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Investor Attention and Crowdfunding Performance

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Abstract

Today's digital era facilitates the rise of crowdfunding markets by allowing entrepreneurs to seek funding directly from crowds. Crowdfunding, as IT-enabled disintermediation, lowers entry barriers for crowds to invest in business projects and entrepreneurs to obtain funding, yet may exacerbate information asymmetry and absorb investor attention to process information about the potential projects. We develop a model wherein investors with limited attention aggregate personalized information about (reward-based) crowdfunding projects and conduct comparative analyses on how rises in investors' unit attention cost (associated with greater distractions) affect investor attention, investment decisions, and crowdfunding performance. We then exploit a novel measure of distraction—news pressure—to test the effects of distraction on investor engagement and crowdfunding performance empirically, and the results support our model predictions.

Keywords: Crowdfunding; Attention Economy; Distraction; Attention-driven Herding

1. Introduction

Reward-based crowdfunding markets provide viable alternative funding channels for entrepreneurs. Entrepreneurs attract funding directly from future customers rather than banks, venture capitalists. Thus, the crowdfunding platform becomes a form of IT-enabled disintermediation. Existing literature documents the benefits and costs of disintermediation ([6]). The process also absorbs individuals' attention to acquire and analyze information about crowdfunding projects with which they may not have expertise. As a result, distractions to investor attention may easily affect investor decisions and crowdfunding outcomes, especially considering many crowdfunding projects are of a small economic scale.

The available information online is vastly greater than what any individual could process, even in a lifetime. In crowdfunding, individual investors need to aggregate original contents into information that is easy-to-process but still useful for decision-making. Yet investor attention is known to be rather limited and scarce. Distractions (e.g., breaking news, social media feeds, etc.) compete for that attention. Hence, investors face opportunity costs when processing information about crowdfunding projects, and their investment decisions may be easily affected by distractions from elsewhere. Thus, understanding the mechanisms as to how investors' limited attention can influence their behavior, and quantifying the effect of distraction on crowdfunding outcomes, are critically important for entrepreneurs as well as crowdfunding platforms.

To understand the mechanism we develop a model of backers with limited attention, wherein backers with heterogeneous preferences pay costly attention to acquire personalized signals about a crowdfunding project and make decisions accordingly. We adopt the assumption from rational inattention literature (henceforth RI) that backers pay costly attention, optimally process information about a crowdfunding project, and make investment decisions accordingly.[1] A

[1]RI builds on the observation that humans cannot pay

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backer's personalized information acquisition can be summarized by a signal structure that maximizes the differences between the benefit of the backer's informed decision-making and his attention cost. As a result, by conducting comparative analyses with respect to unit attention cost, we can better understand the effect of distraction on backers' decisions and crowdfunding performance.

Another key feature of crowdfunding campaigns is that backers who enter late in the campaign can observe the aggregate decisions of other backers who entered the campaign early on. As pointed out by [1], funding propensity increases with accumulated capital and may lead to herding. In a similar spirit, we allow backers to enter in the early or late stages of the crowdfunding campaign. We call those who enter in the early stage leading backers and those who enter in the late stage following backers. We incorporate the feature that backers in the late-stage observe early crowdfunding performance in the model, and investigate whether this leads to their herding behavior through the channel of attention.

Our model predicts that leading backers are on average more enthusiastic about the crowdfunding project, whereas the following backers are less so. As a result, we find that early distraction increases early performance whereas late distraction decreases late performance. The opposite relationships between performance and distraction in the two stages stem from backers' personalized information acquisition resulting from their limited attention as well as preference heterogeneity. Finally, we find the effect of early distraction is persistent, and can be amplified through the following backers' herding behavior.

Next, to support our model predictions, we empirically test (i) the effect of distractions on backers' engagement in the crowdfunding project, (ii) the effect of early/late distractions on early and late performance, and (iii) the presence of attention-driven herding of following backers and the effect of early distraction on late performance through the herding channel. The key is to identify a variable that relates to the unit attention cost but is orthogonal to the characteristics of the crowdfunding project itself. The reason is twofold. First, by regressing early and late performance on that variable, we can study how backers' limited attention affects their own investment decisions. Second, in practice, we only observe backers' decisions in the early and late stages. But a positive correlation between following and leading backers' decisions cannot show the presence of following backers' herding behavior because omitted factors may drive better performance in both stages. To that end, the variable can be used as an instrument to identify the impact of early performance on late performance.

