically significant coefficient on $LeadPledge_i \cdot Unlimited_i$ implies that the positive impact of early pledge on follow-on investment is indeed larger when the only incentive to go in early is to endorse and motivate rather than to compete with followers. Using coefficients from column (4), for a project with a limited provision of rewards, the Lag pledge is expected to be 0.8 times the Lead pledge, whereas a project with unlimited offerings on average receives more pledges in the Lag period than in the Lead period.

4 Conclusion

Society and business are characterized by changes that often require action by a group of individuals to succeed. An example is political revolution, where some individuals take personally risky actions to overthrow a government and others wait to a later time to decide whether or not to join in. Unless a critical mass is reached, the revolution fails. Another example, and the one that is the subject of this work, is investment in a new venture where more capital is needed than can be provided by one investor. In this environment, some opt to play the role of lead investors, while others wait to gauge initial interest before investing. Why does anyone lead, particularly when the return to leaders is the same as that to followers? What conditions are necessary to induce following by others?

Absent collective action, it is always superior to wait for others to go first, essentially free-riding on the actions of others. Of course, if all wait, then change and innovation is never effected. However, when the participation of others is necessary to ensure the success of a venture, there is a rationale for leading, because the actions of early movers influence the behavior of others.

A theory of collective action with learning is presented and tested using Kickstarter data. The idea is that those who receive sufficiently positive signals of a project's value are willing to take the lead because their actions may induce others to follow. Those whose signals are not as positive may jump in later, but are reluctant to lead, so they wait to see if there is sufficient initial investment to suggest that a project has a positive net value. Because others' decisions to follow depend on the actions of early movers, the conventional free-rider intuition that would induce all to wait for others to act is reversed. The need for collective action provides an explicit rationale for leading.

Additionally, according to the theory, there is a particular timing pattern that varies with the eventual success or failure of a project. If many potential investors have positive assessments of a project, then there is a large amount of early investment, and even more following. As such, the timing pattern of successful projects tends to be back-loaded with more followers than leaders. Conversely, if there are few potential investors with positive assessments of the project, then there is a small amount of lead investment and even less following. Failed projects tend to be front-loaded with more leaders than followers.

Projects are not funded on Kickstarter unless a pre-specified monetary goal is reached. Kickstarter provides a perfect setting for testing the predictions of the model, because early investments can be viewed by others who can then make a choice whether to follow or not. All predictions of the theoretical model are supported by the data. Those projects that eventually reach their funding goal tend to have high lead investment and even higher follow-on investment. Those projects that fail tend to have low amounts of lead investment and even lower follow-on investment. Additional implications that relate to available public information, whether the opportunities to invest is limited, and their effects on the investment pattern are also tested and found to hold.

