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

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

Ziyi Yang

Abstract

Learning from others can improve investment decisions, but it may also weaken the incentive to investigate opportunities independently. We study this tradeoff in a two-period model with two types of investors who differ in research costs. In the first period, investors form independent recommendations and decide whether to investigate. In the second, they invest using either their own recommendation or another investor's first-period recommendation. When transmission is sufficiently effective, both researchers and followers obtain higher expected payoffs than under their best independent strategies, after research costs. Researchers benefit from better alternatives after rejecting a risky project. Under the stated parameter restriction, high transmission effectiveness yields partial research participation among low-cost investors. In this region, lower research participation offsets more effective transmission, keeping both types' expected payoffs constant above their independent benchmarks.

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

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Contents

1. Introduction 3
2. Model Environment 5
3. Crowd Learning 7
4. Equilibrium and the Wisdom of Crowds 8
5. Equilibrium and Research Participation 9
6. Numerical Illustration 10
7. Conclusion 14
Appendix A. Derivations and Proofs 15
Appendix B. Numerical Values and Reproducible Code 18
References 22

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1. Introduction

Many individual investors use social investment platforms to exchange views, read analysis, and learn from other investors. On eToro, users can copy others' trades. Xueqiu and StockTwits host discussions of investment ideas, while Seeking Alpha provides research and commentary. These services give investors access to ideas they have not developed themselves. If investors can rely on others' work, however, who will undertake the research? We ask when learning from others improves investment outcomes while preserving the incentive to investigate opportunities independently.

Following another investor saves the cost of investigating an opportunity, but it may also leave fewer investors willing to produce information. Social learning can also raise the expected payoff to investors who investigate. An investor who rules out a risky project can turn to another idea on the platform, reducing the cost of an unfavorable finding. The value of that alternative depends on other investors' choices. We therefore determine research participation and the value of following together.

We study two types of investors who differ in investigation costs. Investigation reveals whether a project is safe or risky, but leaves less money available to invest. Without social learning, low-cost investors prefer to investigate, while high-cost investors invest without investigating. Each investor chooses among four plans: invest randomly, follow another investor, investigate and follow after a risky finding, or investigate and independently select a replacement after a risky finding.

In the first period, investors independently form recommendations. The platform records each recommendation before investors observe others. In the second period, a follower draws one recommendation uniformly from the population. Research improves the quality of the available recommendations, while its private value depends on the expected return from following. Holding asset prices and project supply fixed, we solve for research participation and following payoffs together. We focus on parameters for which all three equilibrium regions described below occur; Section 4.2 states the required restriction.

When transmission is weak, both types use their best independent strategies. At intermediate levels, low-cost investors investigate and follow only after finding a risky project, while high-cost investors follow directly. This allocation is a strict equilibrium over a nonempty range of platform states. After research costs, both types obtain higher expected payoffs than under their best independent strategies.

When transmission is highly effective, some low-cost investors follow without investigating. In equilibrium, the research participation rate makes low-cost investors indifferent between investigation and direct following. Both types' payoffs then remain constant above their independent benchmarks. For each platform state, research participation, the return from following, and each type's payoff are uniquely determined. At the lower threshold, different strategy mixtures yield the same aggregate outcomes. These comparisons describe equilibria at different levels of transmission effectiveness, rather than a dynamic adjustment process.

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 the question of how the research behind such information is sustained. We make research participation part of the equilibrium and compare each type's payoff with its best independent strategy. For low-cost investors, the benchmark includes investigation followed by random replacement, so the comparison accounts for both the value and the cost of independent research.

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

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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 connects the model to 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). The efficiency of experimentation can depend on the equilibrium concept and on how behavior may depend on past observations (Hörner, Klein, and Rady, 2022). Financial applications study information acquisition under competition and information sharing (Hauswald and Marquez, 2006; Karapetyan and Stacescu, 2014), and its relationship with passive ownership and firms' risk choices (Buss and Sundaresan, 2023). In our model, reduced research offsets further improvements in transmission once the upper threshold is reached, limiting payoff gains.

We use wisdom of crowds to mean the payoff gains from decentralized research and following; these gains do not require investors to reach a 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 aggregates dispersed signals accurately, and Kremer, Mansour, and Perry (2014) examine disclosure policies that encourage exploration. Our model instead considers one observation of an earlier recommendation. Research improves initial recommendations; without research, transmission losses make following less attractive than independent investment.

A low research cost does not necessarily mean an investor will investigate. The platform literature studies 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 operates within the investor population: researchers can also use others' recommendations. In the partial-participation region, a larger low-cost group is exactly offset by a lower research rate within that group. With project parameters, costs, and transmission effectiveness fixed, the population research share is unchanged.

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 continuum of risk-neutral investors with total mass one. A share $s \in (0,1)$ has low research costs and is denoted by H; the remaining share $1 - s$ has high research costs and is denoted by L. Both types obtain the same information from investigation. Each investor has zero mass and takes the aggregate information environment as given.

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. Project capacity and rationing do not constrain investment, and following does not affect asset prices or the underlying project payoff distribution.

Each investor can investigate at most one project in the first period. Investigation reveals whether that project is safe or risky. Define

$$p_1 = \lambda + (1 - \lambda)p, \qquad p_2 = \lambda + (1 - \lambda)p_1. \tag{1}$$

An uninvestigated project succeeds with probability p_1. Investigation followed by retention of a safe project or random replacement of a risky one produces a recommendation of quality p_2. Hence $p_2 > p_1 > \lambda$. These probabilities describe the initial recommendations; project returns are realized after second-period investment.

2.2. Costs and investment strategies

Investigation costs are C_H for H and C_L for L, with $0 < C_H < C_L < W$. Costs and population shares are common knowledge, and each investor knows their own type. Write $c_i = C_i/W$ for the normalized research cost of type $i \in \{H, L\}$.

Assumption 1 (research choices without social learning). *The normalized investigation costs satisfy*

$$0 < c_{\mathrm{H}} < c^{\star} < c_{\mathrm{L}} < 1, \qquad c^{\star} = \frac{p_2 - p_1}{p_2}. \tag{2}$$

At $c_i = c^{\star}$, an investor earns the same expected payoff from random investment and from investigation followed by random replacement. Under Assumption 1, H prefers to investigate and replace a risky project at random, whereas L prefers random investment without investigation. These are their best choices without access to others' recommendations.

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.

Let S_k, $k \in \{1,2,3,4\}$, denote a complete plan for first-period research and second-period investment. Let f be the expected return factor from following a first-period recommendation. The normalized payoff $u_i(S_k; f)$ is type i's expected payoff divided by RW. Investors choose their plans before learning project types. The normalized payoff measures expected terminal project payments, not a net profit rate. Table 1 gives the four plans and their payoffs.