We exploit the variable *news pressure* [7] which measures the median number of minutes that US news broadcasts devote to the first three news segments. This variable reflects the extent of newsworthy material available on a given day. News pressure measures distractions from TV news that divert backers' attention, but it does not correlate with the projects' performance and other characteristics. Because news events such as the aforementioned terrorist attack were unrelated to the crowdfunding projects on Kickstarter, such an episode distracts the backers, and their investment decisions, especially for the projects launched right after the event happened. For each project, we aggregate daily news pressure to the early- and late-stage and form early and late distraction variables. We use project-level Kickstarter data from CrowdBerkeley ([19]) to measure the project outcome variables. We use the pledged value to funding goal ratio during early and late-stage to measure early and late performance and use the number of comments posted for each project during early and late stages as proxies for backers' engagement levels.

Our empirical results are consistent with our model predictions. First, we show the total comments posted on a project website in the early- and late-stages of the campaign negatively correlate with early and late distractions, respectively, suggesting backers' engagement level decreases as distractions. Second, we find that early performance increases as early distractions rise, whereas late performance decreases as late distractions rise. Finally, by analyzing the sentiment of backers' comments in different stages, we show that more enthusiastic backers enter early which is consistent with our model prediction. In addition, our analyses have managerial implications for crowdfunding strategies.

full attention to all available sources but can choose to pay more attention to more important things. The literature is pioneered by [17], who notes that "...people having limited attention accords with ordinary experience, as do the basic ideas of the behavioral, learning, and robust control literature. The idea of limited attention is particularly appealing ... it arrives at predictions that do not depend on the details of how information is processed."

1.1. Related Literature

Crowdfunding. Few papers study investors' information acquisition, and how their cost of attention affects crowdfunding outcomes. Most recent theoretical studies on crowdfunding all focus on the information value of crowdfunding campaigns for discovering consumer demand ([18]; [15];). Many recent empirical studies of reward-based crowdfunding investigate the factors for improving crowdfunding performance, including social influence from early contributors ([4]), information hiding of early contributors ([5]), and project risk disclosure ([9]). To the best of our knowledge, we are the first to study the effect of distractions diverting investor attention on crowdfunding performance.

Investors' limited attention. A recent literature empirically studies the consequence of investors' limited attention. [14] uses a measure of news pressure (similar to ours) to examine the effect of distractions on noise traders' attention on institutional trading and market outcomes, and finds that when distraction increases, liquidity and volatility decrease, and prices reverse less. [13] empirically studies the impact of limited attention on the investment performance of hedge fund managers and finds that money managers significantly underperform during a divorce. The influence of agents' attention on their decisions in the online markets has also been studied in the information systems literature. For instance, [16] addresses that attention affects users' contributing content on Twitter.

Herding in online markets. [11] finds that a relational herding effect occurs as the potential lenders are likely to follow their offline friends to bid. [8] studies how perceived anonymity shapes herding behavior in online debt-based crowdfunding markets. Here, unlike in most observational learning (theoretical) literature (pioneered by [2] and [3]), following backers can only observe an aggregate decision of leading backers which affects their perception about the project, and cannot back out individual backer's decision beforehand. A similar modeling strategy has been used in the early study of online reviews, such as [10] and [12]. We believe this fits the crowdfunding setting, as backers only observe the total number of backers on crowdfunding websites instead of dynamic or individual-level data.

2. Analytical Model

Consider a project launched on a reward-based crowdfunding platform that attracts backers in two stages $t = 1, 2$ of a crowdfunding campaign. The project quality is a random variable $\omega = -1, 1$ with equal probabilities, where $\omega = -1$ (resp., $\omega = 1$) represents the state that the project is of low (resp., high) quality.

Each backer is endowed with one unit of asset, and the utility from investing one unit asset to the crowdfunding project in stage t is comprised of the project fit b, project quality ω, and preference shifter η_t. Formally, we define backer b's utility from investing as: $u(b, t) = b + \omega + \eta_t$. Here, project fit varies across backers, and b is assumed to be uniformly distributed on $[-1, 1]$.

Backers who enter the platform in stage t observe the up-to-date crowdfunding performance. We assume only the information related to the aggregate performance of the project will influence backers' investment decisions through the preference shifter η_t. This is motivated by the fact that one observes the aggregate performance but not their fellow backers' decisions on most reward-based crowdfunding platforms such as Kickstarter.

Since there is no previous information about the project's performance at the beginning of the first stage, we normalize $\eta_1 = 0$. At the beginning of the stage 2, we assume that the aggregate performance of the crowdfunding platform in stage 1 will positively affect the preference shifter of backers in stage 2. This assumption can be justified by the fact that a project with a higher total pledged value is more attractive to backers who enter late than a project with a low total pledged value. More specifically, we let η_2 be a function of the aggregate performance of the project in stage 1, which is assumed to be increasing. Without loss of generality, we assume the backer's outside option is 0, thus a backer will invest one unit of the asset in the project at stage t if and only if $u(b, t) \geq 0$.