Figures

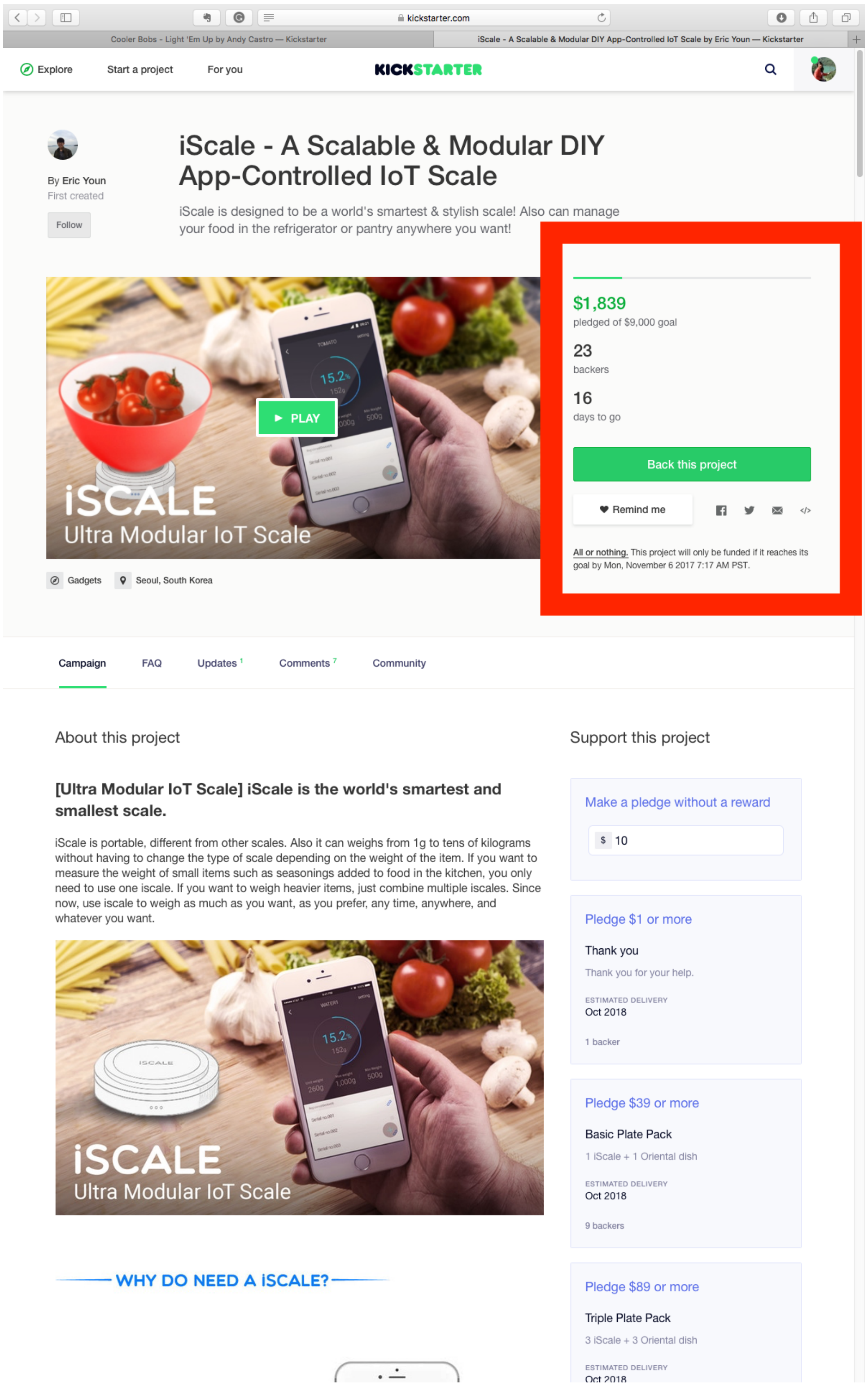
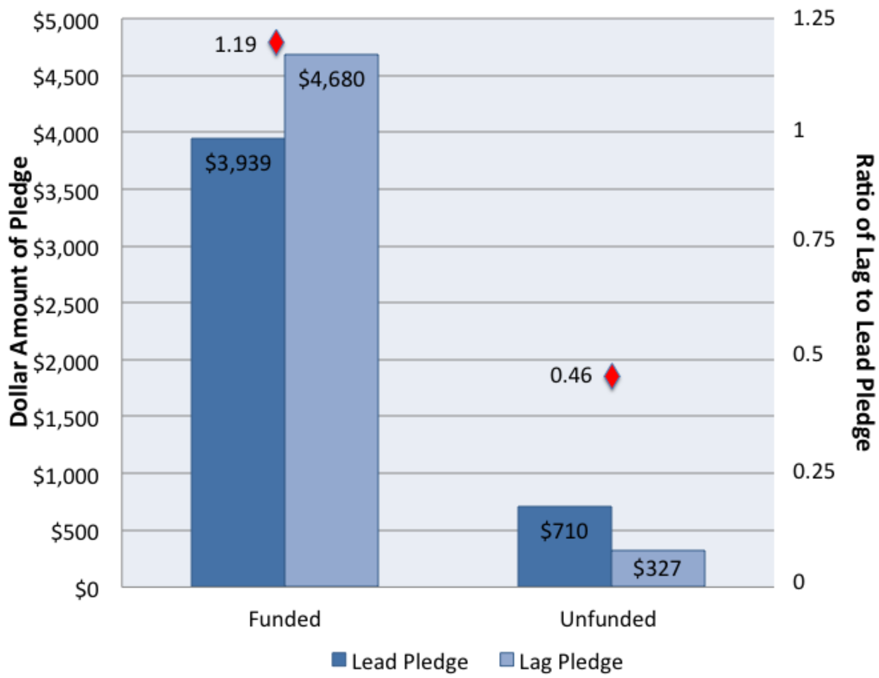
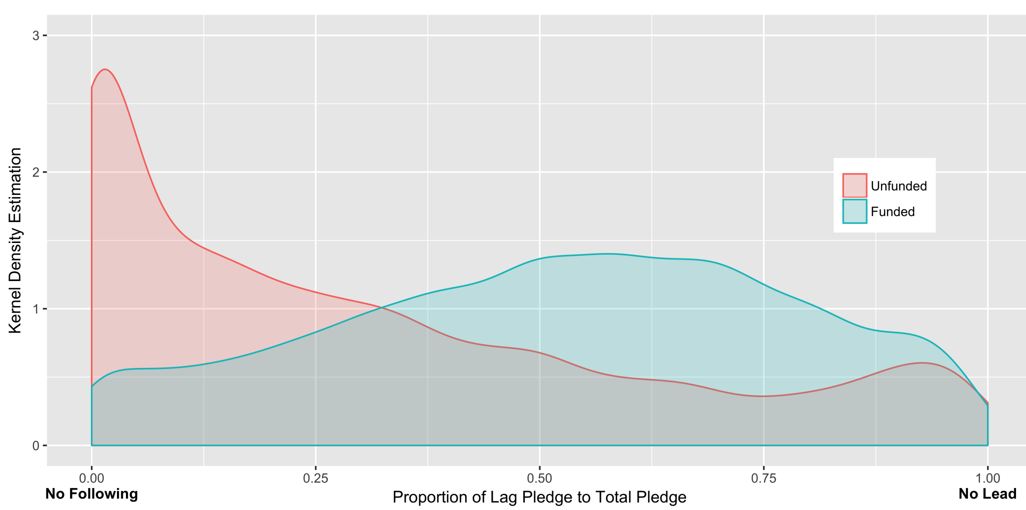


