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论文题目： The Wisdom of Crowds in Investment by Learning from Others on Social Investment Platforms

The Wisdom of Crowds in Investment by Learning from Others on Social Investment Platforms

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Abstract

The wisdom of crowds can improve investment outcomes, but learning from others may weaken investors' incentives to acquire information. We develop a model of social investment platforms in which investors differ in research costs. When investment leads are transmitted sufficiently well, both researchers and followers earn higher expected payoffs than under their best independent investment strategies, even after accounting for research costs. Researchers benefit because access to others' ideas improves their alternatives when they reject a risky project. We identify an endogenous limit to these gains: beyond a threshold, better information transmission induces some researchers to follow others, reducing research enough to leave expected payoffs unchanged above the independent benchmark.

Keywords: Wisdom of crowds; social investment platforms; social learning; information acquisition; research incentives

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1. Introduction

Many individual investors use social investment platforms to exchange views, read analysis, and learn from one another's decisions. On eToro, users can copy other investors' trades. Xueqiu and StockTwits host discussions of investment ideas, while Seeking Alpha gives investors access to research and commentary. These services allow investors to use ideas they have not developed themselves. But if investors can rely on others' work, who will undertake the research? We ask when learning from others improves investment outcomes without removing the incentive to investigate opportunities independently.

Following another investor can save the cost of investigating an opportunity. This makes following attractive, but may leave fewer investors willing to produce information. Social learning can also encourage investigation. An investor who rules out a risky project can turn to an idea found elsewhere on the platform, making an unfavorable investigation less costly. The value of this option depends on the choices of other investors. To understand the resulting gains, we therefore need to determine research participation and the value of following together.

We study a population with two types of investors who differ in investigation costs. Investigation reveals whether a project is safe or risky and leaves less money available to invest. In the absence of social learning, investigation is worthwhile for low-cost investors, while high-cost investors prefer to invest without investigating. Each investor chooses one of four strategies: invest randomly, follow another investor, investigate and follow after finding a risky project, or investigate and select an independent replacement after such a finding.

An investor uses a lead from the platform to invest their own remaining funds. The lead may come directly from an independently initiated investment or reach them through other followers. Its transmission depends on the platform's prevailing information and implementation conditions. We assume anonymous observation: at each step, the source's strategy is drawn according to the population's strategy shares. More research can improve the opportunities available to followers, and the value of following in turn affects the incentive to investigate. We solve for both while holding asset prices and project supply fixed.

Equilibrium takes one of three forms. When transmission is weak, both types use their best independent strategies. At intermediate effectiveness, low-cost investors investigate and follow others only if they find a risky project; high-cost investors follow directly. This division of research is a strict equilibrium over a nonempty range of platform conditions. Both types earn more than under their best independent alternatives, with investigation costs included.

When transmission improves further, some low-cost investors switch to following. The share that continues to investigate adjusts until these investors earn the same payoff from either strategy. Beyond this point, better transmission reduces research participation, but both types' payoffs remain constant above their independent benchmarks. Less research therefore need not mean lower investment payoffs. For each platform state, the following value, investigation rates, and payoffs are unique. Different strategy mixtures are possible at one threshold, but they yield the same outcomes.

1.1. Contributions and related literature

Stock opinions shared on social media contain information (Chen et al., 2014), and access to crowdsourced research is associated with more informative retail trading (Farrell et al., 2022). These findings raise a question about how the underlying research is sustained. The model makes investors' research decisions part of the equilibrium and compares the payoffs of both researchers and followers with their best independent strategies. For low-cost investors, that benchmark includes investigation

followed by random replacement. The comparison therefore accounts for the value of independent research as well as its cost.

Access to shared information need not translate into better investment decisions. Online comments can encourage portfolio copying without helping investors identify portfolios with superior subsequent performance (Ammann and Schaub, 2021). Impression management can reduce the informativeness of shared content (Chen and Hwang, 2022), and users may selectively seek out confirming views (Cookson, Engelberg, and Mullins, 2023). Cookson and Niessner (2020) distinguish differences in investors' information from differences in its interpretation, while Cookson et al. (2024) show that attention and sentiment convey different information and vary across platforms. These findings caution against treating platform use itself as evidence of better investment opportunities.

Social transmission also affects beliefs and asset prices. Transmission biases shape investor behavior (Hirshleifer, 2020; Han, Hirshleifer, and Walden, 2022), and the spread of beliefs through networks affects prices and trading (Pedersen, 2022). Hirshleifer, Peng, and Wang (2025) connect social networks to faster incorporation of public news into prices and persistent trading. The present model keeps prices fixed and assumes rational investors to isolate the effect of social learning on research incentives.

Studies of online lending show why observing others need not identify better investments. Observational learning and herding appear in lending decisions (Zhang and Liu, 2012; Liao et al., 2015), but social ties can attract funding without reliably identifying better repayment performance (Freedman and Jin, 2017). Investors also learn from their own experience (Freedman and Jin, 2011; Wang et al., 2016).

The research decision places the model within the economics of costly information, beginning with Arrow (1962). Learning from others affects incentives for costly experimentation (Bolton and Harris, 1999; Keller, Rady, and Cripps, 2005), whose efficiency can depend on the equilibrium concept and the scope for history-dependent behavior (Hörner, Klein, and Rady, 2022). Financial applications examine information acquisition under competition and information sharing (Hauswald and Marquez, 2006; Karapetyan and Stacescu, 2014), as well as its relationship with passive ownership and firms' risk choices (Buss and Sundaresan, 2023). Here, better transmission eventually induces enough investors to stop investigating that the value of following remains constant. This adjustment limits the payoff gains from improved social learning.

We use the term *wisdom of crowds* to describe gains in investment payoffs from decentralized investigation and following. This differs from asking whether a crowd reaches a correct common belief. Banerjee (1992) and Bikhchandani, Hirshleifer, and Welch (1992) show how rational observation can produce herding and informational cascades. Golub and Jackson (2010) study when repeated averaging accurately aggregates dispersed signals, and Kremer, Mansour, and Perry (2014) examine disclosure policies that encourage exploration. In our setting, independently initiated investments supply the original leads, and investigation improves the opportunities available to the population. Following can transmit these leads, but cannot replace their independent origin. A population in which everyone follows is therefore not an equilibrium.

The model also distinguishes investors' ability to conduct research from their decision to do so. The platform literature emphasizes participation externalities and interactions across user groups (Caillaud and Jullien, 2003; Rochet and Tirole, 2003; Armstrong, 2006; Rochet and Tirole, 2006; Rysman, 2009; Weyl, 2010). Here, the information externality arises within the investor population, since researchers can also use others' leads. In the region with partial participation, increasing the proportion of low-cost investors reduces the investigation rate within that group by exactly enough to leave the total investigation share unchanged, at fixed costs and transmission effectiveness. Attracting more investors capable of research need not increase the amount of research undertaken.

Sections 2 and 3 set out the investment strategies and derive the value of following. Section 4 establishes the specialization equilibrium and compares payoffs with independent investment. Section 5 characterizes all aggregate equilibria and research participation. Section 6 gives numerical examples, and Section 7 discusses the implications. The proofs and numerical code are in Appendices A and B.

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2. Model Environment

2.1. Investors and investment opportunities

Consider a large population of risk-neutral investors who can investigate opportunities themselves or learn from others on a social investment platform. We represent the population by a continuum of total mass one. Each investor is therefore too small to affect the aggregate information environment. A share $s \in (0,1)$ has high information-acquisition ability, denoted by H; the remaining share $1 - s$ has low ability, denoted by L.

Each investor has a budget $W > 0$. A project selected independently is safe with probability $\lambda \in (0,1)$ and risky otherwise. A safe project pays $R > 0$ per unit invested with certainty. A risky project pays the same amount with probability $p \in (0,1)$ and zero otherwise. Each new project is drawn independently from this distribution. Asset prices and project supply are fixed.