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Table 1. Investment strategies and normalized expected payoffs.

Strategy	Action at $t = 1$	Action at $t = 2$	$u_i(S_k; f)$
S_1	Draw an independent candidate without investigation.	Invest the full budget in their own candidate.	p_1
S_2	Draw an independent candidate without investigation.	Follow one first-period record and invest the full budget.	f
S_3	Draw a candidate and investigate once. Retain it if safe; otherwise draw an uninvestigated replacement.	Use the remaining funds: invest in the safe project; after a risky finding, follow one first-period record.	$(1 - c_i)[\lambda + (1 - \lambda)f]$
S_4	Draw a candidate and investigate once. Retain it if safe; otherwise draw an uninvestigated replacement.	Use the remaining funds to invest in the safe project or the replacement.	$(1 - c_i)p_2$

All investors form independent first-period candidates, including those who plan to follow. The platform records these candidates before investors observe others. This pool is then frozen: second-period investment choices do not update its records. A replacement is drawn without investigation; neither research plan permits a second investigation.

2.3. Timing and observation

The platform records the candidate project selected by each investor in the first period. Drawing a candidate is free; learning its type requires investigation. The recording rule is fixed, so investors cannot choose which recommendations to disclose. A recommendation reveals only a project identifier, which provides no additional signal of project quality beyond the recommendation pool's composition. It does not reveal the source's investor type, research decision, or private finding. Followers invest their own funds, and the source's research expenditure does not reduce a follower's budget.

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 $m = (m_1, m_2, m_3, m_4)$.

The parameter $\delta \in (0,1)$ is the fraction of the source project's expected payoff per unit invested that an investor can realize through following. This proportional payoff reduction is specific to following; it does not change the project's underlying payoff distribution. Investors observe δ before choosing their plans and take it as given. The same factor applies to following without research and to following after an unfavorable investigation. It is not a probability of receiving a recommendation: the model has no separately observed transmission failure after which an investor can revert to an independent candidate.

Assumption 2 (random sampling of anonymous recommendations). A follower draws one record uniformly from the first-period recommendations. Sampling is independent of the observer's type and private finding and does not select sources by project quality or realized returns.[1]

Period 1. After observing δ, investors choose their plans and independently draw candidate projects. Those who investigate pay C_i and learn the project type. They retain a safe project and replace a risky one with a fresh, uninvestigated candidate. Investors who do not investigate retain their initial candidate. The platform records these recommendations. Research decisions take account of the opportunity to follow in period 2.

[1] Project returns are realized only after the second-period investment decision. Records identify candidate projects rather than realized payoffs.

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Period 2. Investors retain their own candidate or follow one randomly sampled first-period recommendation. A researcher with a safe project keeps it. After a risky finding, S_3 prescribes following and S_4 prescribes retaining the replacement. Each investor makes one final investment in this period, and all project returns are realized afterward. There is no first-period investment payoff or second-period investigation.

3. Crowd Learning

3.1. The return from following

Investors using S_1 or S_2 submit uninvestigated recommendations of quality p_1; those using S_3 or S_4 submit recommendations of quality p_2. Assumption 2 therefore gives

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

The population research share is $m_3 + m_4$. In period 1, an S_3 investor recommends either a safe project or an independent replacement after a risky finding. The recommendation therefore has quality p_2. Equation (3) determines f from first-period strategy shares, with $\delta p_1 \leq f \leq \delta p_2 < 1$; see Appendix A.1.

If everyone uses S_2, then $m_3 + m_4 = 0$ and $f = \delta p_1 < p_1$. An investor can do better by retaining an independent recommendation under S_1. Universal following is therefore not an equilibrium.

An aggregate equilibrium consists of the type-specific strategy shares (σ_H, σ_L) and the return factor f. The shares determine the recommendation distribution in (3), and each plan used in equilibrium must maximize the investor's expected terminal payoff. Its second-period continuation must also be optimal. Hence

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

A type-specific equilibrium is strict if each type has a unique best plan. If a type uses more than one plan, each must yield its highest payoff. One investor's deviation leaves f unchanged because each has zero mass. Since $f < 1$, a researcher always retains a known safe project.

3.2. The investigation–following allocation

Suppose all H investors use S_3 and all L investors use S_2, so $m = (0,1-s,s,0)$. Let q_I be the final return factor of a researcher before adjusting for the research expenditure, and let q_F be the follower's return factor. Initial H recommendations have quality p_2 and initial L recommendations have quality p_1. Consequently, $f = q_F$ and

$$q_F = \delta[(1-s)p_1 + sp_2], q_I = \lambda + (1-\lambda)q_F. \tag{5}$$

A researcher retains a safe project and otherwise follows. Substituting the return from following into the researcher's payoff gives

$$q_I = \lambda + (1-\lambda)\delta[(1-s)p_1 + sp_2]. \tag{6}$$

The factor q_I describes the researcher's complete investment plan. A researcher's first-period recommendation has quality p_2 because it is formed before social observation. The next section establishes when the proposed allocation is an equilibrium.

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4. Equilibrium and the Wisdom of Crowds

4.1. Incentive comparisons

Let t_i be the value of following at which type $i \in \{H, L\}$ is indifferent between S_3 and S_2. Thus $u_i(S_3; t_i) = t_i$, where

$$u_i(S_3; f) = (1 - c_i)[\lambda + (1 - \lambda)f],$$
$$t_i = \frac{(1 - c_i)\lambda}{\lambda + c_i(1 - \lambda)}. \tag{7}$$

Two payoff differences explain the choice between strategies:

$$u_i(S_3; f) - f = [\lambda + c_i(1 - \lambda)](t_i - f),$$
$$u_i(S_3; f) - (1 - c_i)p_2 = (1 - c_i)(1 - \lambda)(f - p_1). \tag{8}$$

The first identity compares investigation with following, and the second compares following with random replacement after investigation. Assumption 1 implies $t_{\mathrm{H}} > p_1 > t_{\mathrm{L}}$. 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 $p_1 < f < t_{\mathrm{H}}$, and S_2 for $f > t_{\mathrm{H}}$. At $f = p_1$, H is indifferent between S_3 and S_4; at $f = t_{\mathrm{H}}$, H is indifferent between S_2 and S_3. Appendix A.2 establishes this complete best-response partition.