Figure 1: A Sample Kickstarter Project Page



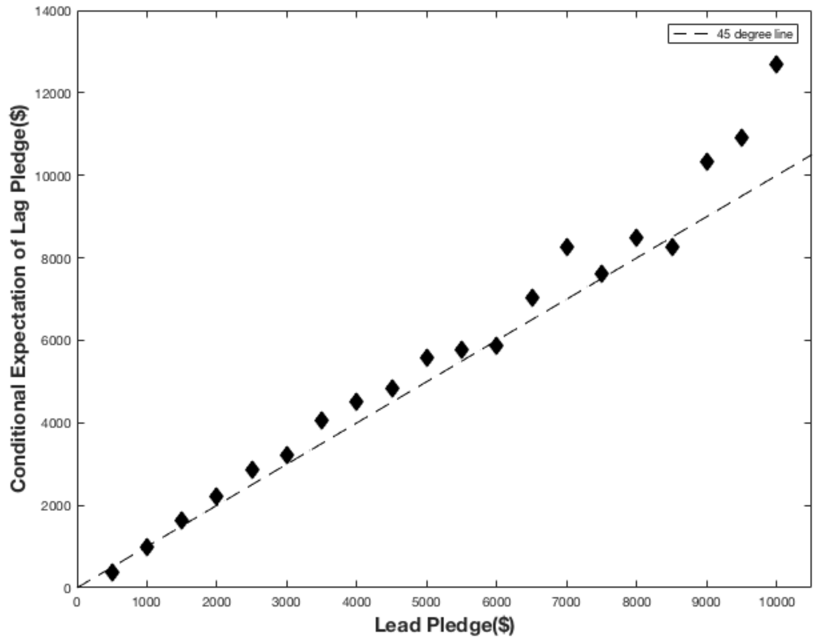
Notes: This chart compares the investment pattern of an average funded project and an average unfunded project, as represented by pledge amount in the Lead and Lag periods. The Lead and Lag periods are defined as the first and second halves of the funding term, respectively. The Lead pledge corresponds to the total dollar amount pledged in the Lead period, and the Lag pledge is the total dollar amount pledged in the Lag period. The two numbers marked by the diamond shape are the ratio of the Lag pledge to the Lead pledge.

Figure 2: Investment Pattern Observed on Kickstarter



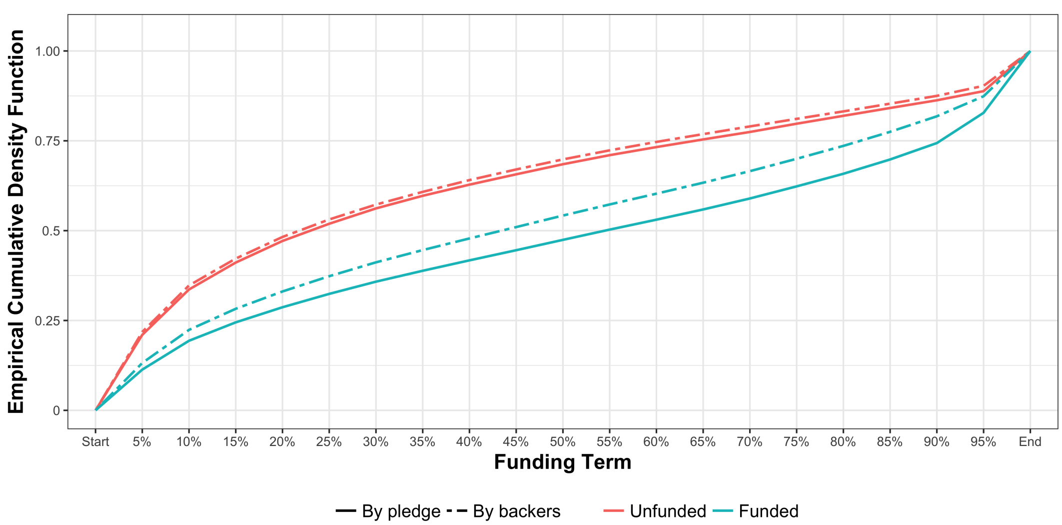
Notes: This figure plots the kernel density estimation of the distribution of investment patterns among funded and unfunded projects represented by the proportion of the Lag pledge to the total pledge. The Lead and Lag periods are defined as the first and second halves of the funding term, respectively. The Lag pledge corresponds to the total amount pledged in the Lag period.

Figure 3: Distribution of Lag to Total Investment on Kickstarter by Funding Outcome



Notes: This figure reports the average Lag pledge, broken down by the level of the Lead pledge in each $500 interval, up until $10,000. Each data point is calculated by taking the average of the Lag pledge for projects that have a Lead pledge in the corresponding range. The Lead and Lag periods are defined as the first and second halves of the funding term, respectively. The Lead pledge corresponds to the total dollar amount pledged in the Lead period, and the Lag pledge is the total dollar amount pledged in the Lag period. 1,278 projects, 3.8% of the main sample, that have Lead pledge more than $10,000 are excluded from the figure.

Figure 4: Conditional Lag



Notes: This figure plots the dynamics of the number of backers and the pledge amount throughout the entire funding term, as represented by the averaged empirical cumulative density function of the funded and unfunded projects. The unit of observation in this figure is standardized to every 5% of the funding term, equal to one to two days depending on the duration of the funding term.