Information structure. We follow RI literature and model a backer's attention strategy as a signal structure that aggregates source information of ω into a personalized opinion about the project quality. A personalized signal structure is a mapping $\Pi : \{-1, 1\} \to \Delta(Z)$, where each $\Pi(\cdot|\omega)$ specifies a probability distribution over a set Z of signal realizations conditional on the state (quality) realization is ω. At stage t, backer b pays attention cost $\lambda_t I(\Pi; b, t)$ for acquiring and processing the personalized signal structure—where λ_t is the unit cost of attention at stage t, and $I(\Pi; b, t)$ is the needed attention level of absorbing signal Π at stage t—then each backer observes signal realizations, updates belief about quality, and makes investment decisions.[2]

Personalized signal. Since a backer's decision is binary (investing or not investing), the optimal personalized signal can have at most two realizations. Thus it is without loss of generality to write the set of signal realization as $Z = \{h, l\}$. We can interpret the signal realization h (resp., l) as the formed opinion that the project is of high (resp., low) quality and worth (resp., not worth) investing in. Given backer b enters the campaign in stage t, we write the probability that the signal realization is h as $\pi(b,t) = \frac{1}{2}\sum_\omega \Pr(h|\omega; b, t)$. So the probability that the signal realization is l is $1 - \pi(b,t)$. Then $\rho_h(b,t) = \dfrac{\sum_\omega \omega\Pi(h|\omega; b,t)}{2\pi(b,t)}$ and $\rho_l(b,t) = \dfrac{\sum_\omega \omega\Pi(l|\omega; b,t)}{2(1-\pi(b,t))}$ are the posterior means of ω conditional on signal realization is h or l, respectively. Since $\omega = -1, 1$ with equal probability, the prior of ω is 0. By Bayesian Plausibility (BP)—the expected posterior probability equals the prior—we have

$$\pi(b,t)\rho_h(b,t) + (1-\pi(b,t))\rho_l(b,t) = 0. \quad (1)$$

Paying attention is beneficial for a backer if and only if it helps the backer make a better decision. Thus, the benefit of acquiring a personalized signal for a backer with $b \leq -\eta_t$ is his expected gain from investing in the project; and the benefit of acquiring a personalized signal for a backer with $b > -\eta_t$ is his expected gain from not investing in the project. Then, in stage t, backer b's expected to gain from acquiring a personalized signal Π given signal realization $Z \in \{l, h\}$ can be written as:

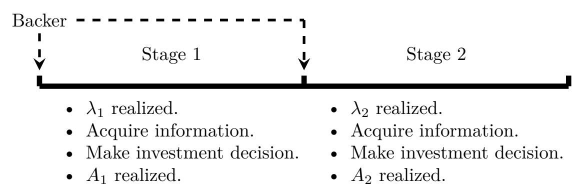
$$\begin{aligned} &V(\Pi; b, t) \\ &= \begin{cases} \pi(b,t)\,[b + \eta_t + \rho_h(b,t)]_+ + (1-\pi(b,t)) \\ [b + \eta_t + \rho_l(b,t)]_+ & \text{if } b \leq -\eta_t \\ \pi(b,t)\,\big|[b + \eta_t + \rho_h(b,t)]_-\big| + (1-\pi(b,t)) \\ \big|[b + \eta_t + \rho_l(b,t)]_-\big| & \text{if } b > -\eta_t \end{cases} \end{aligned} \quad (2)$$

Here, the subscript $+$ (resp., $-$) denotes the positive (resp., negative) value of the expression.

Attention cost. The attention cost is $\lambda_t I(\Pi; b, t)$. To absorb a personalized signal Π at stage t, the needed attention of backer b absorbing the signal structure $I(\Pi; b, t)$ measures the reduction in the variance of ω, before and after acquiring information: $I(\Pi; b, t) = \pi[\rho_h(b,t)]^2 + (1-\pi)[\rho_l(b,t)]^2$. The unit cost of attention λ_t measures how costly one's attention is in processing information about the crowdfunding project. It is increasing in the distractions from elsewhere. That is, pay the same amount of attention to processing information about the crowdfunding project; one's attention becomes more valuable, thus costly when distraction is higher. At the beginning of the campaign, backers do not observe the distraction level over the campaign and thus the unit cost of attention. Here, $\bar{\lambda}$ is the expected unit cost of attention.

Aggregate performance. We define the aggregate performance of the crowdfunding platform in stage $t \in \{1, 2\}$ by A_t, which is the aggregation of backers' propensity to invest in stage t. Formally, we write $A_t := \int_{B_t} \pi(b,t)/2d(b)$, where $B_t := \{b \in [-1, 1] | b \text{ enters stage } t\}$.