4.2. A strict specialization equilibrium

Parameter restriction. We assume $t_H < (1 - s)p_1 + sp_2$. This restriction ensures that the high-transmission region with partial research participation occurs within the admissible range of transmission effectiveness. The two equilibrium thresholds are

$$\delta_{\mathrm{low}} = \frac{p_1}{(1 - s)p_1 + sp_2}, \delta_{\mathrm{high}} = \frac{t_H}{(1 - s)p_1 + sp_2}. \tag{9}$$

Proposition 1 (investigation and following). *Under Assumptions 1-2 and the parameter restriction in Section 4.2, H:S_3, L:S_2 is a strict type-specific equilibrium if and only if*

$$\delta_{\mathrm{low}} < \delta < \delta_{\mathrm{high}}. \tag{10}$$

Together with Assumption 1, the maintained restriction gives $0 < \delta_{\mathrm{low}} < \delta_{\mathrm{high}} < 1$. At either threshold, the allocation is a weak equilibrium.

The condition $p_1 < q_{\mathrm{F}} < t_{\mathrm{H}}$ 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 $c_{\mathrm{L}} > c^{\star}$, these comparisons cover all four strategies. Appendix A.3 proves necessity and sufficiency and shows that the interval is nonempty.

When transmission is weak, H investigates and retains a random replacement after a risky finding. Above δ_{low}, H follows after such a finding, while L follows without investigating. Above δ_{high}, some H also follow without investigating.

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4.3. Gains relative to independent investment

Without observational learning, investors choose between S_1 and S_4. Let u_i^{iso} denote type i's best independent normalized payoff and u_i^{crowd} its normalized equilibrium payoff with social learning. Under Assumption 1, H chooses S_4 and L chooses S_1, giving

$$u_H^{\text{iso}} = (1 - c_H)p_2, \qquad u_L^{\text{iso}} = p_1. \tag{11}$$

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

$$\begin{aligned} u_H^{\text{crowd}} - u_H^{\text{iso}} &= (1 - c_H)(1 - \lambda)(q_F - p_1) > 0, \\ u_L^{\text{crowd}} - u_L^{\text{iso}} &= q_F - p_1 > 0. \end{aligned} \tag{12}$$

The population-average improvement is

$$\Delta\overline{u} = [s(1 - c_H)(1 - \lambda) + (1 - s)](q_F - p_1) > 0. \tag{13}$$

H benefits from a better alternative after rejecting a risky project; L benefits from opportunities identified by other investors. We call these gains for both types the wisdom of crowds in investment. Investigation costs are already reflected in the smaller investment budget. Appendix A.4 derives the payoff differences.

5. Equilibrium and Research Participation

5.1. Partial participation

Write $x = \sigma_{H3} + \sigma_{H4}$ for the research share within H. Since L never investigates in equilibrium, the population research share is $m_3 + m_4 = sx$. Consider an allocation in which a fraction x of H uses S_3 and everyone else uses S_2. Then $m(x) = (0, 1 - sx, sx, 0)$ and $\sigma_{H4} = 0$.

Substituting this composition into (3) gives

$$\begin{aligned} q_F(x) &= \delta[p_1 + sx(p_2 - p_1)], \\ q_I(x) &= \lambda + (1 - \lambda)\delta[p_1 + sx(p_2 - p_1)]. \end{aligned} \tag{14}$$

At a fixed δ, following becomes more attractive as x increases. All H investors face the same research cost. They can use both S_3 and S_2 in equilibrium only when the two payoffs are equal, which by (8) requires $q_F(x) = t_H$.

Proposition 3 (endogenous investigation participation). *Under Assumptions 1-2 and the parameter restriction in Section 4.2, for $\delta_{\text{high}} < \delta < 1$, an equilibrium has a fraction $x^\star$ of H using S_3, the remaining H using S_2, and all L strictly preferring S_2, where*

$$\begin{aligned} x^\star &= \frac{t_H - \delta p_1}{\delta s(p_2 - p_1)} \in (0,1), \\ q_F(x^\star) &= (1 - c_H)q_I(x^\star) = t_H. \end{aligned} \tag{15}$$

Indifference determines how many H investors investigate, but not which ones do so. Equivalently, identical H investors can randomize between the two plans. Appendix A.5 derives (15) and checks deviations; Proposition 4 shows that every equilibrium in this region has these shares.

At $\delta = \delta_{\text{high}}$, equation (15) gives $x^\star = 1$. If fewer H investors investigated, $q_F(x)$ would fall below t_H, making investigation strictly preferable again.

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5.2. Complete equilibrium classification

Proposition 4 (all aggregate equilibria). Under Assumptions 1-2 and the parameter restriction in Section 4.2, the equilibrium following factor is unique for every $0 < \delta < 1$ and satisfies

$$f^{\star}(\delta) = \min\{\delta[(1-s)p_1 + sp_2], t_H\}, 0 < \delta < 1. \tag{16}$$

For $0 < \delta < \delta_{\text{low}}$, the unique equilibrium has H using S_4 and L using S_1, with $m = (1-s, 0, 0, s)$.

For $\delta_{\text{low}} \leq \delta \leq \delta_{\text{high}}$, H using S_3 and L using S_2 is an equilibrium, with $m = (0, 1-s, s, 0)$; it is unique except at the lower boundary. At that boundary, H may mix between S_3 and S_4 and L between S_1 and S_2, without changing the following factor, research share, or payoffs.

For $\delta_{\text{high}} < \delta < 1$, a share $x^{\star}$ of H uses S_3; all others use S_2, with $x^{\star}$ given by (15).

Appendix A.6 proves completeness.

5.3. Research participation and investment payoffs

In the partial-participation region,

$$\begin{aligned} \frac{\partial x^{\star}}{\partial \delta} &= -\frac{t_H}{s(p_2 - p_1)\delta^2} < 0, \\ m_3 + m_4 &= sx^{\star} = \frac{t_H/\delta - p_1}{p_2 - p_1}. \end{aligned} \tag{17}$$

All H investigate when $\delta \leq \delta_{\text{high}}$, so $x = 1$ and $m_3 + m_4 = s$. Above this threshold, research declines according to (17). Within the partial-participation region, $m_3 + m_4$ is independent of s when project parameters, c_H, and δ are fixed. An increase in the low-cost population share is exactly offset by a lower research rate within H.

Corollary 1 (gains across all equilibria). Under Assumptions 1-2 and the parameter restriction in Section 4.2, both types receive their independent benchmark payoffs for $0 < \delta \leq \delta_{\text{low}}$ and strictly higher payoffs for $\delta_{\text{low}} < \delta < 1$. Payoffs increase strictly on $(\delta_{\text{low}}, \delta_{\text{high}})$, and both types' normalized payoffs equal t_H on $[\delta_{\text{high}}, 1)$. The proof is in Appendix A.6.

As $\delta \to 1$, the research share within H converges to $(t_H - p_1)/[s(p_2 - p_1)] \in (0,1)$.