Figure 5: Backer and Pledge Dynamics Among Funded and Unfunded Projects

Tables

Table 1: **Summary Statistics**

Panel A: Project and Entrepreneur Characteristics

Variable	Mean	St. Dev.	Median	Min	Max
		I. Whole Sample: n = 33,302			
Funding goal($)	32,712	947,687.93	4,500	1	100,000,000
Duration (in days)	32.95	11.05	31.00	2	61
Project pitch length	537	489.31	391.00	2	6,106
Has videos	0.76	0.43	1	0	1
Number of rewards tiers	7.26	4.24	7	1	77
Verified ID	0.53	0.50	1	0	1
Has Facebook	0.43	0.50	0	0	1
Biography length	63.92	26.43	75	2	119
Number of projects created	1.73	3.17	1	1	89
Number of projects backed	2.62	11.34	1	0	1,270
Number of Facebook friends	414.57	272.43	381	2	999
		II. Funded: n = 17,165			
Funding goal($)	5,490	10,621	2,500	1	475,000
Duration (in days)	30.85	10.46	31.00	2	61
Project pitch length	520.70	465.31	381.00	2	5156
Has videos	0.78	0.42	1	0	1
Number of rewards tiers	7.05	3.93	7	1	64
Verified ID	0.60	0.49	1	0	1
Has Facebook	0.40	0.49	0	0	1
Biography length	62.82	26.26	74	2	110
Number of projects created	2.01	4.08	1	1	89
Number of projects backed	3.37	14.92	2	0	1270
Number of Facebook friends	352.27	257.43	298	2	999
		III. Unfunded: n = 16,133			
Funding goal($)	56,582.40	1,160,358.05	10,000	9	100,000,000
Duration (in days)	35.17	11.23	31.00	2	61
Project pitch length	554.16	512.94	402	2	6,106
Has videos	0.74	0.44	1	0	1
Number of rewards tiers	7.48	4.53	7	1	77
Verified ID	0.47	0.50	0	0	1
Has Facebook	0.47	0.50	0	0	1
Biography length	65.09	26.56	76	2	119
Number of projects created	1.42	1.69	1	1	74
Number of projects backed	1.82	5.27	1	0	209
Number of Facebook friends	483.55	271.98	479	2	999

Panel B: Final Funding Outcomes

Continued on next page

Table 1 – *Continued from previous page*

Variable	Mean	St. Dev.	Median	Min	Max
		I. Whole Sample: n = 33,302			
Pledged amount($)	4,990	27,625.17	1,030	3	2,262,621
Pledge ratio	3.708	306.245	1.00	0	55,257
Number of backers	68.86	333.36	20	3	20,242
Pledged amount per backer	70.17	110.51	46.81	1	5,500
		II. Funded: n = 17,165			
Pledged amount($)	9,026	38,034.68	3,092	3	2,262,621
Pledge ratio	7.1	426.5	1.124	1	55,267
Number of backers	117.59	457.81	42	3	20,242
Pledged amount per backer	84.11	119.85	58.15	1	5,500
		III. Unfunded: n = 16,133			
Pledged amount($)	1,164.52	3152	310	3	121,633
Pledge ratio	0.109	0.145	0.05	0	0.984
Number of backers	17.28	41.43	8	3	3,252
Pledged amount per backer	55.41	97.53	35.20	1	3,500

Notes: This table presents descriptive statistics for the main sample of the data. Panel A presents the project and entrepreneur characteristics. Panel B presents the final funding outcomes. All variable definitions are in Table A.1.

Table 2: **Funding Outcomes of the Lead Period: First Half of the Funding Term**

Variable	Mean	St. Dev.	Median	Min	Max
		I. Whole Sample: n = 33,302			
Number of backers	37.221	188.176	12	0	11,664.000
Lead pledge ($)	2,370.439	15,314.460	495	0	1,336,889.000
Proportion of goal achieved	8.453	648.604	0.200	0	113,563.900
Lead ratio	0.577	0.360	0.586	0	23.686
		II. Funded: n = 17,165			
Number of backers	61.323	258.977	22	0	11,664.000
Lead pledge ($)	3,938.742	21,149.990	1,113.000	0	1,336,889.000
Proportion of goal achieved	3.512	220.25	0.551	0	28,546.000
Lead ratio	0.474	0.259	0.459	0	1.863
		III. Unfunded: n = 16,133			
Number of backers	11.703	25.035	5	0	1,367.000
Lead pledge ($)	709.969	1,972.287	180.750	0	85,518.000
Proportion of goal achieved	0.068	0.094	0.029	0	0.914
Lead ratio	0.685	0.416	0.770	0	23.686

Notes: This table presents descriptive statistics of the funding outcomes after the Lead period for the main sample of the data. The Lead period is defined as the first half of funding term. Lead pledge is the dollar amount pledged in the Lead period. Proportion of goal achieved is the ratio of Lead pledge to the funding goal. Lead ratio is the ratio of Lead pledge to the total pledge amount.

Table 3: **Final Funding Outcomes by Category**

	Category	Number of projects	Share of total pledge	Average funding goal($)	Success rate
1	Art	2,840	4.40%	13,443	53%
2	Comics	813	0.80%	7,978	38%
3	Dance	840	1.80%	7,083	77%
4	Design	2,144	11.30%	28,341	38%
5	Fashion	1926	5.10%	10,950	38%
6	Food	3,049	6.90%	18,840	33%
7	Film&Video	5,383	17.70%	62,766	61%
8	Games	2,716	18%	24,084	39%
9	Journalism	415	0.90%	15,869	45%
10	Music	3,963	10.10%	10,727	71%
11	Photography	1,228	1.70%	7,820	41%
12	Technology	1,882	9%	168,161	31%
13	Theater	1,988	4.10%	10,724	74%
14	Publishing	3,363	7.60%	11,607	59%
15	Crafts	752	0.60%	4,327	44%

Notes: This table presents descriptive statistics for the final funding outcomes of projects in the main sample by category, in which "Share of total pledge" is the ratio of pledge amount received by each category to the total pledge amount received.