Timeline. (i) A mass of backers decide to enter



the campaign in stage 1 or stage 2. If enters in stage 1, then the backer decides whether to acquire a personalized signal structure in stage 1 after the realization of distraction λ_1. We call the backer a leading backer. If enters in stage 2, then the backer decides whether to acquire a personalized signal structure in stage 2 after the realization of distraction λ_2 and the early performance, A_1, of stage 1 (step (v)). We call the backer the following backer.[3] (ii) Unit attention cost in stage

[2]We assume, at each stage, backers have the same unit attention cost. We make this assumption because in the empirical analysis we only observe cross-time variation but not cross-backer of attention cost. Relaxing this assumption will not affect the result for individual backers but may affect the aggregate outcome.

[3]First, due to backers' limited attention, we assume backers consider the investment decision once—either in stage 1 or 2. Alternatively, we can assume the backers who do not invest in the first stage will decide whether to invest in stage 1. In this case, our results still hold qualitatively. Second, we assume no discount factor for ease. Alternatively, we can assume leading backers' net gain at stage 1 be discounted since they face an opportunity costs for acting early. In this case, our results still hold if the discount rate is sufficiently low (so that leading backers still exist).

1, λ_1, is realized. (iii) Leading backers decide whether to acquire a personalized signal structure and make investment decisions accordingly. (iv) Aggregate performance (decisions) in stage 1 (early performance), A_1, is realized; distraction in stage 2, λ_2, is realized. (v) Following backers observe A_1 and decide whether to acquire a personalized signal structure and make investment decisions accordingly. (vi) Late performance A_2 is realized.

Backers' problem. Each backer chooses which stage to enter through a cost-benefit analysis, then the optimal attention strategy and associated investment decision. Fix any stage t, we show in Appendix that if a backer forms an opinion h (resp., l) about the project quality, then he will invest (resp., not invest) in the project. As a result, π (resp., $1-\pi$) is also the probability that a backer invests (resp., does not invest) in the project. Thus, we can write a backer b's problem at stage t as follows: $\max_{\rho_l,\rho_h,\pi} V(\Pi;b,t) - \lambda_t I(\Pi;b,t)$, such that $\pi\rho_h + (1-\pi)\rho_l = 0$, where $V(\Pi;b,t) = \pi\,(b+\eta_t+\rho_h)_+$, if $b \leq -\eta_t$; and $V(\Pi;b,t) = (1-\pi)\left|(b+\eta_t+\rho_l)_-\right|$, if $b > -\eta_t$.

Therefore, at the beginning of the campaign, given the expected unit cost of attention, $\bar{\lambda}$, backer b solves the following problem:

$$\max_{t\in\{1,2\}} \Big\{ \max_{\{\rho_z\}_{z=l,h},\pi} V(\Pi;b,t) - \bar{\lambda} I(\Pi;b,t),$$
$$\text{s.t. } \pi(b,t)\rho_h + (1-\pi(b,t))\rho_l = 0\Big\}$$

If a backer is indifferent between entering stages 1 and 2, we assume he enters each stage with equal probabilities.

We make two assumptions: (i) $\lambda_t \geq \frac{1}{2}$, which ensures that no investor fully discovers the true quality in each stage. [4] (ii) $\eta_2 = \theta A_1$, which is for analytical convenience. $\theta > 0$ is the marginal influence from aggregate performance of $t-1$ to t.

2.1. Individual Backer's Decision

We first characterize individual backers' strategies given their entry choices and then analyze the entry choices. Lemma 1 characterizes backers' optimal investment decision given they enter the campaign in stage t.

Lemma 1. *Fix any backer b who enters the campaign at t. Under the acquired optimal signal structure, the propensity that the backer b invests in the project is:*

$$\pi(b,t) = \begin{cases} 0 & \text{if } b \leq -\frac{1}{4\lambda_t} - \eta_t; \\ 1 & \text{if } b \geq \frac{1}{4\lambda_t} - \eta_t; \\ \frac{1}{2} + 2\lambda_t(b+\eta_t) & \text{if } b+\eta_t \in (-\frac{1}{4\lambda_t}, \frac{1}{4\lambda_t}). \end{cases} \quad (3)$$

(i) Fix any b, $\pi(b,t)$ is decreasing in λ_t for $b \leq -\eta_t$ and increasing in λ_t for $b > -\eta_t$.
(ii) Fix any λ_t, $\pi(b,t)$ is increasing in b.

Figure 1 depicts backer b's propensity to invest in the project against b. The black (resp., red) curve represents the propensity to invest when the unit attention cost is low (resp., high). As the backer's project fit becomes higher, he is more likely to invest in the project, holding the unit cost of attention fixed. In addition, backers with very low/high project fit will pay no attention since their preferences are so strong that the possibility of receiving gains from information acquisition is fairly low. As the unit cost λ_t increases from the black curve to the red curve, the cost of paying attention increases, and more such backers tune out information. Backers who still pay attention, due to the rise of their attention cost, will pay less attention and act more based on the project fit. As a result, the propensity to invest for backers with relatively low project fit ($b \leq -\eta_t$) decreases, and the propensity to invest for backers with relatively high project fit ($b > -\eta_t$) increases.