An investor can investigate at most one project. Investigation reveals whether that project is safe or risky. Define

$$p_1 = \lambda + (1 - \lambda)p, \quad p_2 = \lambda + (1 - \lambda)p_1. \quad (1)$$

The success probability of an uninvestigated project is p_1 . The probability p_2 applies to an investor who investigates once, invests if the project is safe, and otherwise selects a new project without further investigation. These probabilities satisfy $p_2 > p_1 > \lambda$.

2.2. Costs and investment strategies

Investigating a project costs C_H for H and C_L for L, where $0 < C_H < C_L < W$. Higher ability means that an investor can obtain the same information at a lower cost. Investigation costs and the shares of the two types are common knowledge. For $i \in \{H, L\}$, define the normalized cost $c_i = C_i/W$.

Assumption 1 (cost separation). *The normalized investigation costs satisfy*

$$0 < c_H < c^* < c_L < 1, \quad c^* = \frac{p_2 - p_1}{p_2}. \quad (2)$$

At $c_i = c^*$, an investor earns the same expected payoff from random investment and from investigation followed by random replacement. Under Assumption 1, independent investigation is therefore worthwhile for H but not for L.

Investigation is paid for from the initial budget, leaving $W - C_i$ to invest. We take investment participation as given. Investors choose among the four strategies in Table 1 to maximize expected project payoffs, which we normalize by dividing by RW .

Denote strategy $k \in \{1,2,3,4\}$ by S_k . Let f be the effective expected return factor from following, derived in Section 3. The normalized payoff $u_i(S_k; f)$ is type i 's expected payoff from S_k divided by RW . Each strategy specifies a complete plan before the investor learns the project's type. Table 1 lists the four plans and their payoffs.

Table 1. Investment strategies and normalized expected payoffs.

Strategy	Investment decision	$u_i(S_k; f)$
S_1	Invest the full budget in a random project, without investigation.	p_1
S_2	Follow an observable investment lead, without investigation.	f
S_3	Investigate once; invest if safe and otherwise follow.	$(1 - c_i)[\lambda + (1 - \lambda)f]$
S_4	Investigate once; invest if safe and otherwise make a random replacement.	$(1 - c_i)p_2$

The choice between following and random replacement is made before investigation. Under S_3 , an investor who finds a risky project uses another investor's lead without investigating again. Under S_4 , the investor independently selects a new, uninvestigated project.

2.3. Social investment platforms and the observation rule

A social investment platform gives investors access to investment leads: choices or ideas that identify an opportunity they can act on. An observer invests their own remaining budget in that opportunity. The return factor attached to the lead is therefore distinct from the investigation cost paid by the investor who originated it.

Let $\sigma_{ik} \geq 0$ be the fraction of type $i \in \{H, L\}$ choosing S_k , with $\sigma_{i1} + \sigma_{i2} + \sigma_{i3} + \sigma_{i4} = 1$. Write $\sigma_i = (\sigma_{i1}, \sigma_{i2}, \sigma_{i3}, \sigma_{i4})$. The population share of S_k is $m_k = s\sigma_{Hk} + (1 - s)\sigma_{Lk}$, and $m = (m_1, m_2, m_3, m_4)$.

Let $\delta \in (0, 1)$ describe the effectiveness with which investment leads are transmitted. At each following step, this fraction of the source's effective return factor is retained. The same rule applies to direct following, indirect following, and following after a risky project has been rejected. It captures the platform's current information and implementation conditions. Investors take this state as given.

Assumption 2 (anonymous observation). At each following step, the source is drawn uniformly from the investor population, independently of the observer's type, previous observations, and project types and outcomes.¹

Investors first observe the platform state δ and choose their strategies. They then carry out any investigation, invest according to the chosen strategy, and receive the project payoff. We solve for equilibrium at each platform state, keeping the observation rule and investigation costs fixed.

3. Crowd Learning

3.1. Consistency of following payoffs

For the strategy composition m defined in Section 2.3, the transmission rule and Assumption 2 imply

$$f = \delta[m_1 p_1 + m_2 f + m_3 \{\lambda + (1 - \lambda)f\} + m_4 p_2]. \quad (3)$$

The four terms correspond, respectively, to random investment, direct following, investigation followed by social learning, and investigation followed by random replacement. Under Assumption 2, the population's strategy shares determine the same following factor at every step, including after an

¹ Following does not allow a subsequent switch to random investment. A closed chain with $j \geq 1$ links and no independently initiated investment satisfies $v = \delta^j v$, where v is its effective return factor, so $v = 0$. An infinite chain with uniformly bounded continuation values also has zero value, since $\delta^j \rightarrow 0$. Independently initiated investments in S_1 , S_4 , and the safe branch of S_3 provide the origins of valuable leads.

observer rejects a risky project. The coefficient on f is $\delta[m_2 + (1 - \lambda)m_3] < 1$, so each feasible composition m has a unique bounded following value. The solution is derived in Appendix A.1.

If everyone follows, $m_2 = 1$ and equation (3) reduces to $f = \delta f$, giving $f = 0$. Any investor could earn $p_1 > 0$ by switching to S_1 , so this cannot be an equilibrium. Following requires an independently initiated investment somewhere along the chain. That investment may be based on investigation or on random project selection.

An aggregate equilibrium consists of a strategy profile (σ_H, σ_L) and a following factor f such that equation (3) holds for the induced composition m and

$$\sigma_{ik} > 0 \Rightarrow u_i(S_k; f) \geq u_i(S_j; f) \quad \forall j \in \{1, 2, 3, 4\}. \quad (4)$$

In a strict type-specific equilibrium, each type has a unique best strategy. When investors of one type use several strategies, those strategies must all yield the same highest payoff. Since each individual has zero mass, a unilateral deviation leaves f unchanged.

3.2. The investigation–following allocation

Suppose all H investors use S_3 and all L investors use S_2 , giving $m = (0, 1 - s, s, 0)$. Denote the investigator's effective return factor by q_I , before adjusting for the budget spent on investigation, and the follower's factor by q_F . The subscripts I and F stand for investigation and following. At this allocation, $f = q_F$, and equation (3) becomes

$$q_I = \lambda + (1 - \lambda)q_F, \quad q_F = \delta[sq_I + (1 - s)q_F]. \quad (5)$$

An investigator invests directly after finding a safe project and otherwise uses a social lead. A follower encounters an investigator with probability s and another follower with probability $1 - s$. Solving gives

$$q_F = \frac{\lambda \delta s}{1 - \delta + \lambda \delta s}, \quad q_I = \lambda + (1 - \lambda)q_F. \quad (6)$$

These return factors account for losses as a lead passes between investors. They describe the allocation proposed above; whether it is an equilibrium depends on the strategy comparisons in the next section.

4. Equilibrium and the Wisdom of Crowds

4.1. Incentive comparisons

For $i \in \{H, L\}$, let $D_i(f) = u_i(S_3; f)$ denote type i 's normalized ex ante payoff under S_3 . Let t_i denote the following value at which type i earns the same payoff from S_3 and direct following, S_2 . Thus $D_i(t_i) = t_i$.

$$D_i(f) = (1 - c_i)[\lambda + (1 - \lambda)f], \quad t_i = \frac{(1 - c_i)\lambda}{\lambda + c_i(1 - \lambda)}. \quad (7)$$

Two payoff differences explain the choice between strategies:

$$\begin{aligned} D_i(f) - f &= [\lambda + c_i(1 - \lambda)](t_i - f), \\ D_i(f) - (1 - c_i)p_2 &= (1 - c_i)(1 - \lambda)(f - p_1). \end{aligned} \quad (8)$$

The first identity compares investigation with following, and the second compares following with random replacement after investigation. Assumption 1 implies $t_H > p_1 > t_L$. Type L's best strategy is S_1 when $f < p_1$ and S_2 when $f > p_1$, with both optimal at equality. Type H's best strategy is S_4 for $f < p_1$, S_3 for $p_1 < f < t_H$, and S_2 for $f > t_H$. At $f = p_1$, H is indifferent between S_3 and S_4 ; at $f = t_H$, H is indifferent between S_2 and S_3 . Appendix A.2 establishes this complete best-response partition.