Table 4: **Investment Pattern by Whether a Project is Funded**
(Dependent Variable: LagRatio)

Definition of Lag Period:	50% of Duration		90% of Duration		75% of Duration		25% of Duration		10% of Duration	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Funded	0.210***	0.217***	0.143***	0.138***	0.195***	0.196***	0.174***	0.186***	0.119***	0.132***
	(0.051)	(0.064)	(0.049)	(0.064)	(0.050)	(0.064)	(0.051)	(0.062)	(0.010)	(0.009)
Constant	0.315***		0.664***		0.481***		0.202***		0.137***	
	(0.009)		(0.007)		(0.008)		(0.010)		(0.011)	
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	33,302	33,302	33,302	33,302	33,302	33,302	33,302	33,302	33,302	33,302
Adjusted R^2	0.085	0.211	0.078	0.144	0.093	0.179	0.051	0.292	0.018	0.345

Notes: This table reports the estimation results of equation (1), for a project's LagRatio, defined as the amount pledged in the Lag period divided by total pledge, regressed on whether the project gets funded. Funded is an indicator variable if a project is successfully funded. For columns (1) and (2), the Lead and Lag periods are defined as the first and second halves of the funding term, respectively. In the regressions for the results in columns (3) to (10), I allow the specifications of the Lead and Lag periods to vary. For example, in columns (3) and (4), the Lag period is defined to be the last 90% of funding term, so for a project with a duration of 30 days, the Lag period covers Day 4 to Day 30. Controls include project and entrepreneur characteristics. OLS with standard errors clustered by category are reported in parentheses under parameter estimates. ***, **, *, and + denote statistical significance at the 0.1%, 1%, 5%, and 10% levels, respectively.

Table 5: **Investment Pattern by Whether a Project is Funded: Alternative Specification**
(Dependent Variable: LagPledge)

Definition of Lag Period:	50% of Duration		90% of Duration		75% of Duration		25% of Duration		10% of Duration	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
LeadPledge	0.477***	0.396***	1.242***	0.801***	0.785***	0.559***	0.250***	0.241***	0.136***	0.144***
	(0.053)	(0.062)	(0.133)	(0.165)	(0.080)	(0.098)	(0.034)	(0.036)	(0.028)	(0.028)
Funded	546.898***	746.347***	1,685.770***	1,917.578***	1,081.797***	1,302.810***	299.309**	445.291***	167.440*	267.805***
	(86.278)	(86.948)	(82.793)	(113.673)	(62.241)	(83.124)	(99.975)	(102.924)	(82.903)	(73.164)
LeadPledge · Funded	0.682***	0.702***	1.270***	1.430***	0.948***	1.032***	0.383***	0.375***	0.202***	0.191***
	(0.143)	(0.134)	(0.327)	(0.289)	(0.212)	(0.199)	(0.086)	(0.082)	(0.053)	(0.046)
Constant	91.871***		379.232***		206.266***		58.112**		52.349*	
	(26.589)		(51.210)		(36.534)		(21.531)		(21.683)	
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	32,024	32,024	32,024	32,024	32,024	32,024	32,024	32,024	32,024	32,024
Adjusted R^2	0.345	0.388	0.305	0.373	0.332	0.386	0.330	0.364	0.271	0.318

Notes: This table reports the estimation results of a project's Lag pledge regressed on the Lead pledge and the final outcome. Funded is an indicator if a project is successfully funded. For columns (1) and (2), the Lead period is defined as the first half of funding duration. Lead pledge is defined as the total amount pledged in the Lead period. In the regressions for the results in columns (3) to (10), I allow the specifications of the Lead and Lag periods to vary. For example, in column (3) and (4), the Lag period is defined to be the last 90% of funding term, so for a project with a duration of 30 days, the Lag period covers Day 4 to Day 30. 1,278 Projects, 3.8% of the entire sample, that have more than $10,000 pledge in the first half of funding term are excluded. Controls include project and entrepreneur characteristics. OLS with standard errors clustered by category are reported in parentheses under parameter estimates. ***, **, and * denote statistical significance at the 0.1%, 1%, and 5% levels, respectively.

Table 6: **Evidence of Early Backers Willing to Pay More**

	Dependent Variable:			
	WTP			
	(1)	(2)	(3)	(4)
BeforeSuccess	31.533***	18.876*	20.274*	8.623+
	(8.033)	(7.559)	(9.451)	(4.866)
Early	7.602	12.915+	1.914	8.961
	(5.626)	(6.612)	(7.000)	(5.888)
Project FE	Yes	Yes	Yes	Yes
Observations	13,390	12,586	4,301	4,066
Adjusted R^2	0.142	0.202	0.053	0.122

Notes: This table reports the estimation results of a project's daily average pledge regressed on when the pledge is made. The unit of analysis is a project-day observation. In columns (1) and (2), all projects that have only one category of rewards are included. In columns (3) and (4), a subset of the projects with one category of rewards for which the description contains the keywords "product", "purchase", "shipping", "copy", or "copies" are included. In columns (2) and (4), the project-day observations in which the goal is reached on that day are excluded. The dependent variable WTP, willingness to pay, is defined as the averaged pledge of that day, calculated by daily incremental pledge divided by daily incremental number of backers. BeforeSuccess is an indicator variable that takes value 1 if funding is more than three days into the campaign and is not successful yet as of that day. Early is an indicator variable that takes a value of 1 if that day is in the first three days of funding duration. Project fixed effects are included. OLS with standard errors are clustered by project and reported in parentheses under parameter estimates. ***,**, * and + denote statistical significance at 0.1%, 1%, 5% and 10% level, respectively.