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. The figures and table evaluate analytical payoff formulas and equilibrium outcomes of the two-period model; they are not investor-level Monte Carlo simulations. Calculations use full precision; reported values are rounded to three decimal places.

$$\lambda = 0.400, p = 0.500, c_H = 0.130, c_L = 0.250, s = 0.400. \tag{18}$$

The parameters give $p_1 = 0.700$, $p_2 = 0.820$, and $c^{\star} \approx 0.146$, satisfying Assumption 1. They also satisfy the maintained restriction: $t_H \approx 0.728 < (1-s)p_1 + sp_2 = 0.748$. The thresholds are $\delta_{\text{low}} \approx 0.936$ and $\delta_{\text{high}} \approx 0.973$. At $\delta = 0.950$, $q_F \approx 0.711$ and $q_I \approx 0.826$. H has a normalized payoff of 0.719 against its independent benchmark of 0.713; L receives 0.711 against 0.700. The average gain is 0.009.

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These near-one thresholds follow from the illustrative choices in (18); they are not empirically calibrated cutoffs for real platforms. Other admissible parameter values can shift these thresholds.

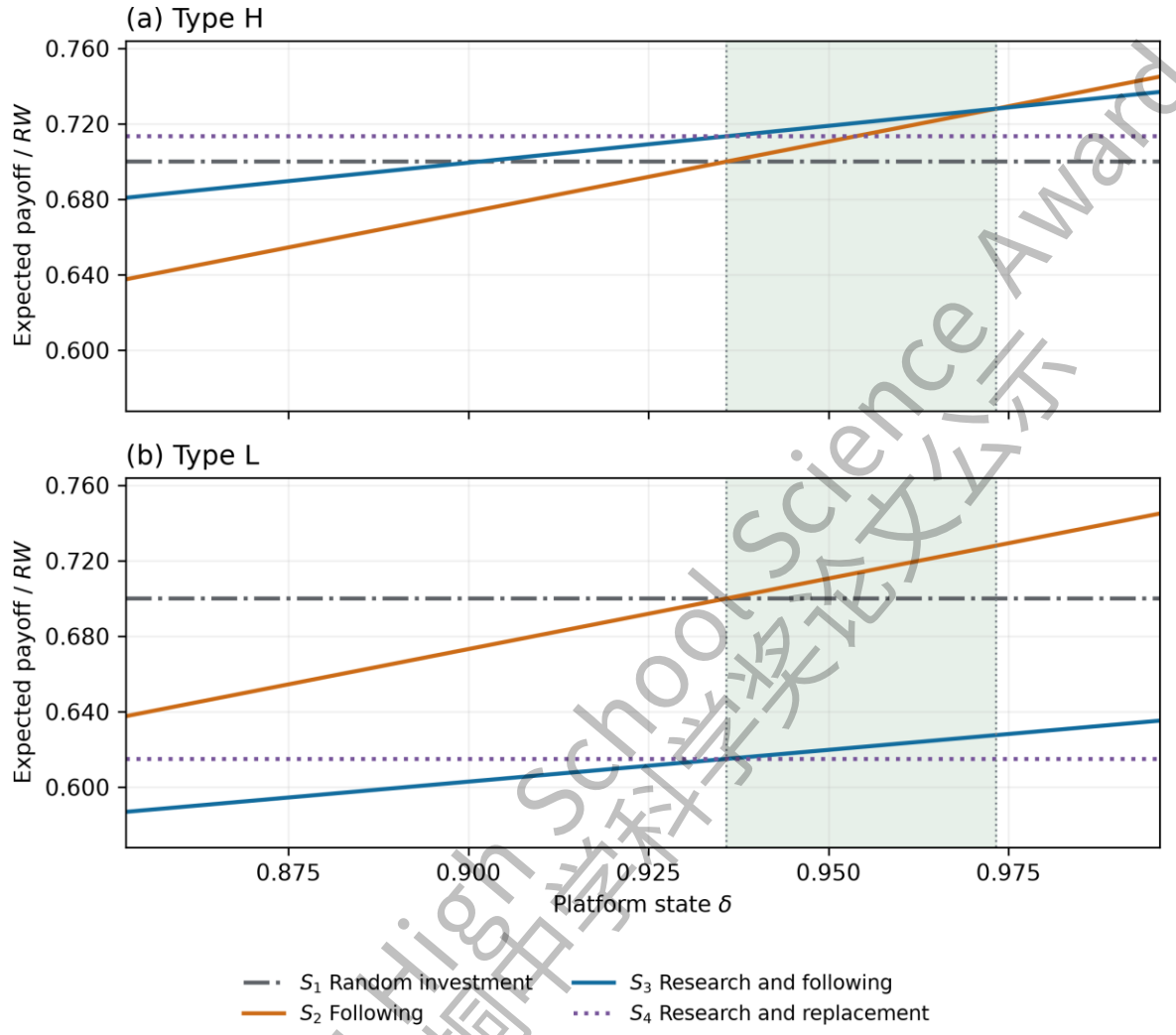


Figure 1. Strategy payoffs under the recommendation distribution generated by H:S_3, L:S_2. Panels (a) and (b) show H and L. The shaded interval supports strict equilibrium. Payoffs are divided by RW.

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 for type i's normalized equilibrium payoff; the population average is $su_H + (1-s)u_L$.

Figures 2-3 and Table 2 report equilibrium outcomes. At $\delta = 0.900$, H uses S_4 and L invests randomly. At $\delta = 0.970$, all H still investigate. At $\delta = 0.980$ and $\delta = 0.990$, the research share within H is 0.894 and 0.737, respectively, while both types' normalized payoffs equal $t_H \approx 0.728$.