4.2. A strict specialization equilibrium

Define two thresholds for the effectiveness of following:

$$\delta_{\text{low}} = \frac{p_1}{p_1 + \lambda s(1 - p_1)}, \quad \delta_{\text{high}} = \frac{1 - c_H}{1 - c_H + c_H s}. \quad (9)$$

Proposition 1 (investigation and following). *Under Assumptions 1–2, the allocation $H: S_3$, $L: S_2$ is a strict type-specific equilibrium if and only if*

$$\delta_{\text{low}} < \delta < \delta_{\text{high}}. \quad (10)$$

The interval is nonempty and lies within $(0,1)$. At either endpoint, the same allocation is a weak equilibrium.

The condition $p_1 < q_F < t_H$ captures the incentives of both types. The lower inequality makes following preferable to random investment for L and to random replacement after H finds a risky project. The upper inequality ensures that H still prefers investigation to direct following. Together with $c_L > c^*$, these comparisons cover all four strategies. Appendix A.3 proves necessity and sufficiency and shows that the interval is nonempty.

When following is weak, H prefers to investigate and select a random replacement if needed. At intermediate effectiveness, H investigates and uses others' leads after finding a risky project, while L follows directly. Above the upper threshold, H has an incentive to switch to following. Section 5 derives the equilibrium in this region.

4.3. Gains relative to independent investment

Without observational learning, investors can choose between S_1 and S_4 . Write Π_i^{iso} for type i 's best independent expected payoff and Π_i^{crowd} for its equilibrium expected payoff with social learning. Under Assumption 1, H chooses S_4 and L chooses S_1 in isolation, giving

$$\Pi_H^{\text{iso}} = RW(1 - c_H)p_2, \quad \Pi_L^{\text{iso}} = RWp_1. \quad (11)$$

Proposition 2 (the payoff gain from crowd learning). *In the strict equilibrium of Proposition 1, both types obtain a higher expected payoff than under their best independent strategy. In particular,*

$$\begin{aligned} \Pi_H^{\text{crowd}} - \Pi_H^{\text{iso}} &= RW(1 - c_H)(1 - \lambda)(q_F - p_1) > 0, \\ \Pi_L^{\text{crowd}} - \Pi_L^{\text{iso}} &= RW(q_F - p_1) > 0. \end{aligned} \quad (12)$$

The population-average improvement is

$$\Delta \bar{\Pi} = RW[s(1 - c_H)(1 - \lambda) + (1 - s)](q_F - p_1) > 0. \quad (13)$$

H benefits from a better alternative after rejecting a risky project. L benefits from opportunities identified through other investors' investigation. We refer to these gains for both types as the wisdom of crowds in investment. The comparison already accounts for investigation costs through the reduction in the investment budget. Appendix A.4 derives the payoff differences.

5. Equilibrium and Research Participation

5.1. Partial participation

Let $x = \sigma_{H3} + \sigma_{H4}$ be the share of H investors who investigate and $\rho = m_3 + m_4$ the investigation share in the whole population. L never investigates in equilibrium, so $\rho = sx$. For states above δ_{high} ,

consider an allocation in which a share x of H uses S_3 and all other investors use S_2 . Then $\sigma_{H4} = 0$ and $m(x) = (0, 1 - sx, sx, 0)$.

Substituting this composition into (3) gives

$$q_F(x) = \frac{\lambda \delta s x}{1 - \delta + \lambda \delta s x}, \quad q_I(x) = \lambda + (1 - \lambda)q_F(x). \quad (14)$$

For fixed $\delta \in (0, 1)$, $q_F(x)$ increases strictly with x because more investigation improves the leads available to followers. H investors are identical, so they can use both S_3 and S_2 in equilibrium only if the strategies yield equal payoffs. By (8), this requires $q_F(x) = t_H$.

Proposition 3 (endogenous investigation participation). *Under Assumptions 1–2, for $\delta_{\text{high}} < \delta < 1$, there is an aggregate equilibrium in which a share x^* of H investors chooses S_3 , the remaining H investors choose S_2 , and all L investors strictly prefer S_2 , where*

$$x^* = \frac{(1 - c_H)(1 - \delta)}{c_H \delta s} \in (0, 1), \quad q_F(x^*) = (1 - c_H)q_I(x^*) = t_H. \quad (15)$$

The indifference condition determines a unique investigation share, although any subset of H investors of that size can conduct the research. Appendix A.5 derives (15) and checks the payoffs from all four strategies. Proposition 4 shows that every aggregate equilibrium above δ_{high} has this allocation.

At $\delta = \delta_{\text{high}}$, equation (15) gives $x^* = 1$, so all H investors investigate. H is indifferent between S_3 and S_2 at this boundary, but the aggregate consistency condition rules out a lower investigation share.

5.2. Complete equilibrium classification

Proposition 4 (all aggregate equilibria). *Under Assumptions 1–2, define $B = (1 - s)p_1 + sp_2$. For every $0 < \delta < 1$, the equilibrium following factor, denoted by $f^*(\delta)$, is uniquely determined by*

$$\begin{aligned} f^*(\delta) &= \delta B, & 0 < \delta < \delta_{\text{low}}; \\ f^*(\delta) &= \frac{\lambda \delta s}{1 - \delta + \lambda \delta s}, & \delta_{\text{low}} \leq \delta \leq \delta_{\text{high}}; \\ f^*(\delta) &= t_H, & \delta_{\text{high}} < \delta < 1. \end{aligned} \quad (16)$$

For $0 < \delta < \delta_{\text{low}}$, the unique equilibrium allocation is $H: S_4$ and $L: S_1$, with $m = (1 - s, 0, 0, s)$. Every H investor still investigates; observational learning is not used.

At $\delta = \delta_{\text{low}}$, every equilibrium is described by $\alpha, \beta \in [0, 1]$, where α is the fraction of H choosing S_3 and β is the fraction of L choosing S_2 . The remaining H choose S_4 and the remaining L choose S_1 , giving

$$m = ((1 - s)(1 - \beta), (1 - s)\beta, s\alpha, s(1 - \alpha)). \quad (17)$$

For $\delta_{\text{low}} < \delta \leq \delta_{\text{high}}$, the unique allocation is $H: S_3$ and $L: S_2$. For $\delta_{\text{high}} < \delta < 1$, it is the partial-participation allocation in Proposition 3. Thus, except at δ_{low} , the strategy shares of each type and the population composition are unique. At the lower threshold, different strategy mixtures still give the same following value, investigation shares, and payoffs. Appendix A.6 proves that these cases cover all equilibria.

5.3. Research participation and investment payoffs

Within the partial-participation region,

$$\frac{\partial x^*}{\partial \delta} = -\frac{1 - c_H}{c_H s \delta^2} < 0, \quad s x^* = \frac{(1 - c_H)(1 - \delta)}{c_H \delta}. \quad (18)$$

For $0 < \delta \leq \delta_{\text{high}}$, all H investors investigate: $x = 1$ and $\rho = s$, including when H uses S_4 . Above δ_{high} , more effective following reduces investigation, as shown in (18). Holding c_H and δ fixed, and remaining within the region of partial participation, the population investigation share $\rho = s x^*$ does not depend on s . An increase in the share of low-cost investors is exactly offset by a fall in the investigation rate within that group.

Corollary 1 (gains across all equilibria). Under Assumptions 1–2, equilibrium payoffs equal the independent benchmark for $0 < \delta \leq \delta_{\text{low}}$ and strictly exceed it for both types whenever $\delta_{\text{low}} < \delta < 1$. At fixed project, cost, and population parameters, payoffs increase strictly on $(\delta_{\text{low}}, \delta_{\text{high}})$ and are constant at normalized value t_H for both types on $[\delta_{\text{high}}, 1)$. Above the upper threshold, the gain from better transmission is offset by reduced investigation. Appendix A.6 proves these statements.