Table 7: **Impact of Early Pledges on Follow-on Investment: Variation by Attributes**

	Dependent Variable:			
	LagPledge			
	(1)	(2)	(3)	(4)
LeadPledge	1.066***	1.006***	0.882***	0.799***
	(0.054)	(0.050)	(0.038)	(0.030)
LeadPledge · Risky	0.139*	0.193**		
	(0.068)	(0.064)		
Risky	-55.678	-166+		
	(9.93.)	(9.82)		
LeadPledge · Unlimited			0.230***	0.217***
			(0.034)	(0.054)
Unlimited			18.616	-73.769+
			(40.064)	(42.398)
Constant	232.496***		198.143***	
	(45.536)		(29.856)	
Controls	No	Yes	No	Yes
Observations	32,024	32,024	36,390	36,390
Adjusted R^2	0.306	0.320	0.297	0.384

Notes: This table reports the OLS estimation results of a project's Lag pledge regressed on the Lead pledge and other attributes. In this estimation, Lead and Lag periods are defined as the first and second halves of the funding term, respectively. LeadPledge is the total amount pledged in the Lead period. For columns (1) and (2), only projects without unlimited investing opportunities are included. Risky is an indicator variable that takes the value 1 if the entrepreneur has previously not created a project nor being verified by Kickstarter. For columns (3) and (4), projects that have limited number of offerings of certain rewards are included. Unlimited is an indicator variable that takes the value 1 if the project offers unlimited number of rewards. Standard errors are clustered by category and reported in parentheses under parameter estimates. ***,**, * and + denote statistical significance at 0.1%, 1%, 5% and 10% level, respectively.

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A A Continuous Time Analog with Symmetric Investors

Consider a common value setting with n symmetric, risk-neutral investors, indexed by $i \in \mathcal{N}$, where $\mathcal{N} = \{1, 2, \ldots, n\}$.

The investment game is played in continuous time, starting at $t = 0$, and ending at the deadline T, $T < \infty$. Funding is successful if at least K agents pledge before T. Otherwise, the funding fails and no money exchanges hands. Conditional on being funded, the true value of the investment is the same for all agents and is an unknown random variable, V. Each investor i has a common prior on V, and observes a private signal, X_i, about the true value. The signals are real-valued informational variables, identically distributed.

Let $f(v, \boldsymbol{x})$ denote the joint density function of V and the vector of signals $X \equiv (X_1, X_2, \ldots X_n)$. It is assumed that f is symmetric in its last n arguments. Let $[\underline{V}, \bar{V}] \times [\underline{X}, \bar{X}]^n$ be the support of f. Further, it is assumed that all the random variables in this model are strictly affiliated. That is, for all $\boldsymbol{x}, \boldsymbol{x}' \in [\underline{X}, \bar{X}]^n$, and for all $v, v' \in [\underline{V}, \bar{V}]$,

$$f((v, \boldsymbol{x}) \vee (v', \boldsymbol{x}'))\, f((v, \boldsymbol{x}) \wedge (v', \boldsymbol{x}')) > f(v, \boldsymbol{x}) f(v', \boldsymbol{x}'),$$

where $\vee$ denotes the component-wise maximum, and $\wedge$ denotes the component-wise minimum.

Each agent i has a unique action available to them, although they can freely choose its timing, they can pledge, which is a promise to pay p if the funding campaign is successful and is denoted by $a_i^t = 1$. The action is irreversible, that is, if $a_i^{t'} = 1$, then $a_i^t \equiv a_i^{t'}$ $\forall t > t'$. Actions are publicly observed, which constitute history $\mathcal{H}^t$. Thus, a strategy for agent i, σ_i, is a function from his private signal X_i , as well as the publicly observed history $\mathcal{H}^t$ to the (possibly infinite) time of his pledge.

Agent i's payoff is given by:

$$U_i(a_i^T, a_{-i}^T, t_i) = (\Sigma a_i^T \geq K) a_i^T (v - p)$$

in which t_i is the time agent i pledges.

The history of agent i consists of his own signal, and the public history consisting of the actions of all agents. Since a good signal reveals fully the agent's type, the uninformed have never observed the good signal. Conditional on a good signal, it is a dominant strategy to stay in the game forever. It is therefore sufficient to specify the exit behavior of the uninformed agents. For the uninformed agents, all relevant information is contained in the public history of past actions, and therefore, I call this public information simply the history.

Formally, a history h^t up until time $t \leq T$ is a sequence of actions:

$$h^t = \{\emptyset \cup \{t_i\} | t_i \leq t, i \in \{1, 2, \ldots, n\}\}$$

Clearly $|h^t|$ is nondecreasing with t, as the number of pledges will only grow as time passes.

A strategy profile in the game is a vector $\sigma = (\sigma_1, \ldots, \sigma_n)$.

Each agent maximizes his expected pay-offs as estimated on the basis of his own signal, observations of the other agents' actions, and the initial prior probability assessment .... By equilibrium, I mean a perfect Bayesian equilibrium of the above game. In an equilibrium, all actions in the support of $\sigma_i(x_i; h_t)$ are best responses to σ_{-i} for all i and for all h_t .

I restrict attention to symmetric perfect-Bayesian equilibria.