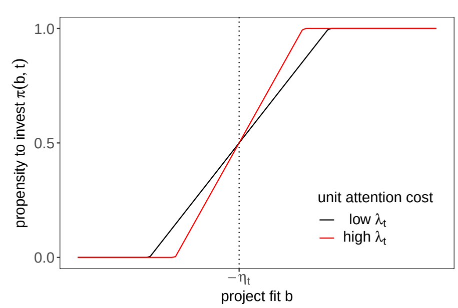


Figure 1. Plot backer's propensity to invest, $\pi(b,t)$, against project fit b when the unit attention cost λ_t is low vs. high.

Lemma 2 characterizes backers' attention paid to acquiring the optimal signal structure given they are entering stage t. Intuitively, the attention paid by a backer decreases as the unit cost of attention decreases.

Lemma 2. *Given any backer b who enters the campaign at t, the attention paid by the backer to*

[4] In reality, it is unlikely for all investors to pay full attention to a crowdfunding project and fully discover the project quality.

acquire the optimal signal structure is

$$I(\Pi;b,t)=\begin{cases}0 & \textit{if } b\geq\frac{1}{4\lambda_t}-\eta_t \\ & \textit{or } b\leq-\frac{1}{4\lambda_t}-\eta_t; \\ \frac{1}{16{\lambda_t}^2}-(b+\eta_t)^2 & \textit{if } -\frac{1}{4\lambda_t}-\eta_t<b \\ & <\frac{1}{4\lambda_t}-\eta_t.\end{cases} \tag{4}$$

Lemma 3 solves for each backer b's optimal entry choice. The result shows that enthusiastic backers with high project fit enter first if θ is not too high. Define $\overline{\theta}(\lambda) := \begin{cases}\frac{64\lambda-16}{56\lambda-16\lambda^2-1} & \text{if } \lambda<\frac{3}{4}; \\ \frac{2}{4\lambda-1} & \text{if } \lambda\geq\frac{3}{4}.\end{cases}$ and $\bar{A}_1 := -\frac{1}{\lambda\theta^2}-\frac{1}{4\lambda\theta}+\frac{\sqrt{2}}{2\lambda\theta^2}\sqrt{2+\theta+2\lambda\theta^2}$.

Lemma 3. *Fix any $\bar{\lambda}$ and $\theta<\overline{\theta}(\bar{\lambda})$. Then $(-\frac{\theta\bar{A}_1}{2},\frac{1}{4\bar{\lambda}})\subseteq B_1$ and $(-\frac{1}{4\bar{\lambda}}-\theta\bar{A}_1,-\frac{\theta\bar{A}_1}{2})\subseteq B_2$; for any backer $b\in[-1,-\frac{1}{4\bar{\lambda}}-\theta\bar{A}_1]\cup[\frac{1}{4\bar{\lambda}},1]$, b belongs to B_1 and B_2 with equal probabilities.*

Figure 2 depicts backer b's expected net gain from paying attention against the project fit b, and illustrates the results of Lemma 3. The black part represents the expected gain from paying attention for those backers who enter the campaign in the early stage; their expected net gain when entering stage 1 is higher than that when entering stage 2. The red part represents the expected net gain from paying attention for those backers who enter the campaign in the late stage; their expected net gain when entering stage 2 is higher than that when entering stage 1. The gray part represents the expected net gain for those backers who are indifferent in entering either stage; their net gain from paying attention is 0 since they would not pay any attention.

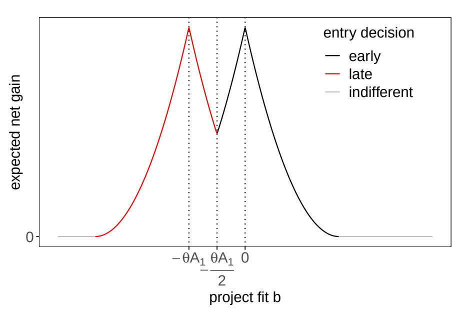


Figure 2. Entry Decisions: Plot backers' expected net gain from paying attention against the project fit b

2.2. Aggregate Outcomes

We aggregate individual backers' decisions, based on which we develop associated testable hypotheses. Proposition 1 discusses how backers' attention level varies with the unit attention cost. As the unit attention cost increases, they pay less attention, so the total attention level decreases.