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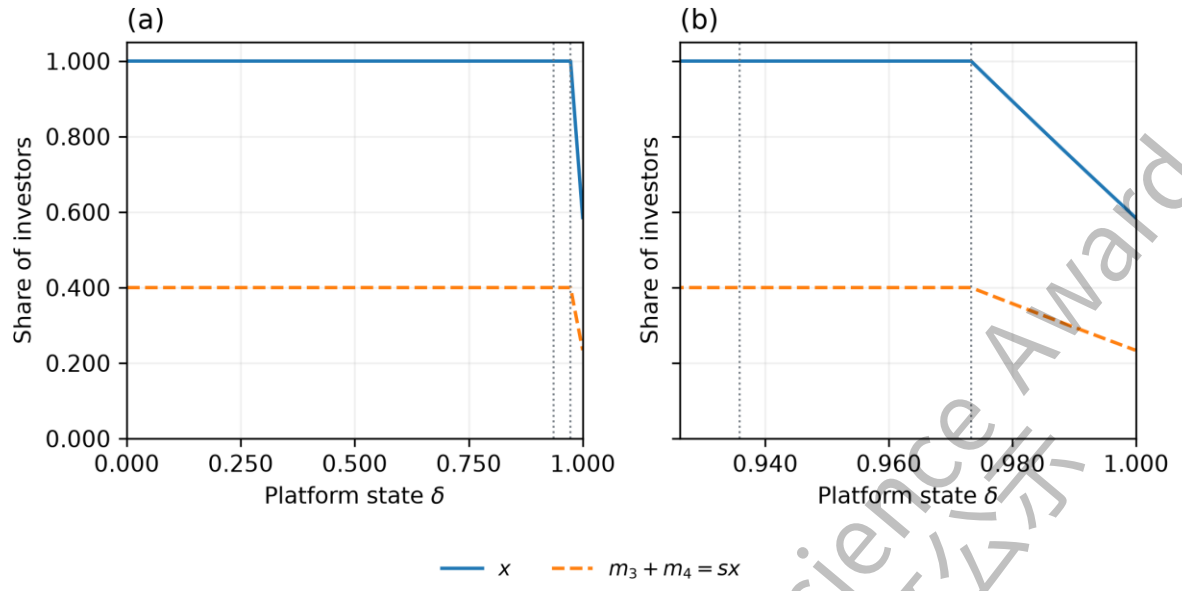


Figure 2. Equilibrium research participation. Solid curves show x; dashed curves show $m_3 + m_4 = sx$. Both are constant up to δ_{high} and decline above it. Panel (a) covers the full domain, and panel (b) enlarges the threshold region. Vertical lines mark the two thresholds.

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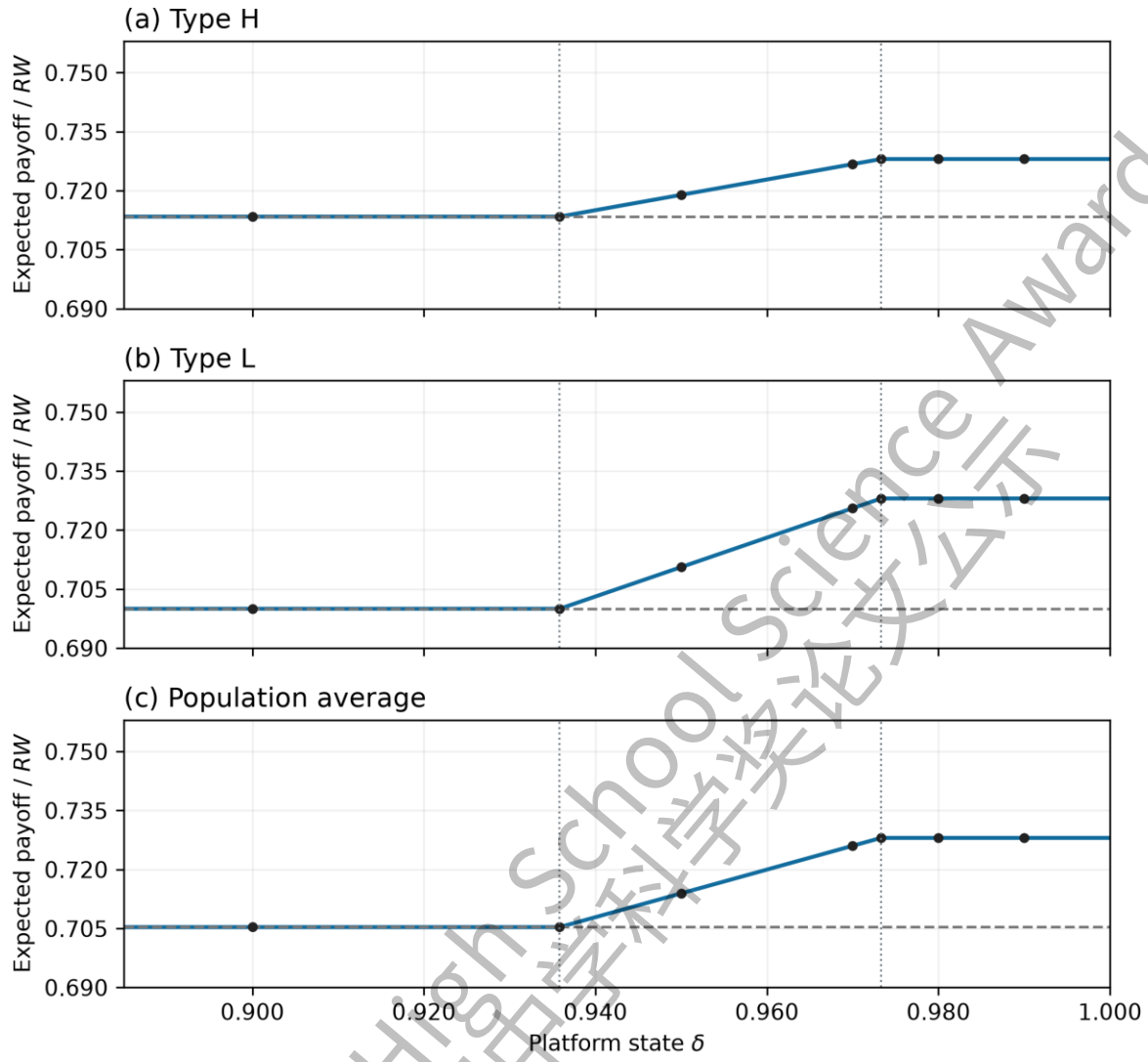


Figure 3. Equilibrium payoffs across platform states. Panels (a)–(c) show H, L, and the population average $su_{\mathrm{H}} + (1-s)u_{\mathrm{L}}$, using identical axes. Solid curves are normalized equilibrium payoffs; dashed lines are the corresponding independent benchmarks. Dots show the seven exact 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}, payoffs equal the independent benchmarks. They rise between the thresholds. Above δ_{high}, payoffs remain constant while research participation falls.

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7. Conclusion

Learning from others can benefit both researchers and followers. Investors first form independent recommendations and then make an investment decision using their own or another investor's recommendation. A researcher who rejects a risky project gains a better alternative; a follower gains access to opportunities improved by others' research. When transmission is sufficiently effective, both obtain higher expected payoffs than under their best independent strategies, after research costs. Under the parameter restriction in Section 4.2, higher transmission effectiveness above the upper threshold is associated with lower equilibrium research participation, while both types' expected payoffs remain constant.