A positive share of investors investigates at every $\delta < 1$. In the partial-participation equilibrium, x^* tends to zero as δ tends to one, while the following factor remains at t_H . The endpoint $\delta = 1$ is excluded. As Appendix A.5 explains, this limit does not imply that positive payoffs could be sustained without an independent source.

6. Numerical Illustration

6.1. Full-participation equilibrium

The following parameter values illustrate the equilibrium thresholds and payoff comparisons; they are not estimated from platform data. Calculations use full precision; reported values are rounded to three decimal places.

$$\lambda = 0.400, \quad p = 0.500, \quad c_H = 0.080, \quad c_L = 0.250, \quad s = 0.400. \quad (19)$$

These values imply $p_1 = 0.700$, $p_2 = 0.820$, and $c^* \approx 0.146$, satisfying Assumption 1. The thresholds in (9) are $\delta_{\text{low}} \approx 0.936$ and $\delta_{\text{high}} \approx 0.966$. At $\delta = 0.950$, $q_I \approx 0.851$ and $q_F \approx 0.752$. Type H obtains approximately $0.783RW$ compared with its independent payoff of $0.754RW$; type L obtains approximately $0.752RW$ compared with $0.700RW$. The average gain is approximately $0.043RW$ per investor.

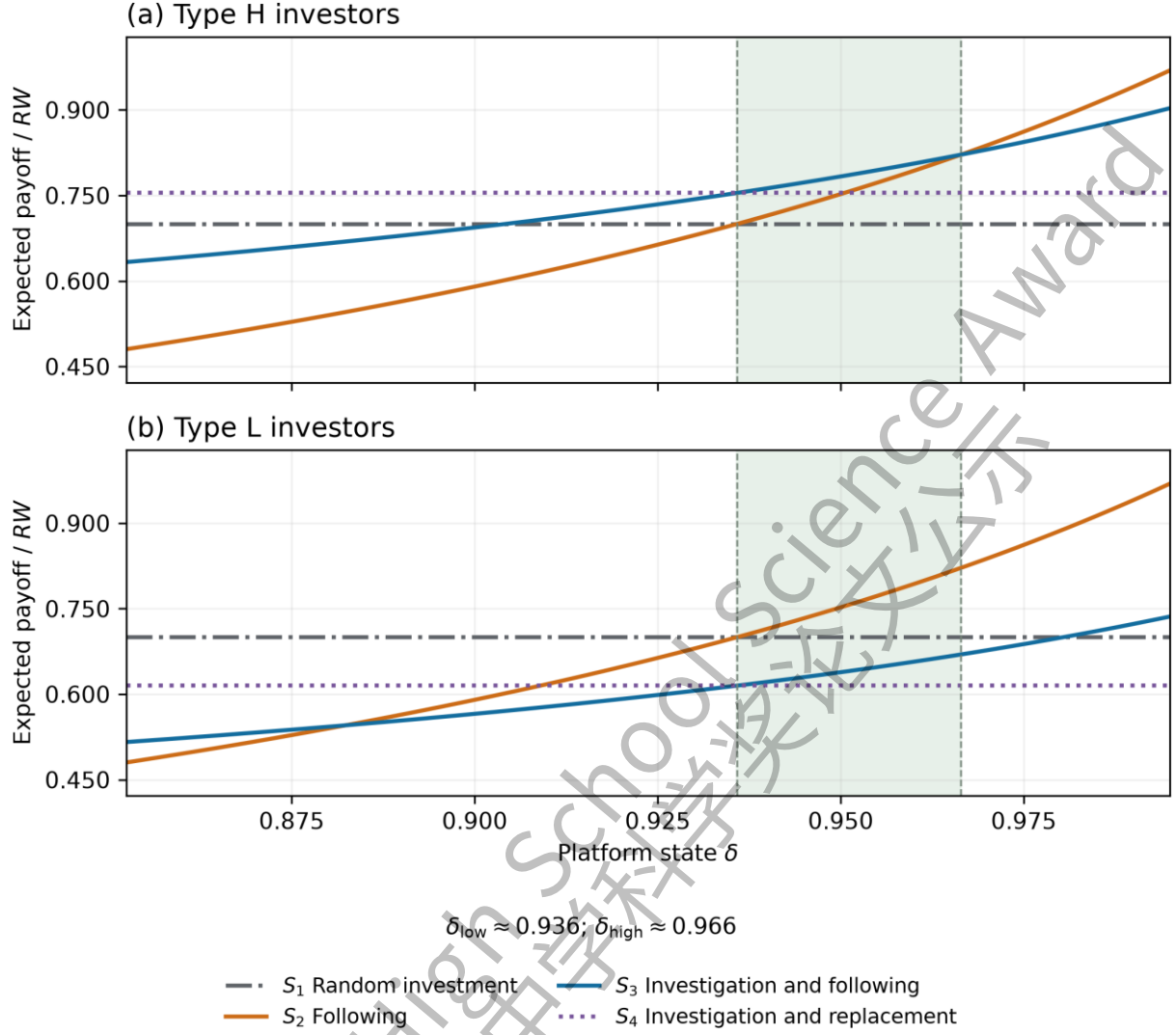


Figure 1. Strategy payoffs when all H investors investigate and all L investors follow. Panels (a) and (b) show H and L on identical axes and with the same line styles. Every curve is evaluated in the information environment generated by $H:S_3$ and $L:S_2$. This allocation is a strict equilibrium in the shaded open interval $(\delta_{\text{low}}, \delta_{\text{high}})$. Outside it, the curves show what an investor would earn by changing strategy while the candidate environment remains fixed. Payoffs are divided by RW .

Panel (a) shows the two constraints on H's strategy. The payoff from S_3 rises above that from S_4 at δ_{low} , but is overtaken by S_2 at δ_{high} . In panel (b), S_2 overtakes S_1 at δ_{low} . Neither investigation strategy is optimal for L. The shaded open interval is therefore the range in which both types strictly prefer their assigned strategies.

6.2. Equilibrium outcomes across all regions

For the numerical results, write $u_i = \Pi_i^{\text{crowd}} / (RW)$ for type i 's normalized equilibrium payoff; the population average is $su_H + (1 - s)u_L$.

Figures 2–3 display the equilibrium outcomes; Table 2 in Appendix B.1 gives the corresponding numerical values. At $\delta = 0.900$, H investigates through S_4 and L invests randomly. At $\delta = 0.970$ and $\delta = 0.990$, investigation within H falls to approximately 0.889 and 0.290, respectively, while both types retain the normalized payoff $t_H \approx 0.821$.