Proposition 1. *For any λ_t' and λ_t'' with $0<\lambda_t'<\lambda_t''$, let the associated attention level be $I'(\Pi;b,t)$ and $I''(\Pi;b,t)$, respectively. Then, the attention level in stage t is decreasing in the unit attention cost in stage t, i.e., $\int I'(\Pi;b,t)d\mathcal{U}(b)\geq\int I''(\Pi;b,t)d\mathcal{U}(b)$, where $\mathcal{U}(b)$ represents uniform distribution.*

In practice, attention level and unit attention cost are hard to observe. Presumably, backers' engagement positively correlates with their attention level and is easier to measure. At the same time, the unit attention cost at stage t is positively correlated with the level of distraction in stage t. Therefore,we form the Hypothesis 1 as follows.

Hypothesis 1. Backers' engagement level decreases in the level of distraction in all stages.

Proposition 2 discusses how backers' aggregate decisions (crowdfunding performance) in different stages vary with the unit attention cost. We show that early performance increases in the early-stage unit attention cost, whereas late performance decreases in the late-stage unit attention cost. The opposite relationships between performance and unit attention cost in the two stages stem from backers' limited attention and preference heterogeneity. Had backers have an infinite amount of attention or homogeneous project fit, they would acquire a non-personalized signal; thus, the effects of unit attention cost on performance will not be opposite in the two stages.

Proposition 2. *Consider λ_t', λ_t'' with $\lambda_t'<\lambda_t''$ for $t=1,2$, and let A_t' and A_t'' be the associated performances in stage t, respectively. Fix any $0<\theta\leq\min\{\overline{\theta}(\bar{\lambda}_t),\overline{\theta}(\lambda_t')\}$. Then, $A_1'\leq A_1''$ and $A_2'\geq A_2''$.*

Since the unit attention cost is increasing in the level of distractions, together with Proposition 2, we form Hypothesis 2 as follows.

Hypothesis 2. This hypothesis has two parts: (i) A project's early performance increases in early distraction; and (ii) A project's late performance decreases in late distraction.

Proposition 3 shows how early performance affects late performance through the attention channel.

Proposition 3. *Fix any λ_2. Consider λ_1' and λ_1'' with $0 < \lambda_1' < \lambda_1''$, and let A_t' and A_t'' be the associated early performance, respectively. Fix any $\theta \in (0, \overline{\theta}(\lambda_1)]$. We have $A_1' \leq A_1''$ and $A_2' \leq A_2''$.*

By Proposition 2, higher unit attention cost in stage 1 leads to better early performance; which, by Proposition 3, results in better late performance. This means: the effect of early distraction is persistent andamplified through the following backers' herding behavior. We form Hypothesis 3:

Hypothesis 3. A project's early performance increases its late performance through the attention channel.

Above results depend on backers' sequence of entry. Proposition 4 discusses the aggregate choices of entry. On average, enthusiastic backers with higher project fit enter first.

Proposition 4. *Fix any $\bar{\lambda}$ and $\theta < \overline{\theta}(\bar{\lambda})$. On average, leading backers' preference about project fit is stronger than that of a following backer. That is,*

As researchers, we do not observe backers' product fit. Presumably, the product fit is a positive relationship with the sentiment. We form Hypothesis 4 as follows.

Hypothesis 4. Leading backers on average have more positive sentiment than following backers.

3. Empirical Analysis

3.1. Data

A key step of our analysis is to identify the factors that affect backers' unit attention cost, such as the level of distraction. We use the *news pressure* variable introduced by [7] to measure distractions to backers from TV news. News pressure is defined as the median number of minutes that US news broadcasts devote to the first three news segments. [7] argues that this variable is a good indicator of the extent of newsworthy material available on a given day. [14] also uses measures of news pressure to document the impact of distraction from TV news on institutional trading and associated market outcomes. For instance, on November 13, 2015, terrorists claiming allegiance to the Islamic State opened fire in coordinated attacks across Paris, killing 130 people and wounding 494 others at the Bataclan concert hall and nearby cafes. That night, ABC, CBS, and NBC devoted all of their first three news segments to that story. The top three news segments compromised an average of 22.5 minutes (out of 30 minutes)—one of the highest values over the sample period. The episode distracts backers and thus increases their attention cost of doing other things during that day. Therefore, news pressure measures the level of distraction from TV news that increases backers' unit attention cost. We use it as a proxy to measure distractions that divert backers' attention.

To that end, for each project i launched on date t, we construct early distraction measure λ_{1t}, by computing the average of news pressure from day t to day $t+2$; we construct late distraction measure λ_{2t}, by computing the average of news pressure from day $t+3$ to the end of the crowdfunding campaign. On average, the daily news pressure is around 8-9 minutes (out of 30 minutes) in either early or late stages.