Policy implications. The results suggest evaluating information sharing by its effects on both investor payoffs and research incentives. A decline in research participation can accompany stable payoffs above the independent benchmark. Research participation alone is therefore insufficient to assess the value of an information-sharing arrangement. The model does not determine whether research rewards, source-disclosure requirements, or investor education would improve outcomes. Evaluating such measures would require additional analysis of their costs and effects on investor behavior.

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, observation is anonymous and limited to first-period recommendations. Allowing investors to choose sources or decide what to disclose would link research incentives to network formation and information disclosure (Jackson and Watts, 2002; Rayo and Segal, 2010). Repeated interaction could also allow investors to assess sources through reputation and realized returns. Such an extension would need to specify when recommendations are updated and when investment decisions become final.

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.

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Appendix A. Derivations and Proofs

A.1. The aggregate return factor

An uninvestigated recommendation has quality p_1. Investigation produces a safe recommendation with probability λ and an independent replacement otherwise, giving quality $\lambda + (1-\lambda)p_1 = p_2$. The respective population shares are $m_1 + m_2$ and $m_3 + m_4$. Using $m_1 + m_2 = 1 - m_3 - m_4$ in (3) gives

$$f(m) = \delta[p_1 + (m_3 + m_4)(p_2 - p_1)]. \tag{A1}$$

Since $0 \le m_3 + m_4 \le 1$ and $p_2 > p_1$,

$$\delta p_1 \le f(m) \le \delta p_2 < 1. \tag{A2}$$

For every strategy profile, the recorded recommendations therefore determine a unique following payoff. If no investor investigates, $m_3 + m_4 = 0$ and $f = \delta p_1 < p_1$, making S_1 preferable to universal following.

Setting $m_3 + m_4 = s$ gives the following factor in (5), and setting $m_3 + m_4 = sx$ gives (14). The researcher's final return factor follows by substituting this value into $q_I = \lambda + (1-\lambda)q_F$.

A.2. Strategy comparisons and cost thresholds

Investigation with random replacement and random investment differ in payoff by

$$(1 - c_i)p_2 - p_1 = p_2(c^\star - c_i). \tag{A3}$$

Under Assumption 1, the difference is positive for H and negative for L. Expanding $u_i(S_3; f) - f$ gives the first identity in (8), and using $p_2 = \lambda + (1-\lambda)p_1$ gives the second. For any cost $c \in (0,1)$, write $t(c)$ for the indifference threshold. Then $t_i = t(c_i)$ and

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

It follows that $t_H > p_1 > t_L$. For L, if $f \le p_1$, then $u_L(S_3; f) \le (1 - c_L)p_2 < p_1$; if $f > p_1$, then $u_L(S_3; f) < f$ because $f > t_L$. Its S_4 payoff is always below p_1. For H, (8) and Assumption 1 make S_4 strictly optimal when $f < p_1$, and S_3 strictly optimal when $p_1 < f < t_H$. When $f > t_H$, S_2 exceeds S_3 as well as $t_H > (1 - c_H)p_2 > p_1$. The equalities are those stated 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.

Conversely, $f < t_H$ gives $u_H(S_3; f) > f$, and $f > p_1$ gives $u_H(S_3; f) > (1 - c_H)p_2 > p_1$. Thus H strictly prefers S_3. Appendix A.2 rules out investigation for L, and $f > p_1$ makes S_2 strictly better than S_1. These choices are also optimal in period 2: a researcher retains a safe project and follows after a risky finding.

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

$$\frac{\partial q_F}{\partial \delta} = (1-s)p_1 + sp_2 > 0, \qquad \delta = \frac{f}{(1-s)p_1 + sp_2}. \tag{A5}$$

Evaluating the inverse at $f = p_1$ and $f = t_H$ gives (9). Assumption 1 and the maintained restriction imply $0 < \delta_{\text{low}} < \delta_{\text{high}} < 1$. At the lower boundary, H is indifferent between S_3, S_4 and L between S_1, S_2. At the upper boundary, H is indifferent between S_3, S_2, while L strictly prefers following.

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A.4. Proof of Proposition 2

In this equilibrium, $u_H^{\text{crowd}} = (1 - c_H)q_I$ and $u_L^{\text{crowd}} = q_F$. 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.

A.5. Proof of Proposition 3 and comparative statics

If positive shares of H use both S_3 and S_2, equilibrium requires $u_H(S_3; q_F(x)) = q_F(x)$. Equation (8) makes this equivalent to $q_F(x) = t_H$. Solving (14) yields

$$sx = \frac{t_H/\delta - p_1}{p_2 - p_1}. \tag{A6}$$

Since $t_H > p_1$ and $\delta < 1$, the numerator is positive. The condition $x < 1$ is equivalent to $\delta > t_H/[(1 - s)p_1 + sp_2] = \delta_{\text{high}}$. The maintained restriction places this threshold below one. Moreover,

$$\frac{\partial q_F(x)}{\partial x} = \delta s(p_2 - p_1) > 0. \tag{A7}$$

This derivative makes the interior research share unique. At $x^\star$, both H plans yield $t_H > p_1$. They also exceed S_4, since $q_I(x^\star) = \lambda + (1 - \lambda)t_H > p_2$. For L, $(1 - c_L)p_2 < p_1 < t_H$ and $(1 - c_L)q_I(x^\star) < (1 - c_H)q_I(x^\star) = t_H$. Thus L strictly prefers S_2, and the proposed shares satisfy (3).

Differentiating (15) with respect to δ gives (17). 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.

As $\delta \to 1$, (15) gives $x^\star \to (t_H - p_1)/[s(p_2 - p_1)] \in (0,1)$ and $f^\star \to t_H$.

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A.6. Proof of Proposition 4 and Corollary 1

The best responses in Section 4.1 leave five cases. If $f < p_1$, H uses S_4 and L uses S_1. Then $m_3 + m_4 = s$, so (3) gives $f = \delta[(1-s)p_1 + sp_2]$. This is below p_1 exactly when $\delta < \delta_{\text{low}}$. If $f = p_1$, H can mix only between S_3 and S_4 and L only between S_1 and S_2. Any such mixture has $m_3 + m_4 = s$ and the same initial recommendation qualities. Hence $p_1 = \delta[(1-s)p_1 + sp_2]$, which requires $\delta = \delta_{\text{low}}$. Conversely, at this boundary every such mixture satisfies (3) and uses only best responses, including the allocation $m = (0, 1-s, s, 0)$.

If $p_1 < f < t_H$, H uses S_3 and L uses S_2, again giving $m_3 + m_4 = s$ and the allocation in Proposition 1. If $f = t_H$, L uses S_2 and H can mix only S_2, S_3. Equation (3) then requires (15), which is feasible for $\delta \geq \delta_{\text{high}}$; equality requires $x = 1$. Finally, $f > t_H$ would make both types use S_2, implying $f = \delta p_1 < p_1 < t_H$, a contradiction. These cases establish (16) and all the stated allocations.