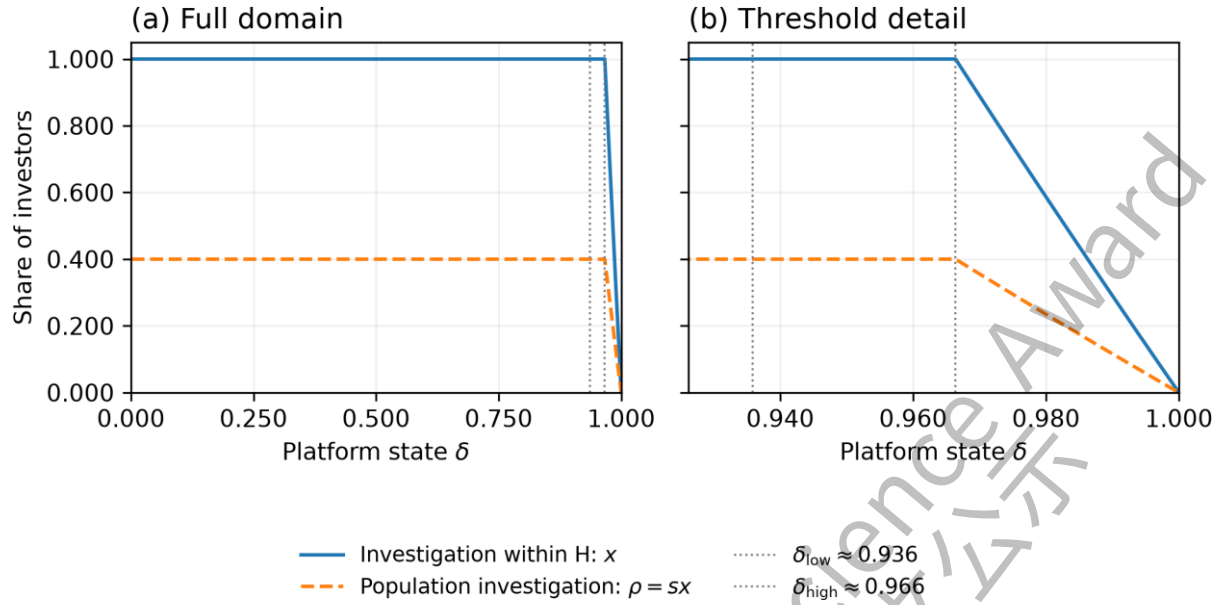


Figure 2. Equilibrium research participation over $0 < \delta < 1$. Investigation within H is x , and population investigation is $\rho = sx$. Both remain constant up to δ_{high} and then decline. The lower threshold changes the continuation strategy after investigation, without changing total investigation. Panel (a) shows the full domain and panel (b) enlarges the region near the thresholds; vertical lines mark both thresholds.

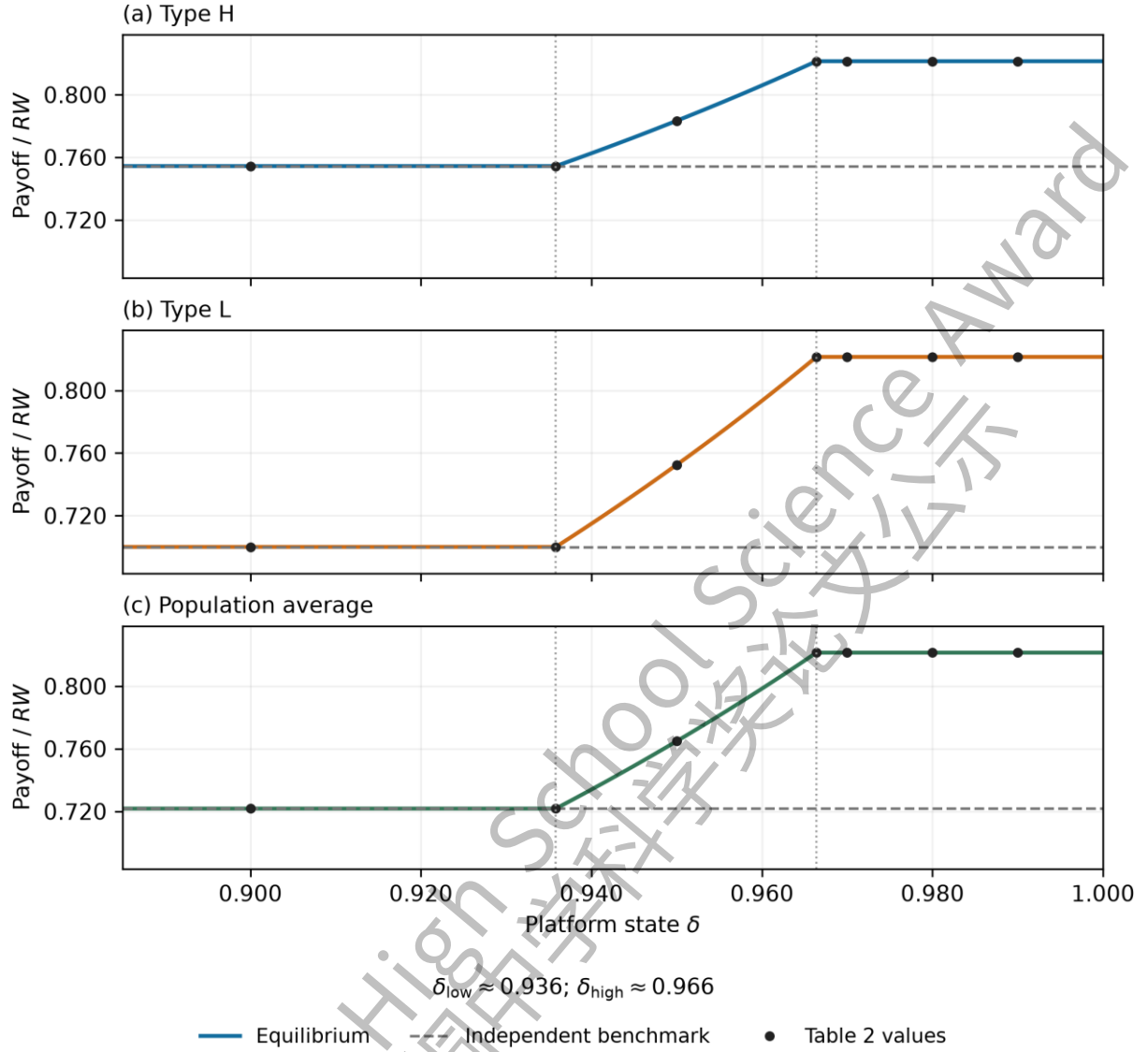


Figure 3. Equilibrium payoffs across platform states. Panels (a)–(c) show H, L, and the population average $su_H + (1 - s)u_L$, using identical axes. Solid curves are normalized equilibrium payoffs; dashed lines are the corresponding independent benchmarks. Dots show the seven exact platform states in Table 2; vertical lines mark δ_{low} and δ_{high} . Payoffs equal the benchmarks below the displayed range as well. The endpoint $\delta = 1$ is excluded.

Below δ_{low} , equilibrium payoffs equal the independent benchmark. Between the thresholds, both types gain from better transmission. Above δ_{high} , payoffs stop rising even as fewer investors investigate. Figures 2 and 3 show these different responses of participation and payoffs, with observation rules and investigation costs held fixed.

7. Conclusion

This paper shows how learning from others can benefit both investors who investigate and those who follow. When transmission is sufficiently effective, researchers gain a better alternative after rejecting a risky project, while followers obtain opportunities identified through others' research. Both can earn higher expected payoffs than under their best independent strategies, with research costs included. These gains have an endogenous limit: further improvements in transmission eventually induce some researchers to follow, and the decline in research offsets the improvement in transmission. Payoffs then remain constant above the independent benchmark.

Policy implications. Our welfare comparison suggests that platforms and regulators should evaluate information-sharing arrangements by their effects on investor payoffs and research incentives. Better transmission can improve investment opportunities for both researchers and followers, but additional improvements need not keep raising payoffs once research participation adjusts. A falling research share therefore does not, by itself, justify intervention. Access to reliable data, affordable analytical tools, and rewards for verifiable original analysis are possible ways to support research. Their value should be assessed against their funding costs and the information they generate.

In addition, transparency can help investors judge the leads they encounter. Platforms could identify original analysis and reposted recommendations, record their sources and dates, and disclose relevant commercial interests. Such measures would help users distinguish independent research from repeated claims, a concern raised by evidence on selective sharing and exposure to confirming views (Chen and Hwang, 2022; Cookson, Engelberg, and Mullins, 2023). Investor education should also make clear that a recommendation's popularity does not establish superior future performance (Ammann and Schaub, 2021). Since platforms convey different information, these measures should be evaluated in the setting where they are introduced (Cookson et al., 2024).