Let $f : [\underline{X}, \overline{X}] \to [a, b] \subseteq [0, T]$ be a strictly decreasing function, then I have, if $h^t = \emptyset$, then $\sigma_i(x)$

For any t_i, the following strategy profile constitutes a Bayesian Perfect Nash Equilibrium,

Each agent makes the pledge decision at and only at its "prescribed" time, that is, at $f(x)$. And there are three possibilities:

(1) There has not been a pledge, or the total number l is less then $K - 2$. Write $h^{f(x)} = \{t_1, \ldots, t_l\}$, then

$$\sigma_i(x; h^{f(x)}) = \begin{cases} 1 \quad \text{if} \begin{cases} v(x; x) \geq 0 & \text{when } h^{f(x)} = \emptyset \\ v(x; f^{-1}(t_1), \cdots, f^{-1}(t_l)) \geq 0 & \text{when } h^{f(x)} = \{t_1, \ldots, t_l\} \end{cases} \\ 0 \quad \text{otherwise} \end{cases}$$

(2) There is just one investor need to meet the funding goal or the funding has already accrued enough, i.e., $l \geq K - 1$, then $\sigma_i(x; h^{f(x)}) = \begin{cases} 1 & \text{if } v(x; f^{-1}(t_1), \cdots, f^{-1}(t_l)) \geq 0 \\ 0 & \text{otherwise} \end{cases}$

As each type has a designated time to take action, the off-equilibrium-path belief is assigned to a probability 1 of the type that is associated with that time. In other words, if it is observed that a pledge is cast at $t = f(x)$, then the remaining agents assign probability 1 that the agent is of type x.

To verify this is a Bayesian Nash Equilibrium is straightforward. I just show that each type of agent is using a best response.

The participation constraint of later investors assures that the expected value of pledging is non-negative if it still requires other investors after one pledge. And the participation constraint of one-self assures that he will not regret pledging if it happens that the venture is funded right after he pledges. Given that, the best each investor can do is to provide accurate information as it is in everyone's interest to pool the dispersed information held by all the agents to the largest extent possible.

Notice, "schedule" f can be arbitrarily chosen. What this proposition tells us is the agents can follow any schedule (mathematically: because types are continuous, yet actions are binary, so agents can take advantage of continuous time to reveal their type perfectly when it is in their best common interest to do so) to pledge, in particular, will not naturally cluster around the deadline. In fact, the deadline need not be binding at all, as the entire schedule can be accomplished in an arbitrarily short amount of time.

B Proofs

B.1 Proof of Proposition 2

Proof. Let $\hat{x} \in (\underline{X}, \overline{X})$ be the solution to $E[v|X_{(M)} = \hat{x}] = p$, and $\mathbf{\hat{x}^2}$ calculated by Lemma 1. It has been proven by Proposition 1 that this is an equilibrium. In this equilibrium, $\text{Prob}[A^2 = A^1|A^2 < M] = 1$, in other words, $\text{E}[\frac{A^2-A^1}{A^2}|A^2 < M] = 0$. Since $\text{Prob}[A^2 > A^1|A^2 \geq M] > 0$, $\text{E}[\frac{A^2-A^1}{A^2}|A^2 \geq M] > \text{E}[\frac{A^2-A^1}{A^2}|A^2 < M]$ holds.

For the second part of the proposition. It can be shown that

$$\text{E}[\frac{A_1}{A_2}|A_2 \geq M] < 1 - \frac{1}{2}\text{Prob}[A_1 < \frac{1}{2}A_2|A_2 \geq M]$$

and

$$\text{E}[\frac{A_1}{A_2}|A_2 < M] > \text{Prob}[A_1 = A_2|A_2 < M]$$

Hence if $\text{Prob}[A_1 = A_2|A_2 < M] + \frac{1}{2}\text{Prob}[A_1 < \frac{1}{2}A_2|A_2 \geq M] > 1$, then $\text{E}[\frac{A_2-A_1}{A_2}|A_2 \geq M] > \text{E}[\frac{A_2-A_1}{A_2}|A_2 < M]$ ensues.

$\text{Prob}[A_1 = A_2|A_2 < M]$ can be seen as proportion of unfunded ventures of which the early investment level is so low that induces no following. It happens when the first period outcome is below anticipated minimum level for which investors are confident that it is a worthwhile venture. $\text{Prob}[A_1 < \frac{1}{2}A_2|A_2 \geq M]$ is the probability that among funded ventures, the probability that early investment level is high enough to encourage more to pledge, but not too high so as to "crowd out" the later investment. □

B.2 Proof of Proposition 3

Proof. It follows from Theorem 3 that $v(x; x^1, A^1)$ is strictly increasing in x^1 and x.

Case 1: If $v(\tilde{x}^1; \tilde{x}^1, A^1) < 0$, then $v(x^1; x^1, A^1) < v(\tilde{x}^1; \tilde{x}^1, A^1) < 0$, hence $x^2(A^1) = \tilde{x}^2(A^1) = -\infty$.

Case 2: if $v(\underline{X}; \tilde{x}^1, A^1) > 0$, then $v(\underline{X}; \tilde{x}^1, A^1) > v(\underline{X}; \tilde{x}^1, A^1) > 0$, hence $x^2(A^1) = \tilde{x}^2(A^1) = +\infty$.

Case 3: Lastly, let $x^2(A^1)$ be an interior solution to $v(x^2(A^1); x^1, A^1) = 0$, then $v(x^2(A^1); \tilde{x}^1, A^1) > v(x^2(A^1); x^1, A^1) = 0$, thus it has to be $x^2(A^1) > \tilde{x}^2(A^1)$ so that $v(\tilde{x}^2(A^1); \tilde{x}^1, A^1) = 0$.