For Corollary 1, every equilibrium at or below δ_{low} gives $(1-c_H)p_2$ to H and p_1 to L. Proposition 2 establishes strict gains in the full-participation learning region. At and above the upper threshold, both types receive t_H, and

$$t_{\text{H}} - (1-c_{\text{H}})p_2 = (1-c_{\text{H}})(1-\lambda)(t_{\text{H}} - p_1). \tag{A8}$$

The right-hand side is positive because $t_H > p_1$. In the full-participation region, (A5) and the positive slopes of $u_H(S_3; f)$ and f imply strictly increasing payoffs. Above the upper threshold, indifference fixes both payoffs at t_H.

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Appendix B. Numerical Values and Reproducible Code

B.1. Numerical values

Table 2. Equilibrium outcomes and the independent investment benchmark.

δ / region	x	$m_3 + m_4$	u_{H}	u_{L}	Average
Independent	1.000	0.400	0.713	0.700	0.705
0.900	1.000	0.400	0.713	0.700	0.705
0.936 (low)	1.000	0.400	0.713	0.700	0.705
0.950	1.000	0.400	0.719	0.711	0.714
0.970	1.000	0.400	0.727	0.726	0.726
0.973 (high)	1.000	0.400	0.728	0.728	0.728
0.980	0.894	0.357	0.728	0.728	0.728
0.990	0.737	0.295	0.728	0.728	0.728

Here $x = \sigma_{H3} + \sigma_{H4}$, $m_3 + m_4 = sx$, and u_i denotes type i's normalized payoff. The last column is $su_H + (1-s)u_L$. All rows use (18), with $c_H = 0.130$. The independent row reports the best independent strategies. Boundary rows are computed at exact thresholds before rounding. The lower-boundary row uses the allocation $m = (0, 1-s, s, 0)$; the other admissible mixtures give the same displayed outcomes.

2026 S.-T. Yau High School Science Award
仅用于2026丘成桐中学科学奖论文公示

B.2. Reproducible code

The following Python 3 program reproduces Figures 1-3 and Table 2. It requires NumPy and Matplotlib. Save the code as reproduce_two_period.py and run python reproduce_two_period.py en; replace en with zh for the Chinese figures. Outputs are saved in results_en or results_zh. The parameters in (18) satisfy the maintained restriction. Exact thresholds are used before display rounding.

```
"""Reproduce Figures 1-3 and Table 2 for the two-period model."""
from pathlib import Path
import csv
import sys
import numpy as np
import matplotlib
matplotlib.use('Agg')
import matplotlib.pyplot as plt
from matplotlib.ticker import FormatStrFormatter, MaxNLocator

# Run: python reproduce_two_period.py en  (or zh).
lang = sys.argv[1] if len(sys.argv) > 1 else 'en'
if lang not in ('en', 'zh'):
    raise ValueError('Language must be en or zh.')
lam, p, s, ch, cl = 0.400, 0.500, 0.400, 0.130, 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 lie strictly between zero and one.')
p1 = lam + (1-lam)*p
p2 = lam + (1-lam)*p1
gap = p2-p1
cs = gap/p2
if not ch < cs < cl:
    raise ValueError('Assumption 1 requires 0 < cH < c* < cL < 1.')
lo = p1/((1-s)*p1+s*p2)

def threshold(c):
    if not 0 < c < cs:
        raise ValueError('The low research cost must be below c*.')
    return (1-c)*lam/(lam+c*(1-lam))

th = threshold(ch)
hi = th/((1-s)*p1+s*p2)
if not th < (1-s)*p1+s*p2:
    raise ValueError('The maintained restriction requires tH < (1-s)*p1+s*p2.')

def following(d):
    """Equation (5), in the fixed H:S3, L:S2 environment."""
    return np.asarray(d)*((1-s)*p1+s*p2)

def payoffs(f, c):
    f = np.asarray(f, dtype=float)
    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, c=ch):
    """Return x, m3+m4, uH, uL, and the population-average payoff."""
    d = np.asarray(d, dtype=float)
    if np.any(~np.isfinite(d) | (d <= 0) | (d >= 1)):
        raise ValueError('Platform states must lie strictly between zero and one.')
    t = threshold(c)
    if not t < (1-s)*p1+s*p2:
        raise ValueError('The maintained restriction requires tH < (1-s)*p1+s*p2.')
    f = np.minimum(d*((1-s)*p1+s*p2), t)
    x = np.minimum(1.0, (t/d-p1)/(s*gap))
    uh = np.where(d <= lo, (1-c)*p2, (1-c)*(lam+(1-lam)*f))
    ul = np.maximum(p1, f)
    return np.array([x, s*x, uh, ul, s*uh+(1-s)*ul])
```

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```
def style(ax, ylabel):
    label = r'Platform state $\delta$' if lang == 'en' else r'平台状态 $\delta$'
    ax.set(xlabel=label, ylabel=ylabel)
    for axis in (ax.xaxis, ax.yaxis):
        axis.set_major_formatter(FormatStrFormatter('%.3f'))
        axis.set_major_locator(MaxNLocator(6))
    ax.grid(alpha=0.18)

def main():
    out = Path(__file__).resolve().parent/('results_'+lang)
    out.mkdir(exist_ok=True)
    font = 'DejaVu Sans' if lang == 'en' else 'Microsoft YaHei'
    plt.rcParams.update({'font.family': font, 'axes.unicode_minus': False,
                         'font.size': 10})
    ylabel = 'Expected payoff / $RW$' if lang == 'en' else '期望收益 / $RW$'
    edges = [(lo, 'low'), (hi, 'high')]
    def mark(ax):
        for edge, name in edges:
            ax.axvline(edge, ls=':', lw=0.9, color='#737b83')
    def save(fig, name):
        fig.savefig(out/name, dpi=300)
        plt.close(fig)