Limitations and future research. First, the model does not include the platform's own decisions. An extension could allow the platform to price access, choose recommendation rules, and compensate research contributors, while accounting for operating costs. Models of two-sided pricing and information sales provide a basis for studying these decisions (Rochet and Tirole, 2003; Hörner and Skrzypacz, 2016). The central question is whether a platform's profit-maximizing design also improves investor welfare and which policies could bring these objectives into closer agreement.

Second, investors observe anonymous sources and cannot choose whom to follow or what to disclose. Extensions with endogenous networks and disclosure decisions could examine how these choices affect research participation (Jackson and Watts, 2002; Rayo and Segal, 2010). A repeated setting would also allow investors to assess sources through reputation and realized returns. Such a model could ask whether investors learn to distinguish independent research from repeated claims, and whether this learning sustains incentives to investigate.

Third, the model holds asset prices and project supply fixed, takes investment participation as given, and assumes risk-neutral investors. A market setting with price responses, risk aversion, and a choice between cash and diversified portfolios could change the gains from following. The welfare comparison would then need to account for how crowded investment affects prices and how common exposures affect risk, as well as how much investigation investors undertake.

Appendix A. Derivations and Proofs

A.1. The aggregate return factor

For any admissible m , let $a = m_1 p_1 + m_3 \lambda + m_4 p_2$ and $b = m_2 + (1 - \lambda)m_3$. Equation (3) is $f = \delta(a + bf)$, with $0 \leq b \leq 1$ and $0 \leq a \leq 1 - b$. Hence

$$f(m) = \frac{\delta(m_1 p_1 + m_3 \lambda + m_4 p_2)}{1 - \delta[m_2 + (1 - \lambda)m_3]} = \frac{\delta a}{1 - \delta b}. \quad (\text{A1})$$

The denominator is at least $1 - \delta > 0$, establishing existence and uniqueness. Moreover, $0 \leq f \leq \delta(1 - b)/(1 - \delta b) < 1$. Iterating the payoff recursion gives

$$f = \delta a \sum_{\ell=0}^{\infty} (\delta b)^\ell. \quad (\text{A2})$$

Each term in this series accounts for an independently initiated source reached after a given number of following steps. If $m_2 = 1$, then $a = 0$ and $f = 0$. An investor could switch to S_1 and earn $p_1 > 0$ without changing the population composition, ruling out universal following as an equilibrium. If $m_1 > 0$ but no one investigates, following can still have positive value: random investment supplies a source, even though it produces no private information.

Substituting $m = (0, 1 - s, s, 0)$ into (A1) gives (6), and substituting $m(x) = (0, 1 - sx, sx, 0)$ gives (14). Both participation cases, as well as the case with no independent source, follow from the same observation rule.

A.2. Strategy comparisons and cost thresholds

Investigation with random replacement and random investment differ in payoff by

$$(1 - c_i)p_2 - p_1 = p_2(c^* - c_i). \quad (\text{A3})$$

Under Assumption 1, this difference is positive for H and negative for L. Expanding $D_i(f) - f$ gives the first identity in (8); substituting $p_2 = \lambda + (1 - \lambda)p_1$ gives the second. For any normalized cost $c \in (0, 1)$, write $t(c)$ for the indifference threshold, so that $t_i = t(c_i)$. Then

$$t(c) = \frac{(1 - c)\lambda}{\lambda + c(1 - \lambda)}, \quad t(c^*) = p_1, \quad t'(c) = -\frac{\lambda}{[\lambda + c(1 - \lambda)]^2} < 0. \quad (\text{A4})$$

Thus $t_H > p_1 > t_L$. For L, if $f \leq p_1$, then $D_L(f) \leq D_L(p_1) = (1 - c_L)p_2 < p_1$. If $f > p_1$, then $D_L(f) < f$ because $f > t_L$. Its S_4 payoff is always below p_1 . For H, when $f < p_1$, S_4 is strictly better than S_3 by (8) and is better than both S_1 and S_2 by Assumption 1. When $p_1 < f < t_H$, both identities in (8) make S_3 strictly optimal. When $f > t_H$, S_2 is better than S_3 and exceeds $t_H > (1 - c_H)p_2 > p_1$. Equality occurs only at the indifference points listed in Section 4.1.

A.3. Proof of Proposition 1

At the proposed allocation, $f = q_F$. First consider necessity. For L to strictly prefer S_2 to S_1 , we need $f > p_1$. For H to strictly prefer S_3 to S_2 , equation (8) requires $f < t_H$. Hence $p_1 < f < t_H$ is necessary.

For sufficiency, $f < t_H$ implies $D_H(f) > f$, while $f > p_1$ implies $D_H(f) > (1 - c_H)p_2 > p_1$. Thus H strictly prefers S_3 to S_2 , S_4 , and S_1 . For L, Appendix A.2 rules out investigation, and $f > p_1$ makes S_2 strictly preferable to S_1 . Neither type can gain by deviating.

The following factor is strictly increasing in δ , and its inverse relation is

$$\frac{\partial q_F}{\partial \delta} = \frac{\lambda s}{(1 - \delta + \lambda \delta s)^2} > 0, \quad \delta = \frac{f}{f + \lambda s(1 - f)}. \quad (\text{A5})$$

Evaluating the inverse at $f = p_1$ yields δ_{low} . At $f = t_H$, the identity $\lambda(1 - t_H)/t_H = c_H/(1 - c_H)$ yields δ_{high} . Since $t_H > p_1$, the interval is nonempty. Both endpoints lie in $(0,1)$. At the lower endpoint, H is indifferent between S_3 and S_4 , and L is indifferent between S_1 and S_2 . At the upper endpoint, H is indifferent between S_3 and S_2 , while L strictly prefers following. The stated allocation is a weak equilibrium at either endpoint. $\square$

A.4. Proof of Proposition 2

H and L receive $RW(1 - c_H)q_I$ and RWq_F , respectively. Equation (5) and the definition of p_2 give $q_I - p_2 = (1 - \lambda)(q_F - p_1)$. Subtracting the independent payoffs in (11) yields (12), and weighting the differences by s and $1 - s$ yields (13). Both differences are strictly positive under the conditions of Proposition 1. The smaller investment budget already accounts for the investigation cost. $\square$

A.5. Proof of Proposition 3 and comparative statics

If a positive fraction of H uses each of S_3 and S_2 , equilibrium requires $D_H(q_F(x)) = q_F(x)$. By (8), this is equivalent to $q_F(x) = t_H$. Solving (14) for sx gives

$$sx = \frac{t_H(1 - \delta)}{\delta\lambda(1 - t_H)} = \frac{(1 - c_H)(1 - \delta)}{c_H\delta}. \quad (\text{A6})$$

The solution is positive for $\delta < 1$, and $x < 1$ is equivalent to $\delta > \delta_{\text{high}}$. The derivative

$$\frac{\partial q_F(x)}{\partial x} = \frac{\lambda\delta s(1 - \delta)}{[1 - \delta + \lambda\delta sx]^2} > 0 \quad (\text{A7})$$

implies a unique interior participation share. At x^* , both strategies used by H yield $t_H > p_1$. Since $q_I(x^*) = \lambda + (1 - \lambda)t_H > p_2$, these strategies are strictly better than S_4 as well. For L , $(1 - c_L)p_2 < p_1 < t_H$ and $(1 - c_L)q_I(x^*) < (1 - c_H)q_I(x^*) = t_H$. Hence L strictly prefers S_2 . Aggregate consistency holds by construction. $\square$

Differentiating (15) with respect to δ gives (18). Multiplying by s gives the population investigation share, and s cancels from the expression. Within the interior region, indifference fixes the payoff of every strategy used in equilibrium at t_H . This payoff does not depend on δ or s when λ, c_H are held fixed.