We construct project performance measures using Kickstarter project launch-date level data obtained from CrowdBerkeley ([19]). Based on this dataset, we construct the early performance of project i launched on date t, $A_{1i,t}$ by the total pledged value obtained from day t to day $t+2$ divided by its funding goal. We construct the late performance of project i launched on date t, $A_{2i,t}$ by the total pledged value from date $t+3$ till the end of its crowdfunding campaign divided by its funding goal. On average, the total pledged value to funding goal ratio across all projects is about 1.3, the ratio in the early is about 0.38, and the ratio in the late stage is about 0.89.

We use the daily average number of comments on each crowdfunding project on Kickstarter as a proxy for backers' engagement level. In particular, for each project i launched on date t, we construct early comments—as a proxy leading backers' engagement in the early stage—by the natural logarithm of the daily average number of comments posted on the project i website from day t to day $t+2$, and late comments—as a proxy for the following backers' engagement in the late stage—by the natural logarithm of the daily average number of comments posted on the project i website from day $t+3$ to the end of the campaign.

Using the same dataset, we also construct the list of controls $\boldsymbol{X}_{i,t}$ including (i) the natural logarithm of the project's funding goal (Log Funding Goal); (ii) the natural logarithm of the number of days of the crowding campaign (Log Funding Duration); (iii) a dummy variable that indicates if the creator of the project has ever found a project on Kickstarter (Series Founder); (iv) a dummy variable that indicates if the creator of the project has ever found a project on Kickstarter with successful experience (Series Founder with Success); (v) the number of projects within the same category launched on the same day; and (vi) the number of projects launched on the same day. Our sample is from 2015 to 2018 with 34536 projects.

3.2. Empirical Results

In this section, we focus on how early and late distractions affect backer engagement and project performance. We first test Hypothesis 1 and investigate if distraction affects backers' engagement in the crowdfunding project. We regress project level comments on distraction in early and late stages as well as over the whole campaign. In fact, more than 50% of projects in our sample have zero comments. Thus, we adopt the Tobit regression model.

Table 1 presents the results. Column 1 reports the effect of overall distraction on overall engagement level for the whole campaign; column 2 reports the effect of early distraction on early-stage engagement level and column 3 reports the effect of late distraction on late-stage engagement level. The number in the parentheses represents the standard error of the estimates. Across all columns, we include the control variable $\boldsymbol{X}_{i,\tau}$ as well as month and day-of-the-week fixed effects. For Column (3), we also control for early performance. Across all columns, the coefficients on distraction remain negative and statistically significant, which supports our model prediction that backers pay less attention as distractions increase, resulting in less engagement in the project.

In what follows, we investigate how early distraction contributes to early and late performance by testing Hypotheses 2 and 3. In particular, we adopt the IV approach and use early distraction as an instrument to identify the effect of early performance on late performance. In general, identifying the causal impact of early performance on late performance is difficult because of omitted variables. For instance, a project with better quality can attract both leading and following backers. To address this concern, we use early distraction to instrument early performance, assuming that early distraction only affects late performance through early performance. Our first stage regression relates early performance to early distraction. The estimating regression takes the form

Variable	Overall engagement	Early engagement	Late engagement
	(1)	(2)	(3)
Overall distraction	-1.201*** (0.050)		
Early distraction		-3.823*** (0.428)	
Late distraction			-1.679*** (0.090)
Early performance	No	No	Yes
Control	Yes	Yes	Yes
Month FE	Yes	Yes	Yes
DOW FE	Yes	Yes	Yes
Observation	34,536	34,536	34,536
Log likelihood	-646.664	-14986.135	-4316.773

Table 1. Effect of Distraction on Engagement

$$A_{1i,\tau} = \boldsymbol{\alpha}_1 + \gamma\phi_{1i,\tau} + \boldsymbol{\beta}_1^T \boldsymbol{X}_{i,\tau} + \varepsilon_{i,\tau}, \qquad (5)$$

where $A_{1i,\tau}$ represents the early performance of project i that launched at date τ; $\phi_{1i,\tau}$ represents daily average distraction of project i that launched at date τ over the early stage, and is positively correlated with the unit attention cost in early stage; $\boldsymbol{\alpha}_1$ represents the fixed effects including the launch day of week and month fixed effects, $\boldsymbol{X}_{i,\tau}$ represents the set of control variables, and $\varepsilon_{i,\tau}$ is the error term. The regression addresses Hypothesis 2 (i). Similarly, to address Hypothesis 2 (ii), we regress $A_{2i,\tau}$ on $\phi_{2i,\tau}$, with controls $\boldsymbol{X}_{i,\tau}$, fixed effects $\boldsymbol{\alpha}_2$, as well as the early performance $A_{1i,\tau}$.