    left = max(0.001, lo-1.3*(1-lo))
    right = min(0.9999, hi+0.85*(1-hi))
    d = np.unique(np.r_[np.linspace(left, right, 500), lo,
                        [hi]])
    fig, axes = plt.subplots(2, 1, figsize=(7.4, 6.6), sharex=True,
                             sharey=True)
    labels = ['Random investment', 'Following', 'Research and following',
              'Research and replacement'] if lang == 'en' else [
              '随机投资', '直接跟随', '调查后跟随', '调查后随机更换']
    colors = ['#5f6368', '#cc6b16', '#126c9e', '#77549a']
    lines = ['-.', '-', '-', ':']
    for ax, c, tag in zip(axes, (ch, cl), ('H', 'L')):
        for k, u in enumerate(payoffs(following(d), c)):
            ax.plot(d, u, lines[k], color=colors[k], lw=1.8,
                    label=f'$S_{k+1}$ '+labels[k])
        ax.axvspan(lo, hi, color='#dfece2', alpha=0.75)
        mark(ax)
        title = 'Type '+tag if lang == 'en' else tag+' 类投资者'
        ax.set_title(('(a) ' if tag == 'H' else '(b) ')+title, loc='left')
        style(ax, ylabel)
    axes[0].set_xlabel('')
    values = [payoffs(following(d), c) for c in (ch, cl)]
    ymin, ymax = min(v.min() for v in values), max(v.max() for v in values)
    margin = max(0.012, 0.12*(ymax-ymin))
    axes[0].set_ylim(max(0, ymin-margin), ymax+margin)
    axes[1].set_xlim(left, right)
    fig.legend(*axes[0].get_legend_handles_labels(), loc='lower center',
               bbox_to_anchor=(0.5, 0.005), ncol=2, fontsize=9, frameon=False)
    fig.tight_layout(rect=(0, 0.1, 1, 1), h_pad=1.1)
    save(fig, 'figure_1.png')

    d = np.unique(np.r_[np.linspace(0.001, 0.9999, 500), lo,
                        [hi]])
    x = equilibrium(d)[0]
    m3 = np.where(d >= lo, s*x, 0.0)
    m4 = np.where(d < lo, s*x, 0.0)
    fig, axes = plt.subplots(1, 2, figsize=(7.4, 3.8), sharey=True)
    for ax in axes:
        ax.plot(d, x, label=r'$x$')
        ax.plot(d, m3+m4, '--', label=r'$m_3+m_4=sx$')
        mark(ax)
        style(ax, 'Share of investors' if lang == 'en' else '投资者比例')
        ax.set_ylim(0, 1.05)
```

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```
        ax.xaxis.set_major_locator(MaxNLocator(4))
    axes[0].set_xlim(0, 1)
    axes[1].set_xlim(max(0, lo-0.15*(1-lo)), 1)
    axes[0].set_title('(a)', loc='left')
    axes[1].set_title('(b)', loc='left')
    fig.legend(*axes[1].get_legend_handles_labels(), loc='lower center',
               bbox_to_anchor=(0.5, 0.005), ncol=2, fontsize=9, frameon=False)
    fig.tight_layout(rect=(0, 0.11, 1, 1))
    save(fig, 'figure_2.png')

    states = np.unique([0.9, 0.95, 0.97, 0.98, 0.99, lo]
                       + ([hi]))
    table = equilibrium(states)
    base = [(1-ch)*p2, p1, s*(1-ch)*p2+(1-s)*p1]
    d = np.unique(np.r_[np.linspace(0.885, 0.9999, 500), states])
    fig, axes = plt.subplots(3, 1, figsize=(7.4, 6.9), sharex=True,
                             sharey=True)
    names = ['Type H', 'Type L', 'Population average'] if lang == 'en' else [
             'H 类投资者', 'L 类投资者', '总体平均']
    for j, ax in enumerate(axes):
        ax.plot(d, equilibrium(d)[j+2], color='#126c9e', lw=1.8)
        ax.axhline(base[j], color='#777777', ls='--', lw=1.2)
        ax.plot(states, table[j+2], 'o', color='#222222', markersize=3.5)
        mark(ax)
        style(ax, ylabel)
        ax.set_title(f'({chr(97+j)}) '+names[j], loc='left')
        ax.set(xlim=(0.885, 1),
               ylim=(min(base)-0.01, max(th, (1-s)*p1+s*p2)+0.01))
        if j < 2:
            ax.set_xlabel('')
    fig.tight_layout(h_pad=1.1)
    save(fig, 'figure_3.png')

    with (out/'table_2.csv').open('w', encoding='utf-8', newline='') as f:
        writer = csv.writer(f)
        writer.writerow(['delta', 'region', 'x', 'm3+m4', 'uH', 'uL', 'average'])
        writer.writerow(['Independent', 'benchmark', 1, s]+base)
        for d0, values in zip(states, table.T):
            region = ('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([d0, region]+values.tolist())
    print('p1, p2, c*, lower, upper, tH:', p1, p2, cs, lo, hi, th)
    print('Results saved in', out)

if __name__ == '__main__':
    main()
```

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2026 S. T. Yau High School Science Award
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致谢

一 研究背景与选题来源

社交投资平台方便投资者借鉴他人的观点，也可能削弱自行调查的意愿。我希望研究：当调查成本不同，投资者先独立形成候选项目、再从平台学习时，跟随在什么条件下能提高研究者与跟随者的预期收益，又会在什么条件下减少调查？本研究采用两期理论模型与数值计算，不涉及问卷、访谈、人体或动物实验，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。本研究由本校施一宁老师和天津大学管理与经济学部韩昊哲老师指导，两位老师均无偿指导，未收取费用。施一宁老师就选题、论文结构和答辩方法提出建议；韩昊哲老师就模型假设、均衡分析、计算验证及英文表述提供指导。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

我负责检索和阅读文献、提出研究问题、建立模型，推导均衡条件、阈值与比较静态结果，并编写、运行 Python 代码核对数值和制作图表。我撰写英文初稿，并逐项复核模型、证明和数值。两位老师通过讨论指出需要澄清的问题，我再回到模型与推导检查、修改。

四 研究中的困难与解决过程

主要困难是解释调查如何改善候选项目，以及跟随收益如何影响调查意愿。我将候选项目的形成与使用分为两期：第一期独立选择项目并决定是否调查；第二期保留自己的候选项目，或随机抽取他人的第一期候选项目跟随。两期决策后只进行一次最终投资，第二期的跟随结果不再放回候选池传播。明确时序后，我比较四种策略的收益，并用数值计算核对阈值顺序、调查比例及收益；发现不一致时，回查策略定义与最优反应条件。

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），仅用于英文表述的语言润色和语法检查，以及把

2026 Tsinghua High School Science Award
仅用于2026年成桐中学科学奖公示

已经完成的论文排入模板。该工具没有参与选题、建模、证明、数值计算或代码编写。论文的研究内容和最终表述由我本人复核并负责。

六 提交后的模型修订

原稿提交后，我认为决策的先后顺序还需说明得更明确，于 2026 年 11 月 4 日改为两期设定，并统一了策略、收益、均衡推导及数值计算。研究问题没有改变。本次修改主要压缩说明文字、补充示例参数的适用限定并调整排版，未改动核心公式、命题或数值结果。

参赛学生：杨子熠



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