The limit at $\delta = 1$ depends on how it is approached. For any fixed $\delta < 1$, setting $x = 0$ in (14) gives zero. Along the equilibrium path, x^* and $1 - \delta$ approach zero together, but $q_F(x^*) = t_H$. At $(\delta, x) = (1, 0)$, both the numerator and denominator in (14) vanish. There is therefore no unique limiting value at this point, and no implication that positive payoffs can be sustained without independently initiated investments.

A.6. Proof of Proposition 4 and Corollary 1

The strategy comparisons in Section 4.1 leave five cases. If $f < p_1$, H must use S_4 and L must use S_1 . Equation (3) gives $f = \delta B$, and $f < p_1$ holds exactly when $\delta < \delta_{\text{low}}$. If $f = p_1$, H can mix only S_3, S_4 and L only S_1, S_2 . Before adjusting for the investigation budget, both H strategies have return factor p_2 ; both L strategies have factor p_1 . For every mixture in (17), equation (3) thus reduces to $p_1 = \delta B$, which requires $\delta = \delta_{\text{low}}$.

If $p_1 < f < t_H$, H must use S_3 and L must use S_2 , so Proposition 1 applies. If $f = t_H$, L must use S_2 and H may mix only S_2, S_3 . Aggregate consistency requires (15), which is feasible exactly when $\delta \geq \delta_{\text{high}}$. At equality, it requires $x = 1$. Finally, if $f > t_H$, both types must follow, but (3) would imply $f = 0$, a contradiction. These cases prove (16), the complete set of allocations, and the uniqueness statements. $\square$

To prove Corollary 1, note that the allocation below the lower threshold and all mixtures at that threshold give payoffs $(1 - c_H)p_2$ for H and p_1 for L. Proposition 2 establishes strict gains in the middle region. Above the upper threshold, both types earn t_H , and

$$t_H - (1 - c_H)p_2 = (1 - c_H)(1 - \lambda)(t_H - p_1). \quad (\text{A8})$$

The right-hand side is strictly positive because $t_H > p_1$. Thus both types retain a strict gain in the partial-participation region and at the upper boundary. Equation (A5) and the positive slopes of $D_H(f)$ and f give strictly increasing payoffs in the middle region; indifference fixes payoffs at t_H thereafter. This proves Corollary 1. $\square$

Appendix B. Numerical Values and Reproducible Code

B.1. Numerical values

Table 2. Equilibrium outcomes and the independent investment benchmark.

δ / region	x	ρ	u_H	u_L	Average
Isolated	1.000	0.400	0.754	0.700	0.722
0.900	1.000	0.400	0.754	0.700	0.722
0.936 (low)	1.000	0.400	0.754	0.700	0.722
0.950	1.000	0.400	0.783	0.752	0.765
0.966 (high)	1.000	0.400	0.821	0.821	0.821
0.970	0.889	0.356	0.821	0.821	0.821
0.980	0.587	0.235	0.821	0.821	0.821
0.990	0.290	0.116	0.821	0.821	0.821

Here $x = \sigma_{H3} + \sigma_{H4}$, $\rho = m_3 + m_4 = sx$, and $u_i = \Pi_i / (RW)$ denotes type i 's normalized equilibrium payoff, where $\Pi_i = \Pi_i^{\text{crowd}}$. The last column is the population average $su_H + (1 - s)u_L$. The independent row uses Π_i^{iso} and has $x = 1$, $\rho = s$. Boundary rows use exact thresholds before rounding; the lower-boundary row selects $\alpha = \beta = 1$ in (17), and all admissible mixtures give the same displayed investigation shares and payoffs.

B.2. Reproducible code

```

from pathlib import Path
import csv
import numpy as np
import matplotlib.pyplot as plt
from matplotlib.ticker import FormatStrFormatter, MaxNLocator

# lam denotes lambda; costs are divided by W. Edit these five inputs if needed.
lam, p, s, ch, cl = 0.400, 0.500, 0.400, 0.080, 0.250
if not all(np.isfinite(v) and 0 < v < 1 for v in (lam, p, s, ch, cl)):
    raise ValueError('All five inputs must be strictly between zero and one.')
p1 = lam + (1-lam)*p
p2 = lam + (1-lam)*p1
cs = (p2-p1)/p2
if not ch < cs < cl:
    raise ValueError('Assumption 1 requires 0 < ch < c* < cl < 1.')
B = (1-s)*p1 + s*p2
lo = p1/B
hi = (1-ch)/(1-ch+ch*s)
th = (1-ch)*lam/(lam+ch*(1-lam))
if not 0 < lo < hi < 1:
    raise ValueError('Thresholds are unresolved at floating-point precision.')

def following(d):
    """Equation (6): all H investigate and all L follow."""
    return lam*d*s/(1-d+lam*d*s)

def payoffs(f, c):
    """Table 1: payoffs of S1, S2, S3, S4, divided by RW."""
    return np.array([np.full_like(f, p1), f,
                     (1-c)*(lam+(1-lam)*f), np.full_like(f, (1-c)*p2)])

def equilibrium(d):
    """Propositions 3-4 and Corollary 1: x, rho, uH, uL, average."""
    d = np.asarray(d, dtype=float)
    if np.any(~np.isfinite(d) | (d <= 0) | (d >= 1)):
        raise ValueError('Platform states must lie strictly between 0 and 1.')
    f = np.where(d < lo, d*B, np.where(d <= hi, following(d), th))
    x = np.where(d <= hi, 1, (1-ch)*(1-d)/(ch*d*s))
    uh = np.where(d < lo, (1-ch)*p2, (1-ch)*(lam+(1-lam)*f))
    ul = np.where(d < lo, p1, f)
    return np.array([x, s*x, uh, ul, s*uh+(1-s)*ul])

def style(ax, ylabel):
    ax.set(xlabel=r'Platform state $\delta$', ylabel=ylabel)
    for axis in (ax.xaxis, ax.yaxis):
        axis.set_major_formatter(FormatStrFormatter('%3f'))
        axis.set_major_locator(MaxNLocator(6))
    ax.grid(alpha=0.180)

def save(fig, out, name):
    fig.savefig(out/name, dpi=300)
    plt.close(fig)

def main():
    out = Path(__file__).resolve().parent/'english_results'
    out.mkdir(exist_ok=True)
    plt.rcParams.update({'font.family': 'DejaVu Sans',
                        'axes.unicode_minus': False, 'font.size': 10})
    # Figure 1 evaluates deviations in the fixed H:S3, L:S2 environment.
    left, right = max(0, lo-1.300*(1-lo)), hi+0.850*(1-hi)
    d = np.unique(np.r_[np.linspace(left, right, 500), lo, hi])
    f = following(d)
    fig, axes = plt.subplots(2, 1, figsize=(7.400, 6.600), sharex=True, sharey=True)
    labels = [r'$S_1$ Random investment', r'$S_2$ Following',

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        r'$S_3$ Investigation and following',
        r'$S_4$ Investigation and replacement']
colors, styles = ['#5f6368', '#cc6b16', '#126c9e', '#77549a'], ['-.-', '-', '-', ':']
all_u = [payoffs(f, c) for c in (ch, cl)]
ymin, ymax = min(u.min() for u in all_u), max(u.max() for u in all_u)
margin = max(0.040, (ymax-ymin)*0.120)
for ax, u, tag, kind in zip(axes, all_u, ['a', 'b'], ['H', 'L']):
    for k in range(4):
        ax.plot(d, u[k], styles[k], color=colors[k], lw=1.800, label=labels[k])
    ax.axvspan(lo, hi, color='#dfece2', alpha=0.750)
    for edge in (lo, hi):
        ax.axvline(edge, color='#738377', ls='--', lw=0.800)
    ax.set_title(f'({tag}) Type {kind} investors', loc='left')
    style(ax, r'Expected payoff / $RW$')
    ax.set(xlim=(left, right), ylim=(max(0, ymin-margin), ymax+margin))
axes[0].set_xlabel('')
handles, names = axes[0].get_legend_handles_labels()
fig.legend(handles, names, loc='lower center', bbox_to_anchor=(0.500, 0.005),
           ncol=2, fontsize=9, frameon=False)
thresholds = (rf'$\Delta_{\{\mathrm{{low}}\}}\approx\{lo:.3f\}$; '
              rf'$\Delta_{\{\mathrm{{high}}\}}\approx\{hi:.3f\}$')
fig.text(0.500, 0.110, thresholds, ha='center', fontsize=10)
fig.tight_layout(rect=(0, 0.150, 1, 1), h_pad=1.100)
save(fig, out, 'figure_1.png')
# Figure 2 includes both investigation strategies in x.
d = np.unique(np.r_[np.linspace(0.001, 0.999, 400),
                   np.linspace(lo, 1-(1-hi)*1e-3, 400), lo, hi])
x, rho = equilibrium(d)[2:]
fig, axes = plt.subplots(1, 2, figsize=(7.400, 3.800), sharey=True)
for ax in axes:
    ax.plot(d, x, label=r'Investigation within H: $x$')
    ax.plot(d, rho, '--', label=r'Population investigation: $\rho=sx$')
    for edge, name in [(lo, 'low'), (hi, 'high')]:
        ax.axvline(edge, ls=':', lw=0.900, color='#737b83',
                   label=rf'$\Delta_{\{\mathrm{{name}}\}}\approx\{edge:.3f\}$')
    ax.set(ylim=(0, 1.050))
    style(ax, '')
    ax.xaxis.set_major_locator(MaxNLocator(4))
axes[0].set(xlim=(0, 1), ylabel='Share of investors')
axes[1].set_xlim(max(0, lo-0.150*(1-lo)), 1)
axes[0].set_title('(a) Full domain', loc='left')
axes[1].set_title('(b) Threshold detail', loc='left')
handles, names = axes[0].get_legend_handles_labels()
fig.legend(handles, names, loc='lower center', bbox_to_anchor=(0.500, 0.005),
           fontsize=9, ncol=2, frameon=False)
fig.tight_layout(rect=(0, 0.205, 1, 1))
save(fig, out, 'figure_2.png')
# Use exact thresholds in Table 2; round only when displaying results.
table_d = np.unique([0.900, 0.950, 0.970, 0.980, 0.990, lo, hi])
table = equilibrium(table_d)
benchmark = [(1-ch)*p2, p1, s*(1-ch)*p2+(1-s)*p1]
left3 = max(0, table_d.min()-0.150*(1-table_d.min()))
end3 = 1-max(1e-6, (1-hi)*1e-3)
d3 = np.unique(np.r_[np.linspace(max(left3, 1e-6), end3, 500), table_d])
curves = equilibrium(d3)[2:]
fig, axes = plt.subplots(3, 1, figsize=(7.400, 6.900), sharex=True, sharey=True)
titles = ['(a) Type H', '(b) Type L', '(c) Population average']
colors = ['#126c9e', '#cc6b16', '#347858']
margin = max(0.010, (th-min(benchmark))*0.140)
for ax, u, points, base, color, title in zip(
    axes, curves, table[2:], benchmark, colors, titles):
    ax.plot(d3, u, color=color, lw=1.800, label='Equilibrium')
    ax.axhline(base, color='#777777', ls='--', lw=1.200,
               label='Independent benchmark')
    ax.plot(table_d, points, 'o', color='#222222',
            markersize=3.500, label='Table 2 values')