Using the predicted values from Equation (5) $\widehat{A_1}_{i,\tau}$, we then estimate the second stage regression of the form

$$A_{2i,\tau} = \boldsymbol{\alpha}_2 + \eta\widehat{A_1}_{i,\tau} + \boldsymbol{\beta}_2^T \boldsymbol{X}_{i,\tau} + \xi_{i,\tau} \qquad (6)$$

where $A_{2i,\tau}$ represents the late performance of project i that launched at date τ, $\widehat{A_1}_{i,\tau}$ is the predicted value for early performance obtained from estimating Equation (5), $\boldsymbol{\alpha}_2$ represents the fixed effects including the launch day of week and month fixed effects, $\boldsymbol{X}_{i,\tau}$ represents the set of control variables, and $\xi_{i,\tau}$ is the error term.

We present the results from estimating the effect of distraction on performance in Table 2. Column 1 reports the effect of overall distraction on overall performance; column 2 reports the effect of early distraction on early performance and column 3 reports the effect of late distraction on late performance.

Variable	Overall performance	Early performance	Late performance
	(1)	(2)	(3)
Overall distraction	0.137*** (0.027)		
Early distraction		0.191*** (0.056)	
Late distraction			-0.104*** (0.017)
Early-stage Performance	No	No	Yes
Control	Yes	Yes	Yes
Month FE	Yes	Yes	Yes
DOW FE	Yes	Yes	Yes
Obs.	34,536	34,536	34,536
R^2	0.199	0.178	0.444

Table 2. Effect of Distraction on Performance

For all columns, we include the control variable $\boldsymbol{X}_{i,\tau}$ as well as month and day-of-week fixed effects. For Column (3), we also control for early performance. Consistent with our model predictions, early distractions increase early performance whereas late distractions decrease late performance. Moreover, the effect of distraction on overall performance is also positive. This implies that the effect of early distraction on crowdfunding performance dominates the effect of late distraction. One potential mechanism might be due to Proposition 4—following backers herd onto leading backer's aggregate decision, early performance—which we address later by testing Hypothesis 4.

We present our findings from estimating Equation (6) in Table 3. We find consistent results. In each case, the coefficient of $\widehat{A_1}_{i,t}$ remains positive and statistically significant, suggesting that following backers herd on leading backers' aggregate decisions. The result supports our model prediction and shows that attention-driven herding amplifies the effect of early distraction on crowdfunding performance.

Variable	Late Performance $A_{2i,\tau}$		
	(1)	(2)	(3)
Early performance	0.081*** (0.018)	0.114*** (0.015)	0.084** (0.037)
Control	Yes	No	Yes
Month FE	No	Yes	Yes
DOW FE	No	Yes	Yes
KP F statistic	51.702	62.076	11.844
Obs.	34,536	34,536	34,536
R^2	0.425	0.421	0.430

Table 3. Early Performance on Late Performance

Finally, we address Hypothesis 4 by comparing backer sentiment from their comments at comment and project level, respectively. Table 4 presents the results.

Variable	Comment level		Project Level	
	(1)	(2)	(3)	(4)
Early	0.036*** (0.002)	0.017*** (0.001)	0.016*** (0.001)	0.037*** (0.001)
Project FE		Yes		Yes
User FE		Yes		
Post W FE		Yes		
Post DOW FE		Yes		
Launch W FE		Yes		
Launch DOW FE		Yes		
Obs.	13,849,149	13,118,649	230,334	136,670
R^2	0.002	0.128	0.002	0.600

Table 4. Backer Sentiment in different stage

Columns (1) and (2) provide results at comment level. Column 1 suggests that comments posted at the early stage of the crowdfunding projects are more likely to have positive sentiments. Column 2 adds various fixed effects to control for unobserved heteogeneities at project, user, post week, post day-of-the-week, launch week, and launch day-of-the-week levels. The positive relationship is still robust regarding to the inclusion of all these fixed effects. One caveat of the above analysis is that the results are likely driven by the unequal weights from the differences in the number of comments for each crowdfunding project. To mitigate this concern, Columns 3 and 4 provide results at project-stage level. To do that, we aggregate comment level sentiment to project-stage level sentiment, and effectively we have two observations per one crowdfunding project: one for early stage and one for later stage. Column 3 shows that early comments are more likely to have positive sentiments at project-stage level. Column (4) adds project fixed effect to control for the unobserved characteristics of the project and the result is still consistent. Therefore, it is quite evident that early comments are associated with more positive sentiments for crowdfunding projects.

All our results are robust to replace the month fixed effect with a more granular week fixed effect. In Online Appendix, we conduct supplementary analyses to examine the effects of late distraction and early performance on total attention received in late stage. One caveat of our empirical analysis is the absence of backer-level analysis due to data unavailability. Should the data about backer-level characteristics and crowdfunding decision variables become available in the future, we can further investigate heterogeneous effects of distractions across backer groups and/or conduct counterfactual analysis through structure estimation.

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Online Appendix

Please see `https://www.dropbox.com/s/fqzd100jy5gbifv/Hicss-apx.pdf?dl=0`