□

C Additional Figures and Tables

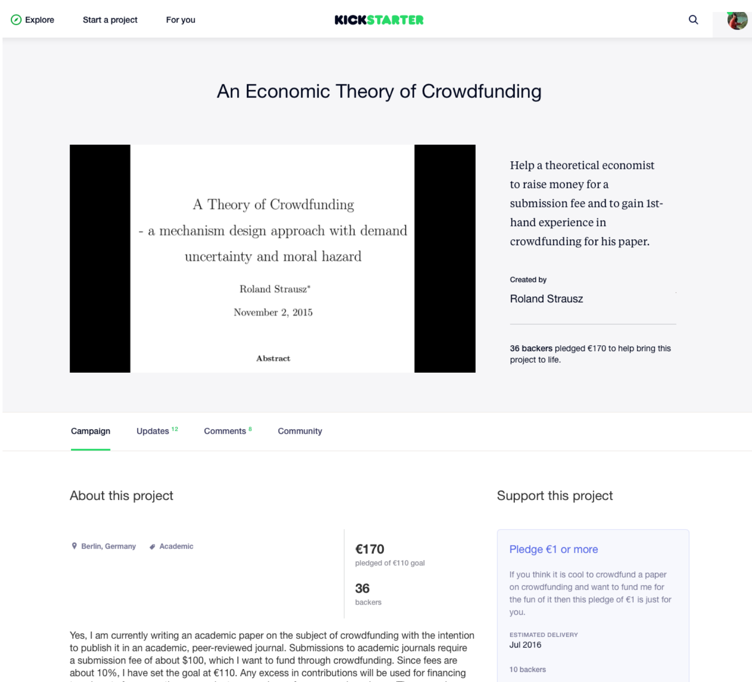

Figure A.1: A Sample Achieved Kickstarter Project

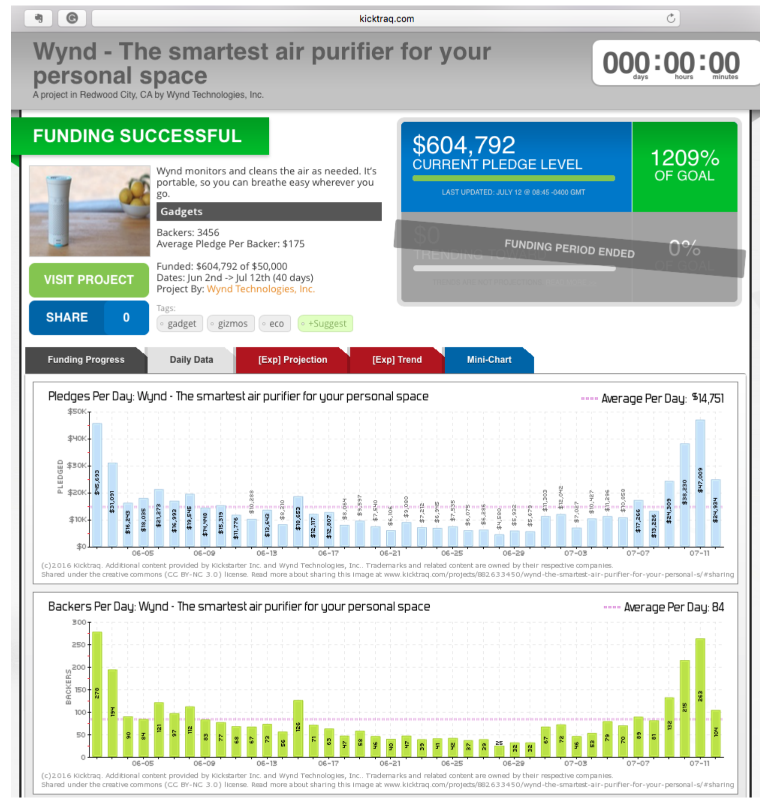

Figure A.2: A Sample Kicktraq Page

Table A.1: **Variable Definitions**

Variable Name	**Definition**
Funding goal	The funding goal amount (in $) set by entrepreneurs for their venture. Amount in other currencies are converted to US dollar based on the exchange rate in the month of the project launch.
Pledged amount	Amount (in $) pledged by the backers by the end of the project's funding window.
Pledge ratio	The ratio between Pledged amount and goal amount. When this ratio is larger than or equal to one, the project is funded and the pledged amount is transferred to the entrepreneurs. When this ratio is less than one, the project is unfunded and backers are not charged.
Funded	A dummy variable indicating the project is successfully funded. This happens when the pledged amount reaches or exceeds the goal amount, that is, pledge ratio equal to or larger than one.
Number of backers	The number of backers that pledged for the project.
Pledged amount per backer	The average amount pledged by each backer.
Duration (in days)	The number of days the entrepreneur set for the funding of the project, the length of the funding term.
Project pitch length	The number of words in venture's main pitch
Has videos	A dummy indicating that videos are used in the venture pitch.
Number of rewards tiers	The number of reward tiers offered to backers. Each reward tier corresponds to a price threshold. Backers backing an amount above the threshold are promised the corresponding reward before an estimated delivery date.
Number of projects created	The number of Kickstarter projects created by the entrepreneur as of the project launch date.
Number of projects backed	The number of Kickstarter projects backed by the entrepreneur as of the venture launch date.
Number of Facebook friends	The number of Facebook friends the entrepreneur has, conditional on the entrepreneur having Facebook linked to Kickstarter.
Has Facebook	A dummy equal to one if the entrepreneur has Facebook linked to Kickstarter.
Biography length	The number of words in the entrepreneur's biography
Reward price	The minimum pledge amount specified by the creator in exchange for the reward offered by projects with only one reward