```

```

for edge in (lo, hi):
    ax.axvline(edge, color='#969696', ls=':', lw=0.900)
ax.set_title(title, loc='left', fontsize=10)
style(ax, r'Payoff / $RW$')
ax.set(xlim=(left3, 1), ylim=(max(0, min(benchmark)-margin), th+margin))
ax.yaxis.set_major_locator(MaxNLocator(4))
if ax is not axes[-1]:
    ax.set_xlabel('')
handles, names = axes[0].get_legend_handles_labels()
fig.legend(handles, names, loc='lower center', bbox_to_anchor=(0.500, 0.005),
           ncol=3, fontsize=9, frameon=False)
fig.text(0.500, 0.070, thresholds, ha='center', fontsize=10)
fig.tight_layout(rect=(0, 0.100, 1, 1), h_pad=0.650)
save(fig, out, 'figure_3.png')
with (out/'table_2.csv').open('w', encoding='utf-8', newline='') as stream:
    writer = csv.writer(stream)
    writer.writerow(['delta', 'regime', 'x', 'rho', 'uH', 'uL', 'average'])
    writer.writerow(['Isolated', 'benchmark', '1.000', f'{s:.3f}']
                    + [f'{v:.3f}' for v in benchmark])
    for d0, values in zip(table_d, table.T):
        regime = ('low' if d0 < lo else 'lower boundary' if d0 == lo else
                  'full' if d0 < hi else 'upper boundary' if d0 == hi else 'partial')
        writer.writerow([f'{d0:.3f}', regime] + [f'{v:.3f}' for v in values])
print('p1, p2, c*, lower, upper, tH:',
      ', '.join(f'{v:.3f}' for v in [p1, p2, cs, lo, hi, th]))
print('Results saved in', out)

if __name__ == '__main__':
    main()

```

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致谢

一 研究背景与选题来源

社交投资平台让投资者能够阅读、转发或跟随他人的投资观点。获取线索因此变得更方便，但自行调查的意愿也可能随之减弱。本研究由此展开：当投资者的调查成本不同、信息可以在平台上多层传播时，向他人学习在什么条件下能提高研究者与跟随者的预期收益，又会在什么条件下抑制新的信息生产？我采用理论建模与数值计算方法讨论这一问题。研究不涉及问卷、访谈、人体实验或动物实验，也未使用未公开的个人数据。

二 师生关系与指导性质

我叫杨子熠，就读于中国人民大学附属中学。本研究得到中国人民大学附属中学施一宁老师和天津大学管理与经济学部韩昊哲老师的指导。两位老师均无偿提供学术指导，未收取任何指导费用。施一宁老师就选题、论文写作和答辩方法给予建议，韩昊哲老师在选题、理论分析、计算和论文写作方面提供指导。感谢两位老师在研究和论文修改过程中付出的时间与耐心。研究内容、推导过程及最终报告由我本人负责。

三 研究过程与具体分工

研究过程中，我负责检索和阅读文献、提出研究问题，并建立投资者策略与信息传播机制。在此基础上，我完成了均衡条件、阈值和比较静态结果的推导，编写并运行 Python 代码核对数值结果、制作图表，随后撰写英文论文初稿，并根据讨论意见修改。施一宁老师针对题目表达、文章结构、论证的可读性及答辩呈现提出建议；韩昊哲老师则就模型假设、均衡推导、计算验证和英文表述提出建议。论文中的核心模型、证明、数值结果和最终表述均由我逐项复核。

四 研究中的困难与解决过程

研究的主要困难在于，信息线索的多层传播、调查行为对线索质量的影响，以及跟随收益对调查意愿的影响需要在同一模型中得到解释。我首先区分了独立发起的投资与沿平台传播的投资线索，避免混淆信息的传播与创造，并排除所有投资者都只跟随他人的退化情形。之后，我比较四种投资策略的收益，推导不同平台状态

下的均衡区间，再通过数值计算检查阈值顺序、参与率和收益函数，用图表呈现完整参与、部分参与及独立投资基准之间的关系。遇到表述或计算不一致的地方，我回到模型定义与最优反应条件逐项核对，以确认推导和结果是否一致。

五 他人协助与 AI 使用说明

除两位指导老师外，无其他人员参与本研究或论文写作。在论文最后整理阶段，我使用 OpenAI Codex (GPT-5)，使用范围仅限于对英文表述进行语言润色和语法检查板，以及将原论文放入模。论文的研究内容和最终表述由我本人复核并负责。相关对话记录将予以保存，并按要求提交。

杨子熠

参赛学生：杨子熠

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