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From rational minds to herding hearts: the impact of stock performance transparency on risk preference

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Abstract. This research examines how performance transparency affects individual sideways shifting of risk preferences within rational assessment and herding frameworks. In three conditions (no disclosure, peer choice visibility, and peer earnings visibility), participants in some control experiments took turns making investment decisions under the three conditions as described. The hypothesis was confirmed, whereby the disclosure of choices and the earnings report in some scenario played a part in determining transparency in relation to conformity and complete rational reassessment. Diversification of behavior manifested in fully rational reassessment and rational diversification of behavior. Different stages of the experiments reflected changes in the risk tolerance in a statistically significant way, and the risk disclosure was the most powerful mechanism to effect change. Individual risk tolerance was the strongest determinant of the extent of imitation, herding behavior in risk-averse participants, while risk-seeking behavior was associated with autonomy. Recurrent feedback responses, cascades, and their reversal refine the Informational Cascade Theory. The junction of reference-dependent framing and transparency adds to Prospect Theory. Analytical reasoning, social influence, and Rational Thinking Theory coincide as social influence was shown to be mitigated by rational thinking. In general, performance transparency is a double-edged sword; with context and framing around the risk, it can trigger imitation or rational independence.

Keywords: herding behavior, risk preference, performance transparency, rational thinking, informational cascades

1. Introduction

Traditional economic theory assumes that individuals act rationally and maintain fixed attitudes toward risk. However, behavioral and experimental research suggests that risk preferences are context-dependent and may shift when performance transparency—the visibility of others' outcomes—alters the perceived trade-off between risk and return. Under full disclosure of peers' investment performance, both herding behavior and rational assessment can influence individual decisions.

Herding behavior, defined as the tendency to imitate others even against private information (Banerjee, 1992; Bikhchandani, Hirshleifer, & Welch, 1992), is a key social factor explaining shifts in risk preference. It often amplifies financial instability, fueling bubbles and crashes. For instance, during the 2008 subprime mortgage crisis and subsequent Bitcoin boom, many investors followed others' profitable moves despite growing risks, demonstrating how herding can override rational judgment and lead to collective losses.

Yet prior studies also emphasize the role of rational evaluation in counteracting imitation. Stanovich (2016) and Stanovich and West (2014) argue that individuals with stronger analytical reasoning better resist conformity pressures. With regards to individual versus social decision making, Baddeley et al. (2010) demonstrated that those investors with a greater need for independent thinking exercised even more decision autonomy. Further, Christoffersen and Stæhr (2019) illustrated that higher risk tolerance correlates with a lower tendency to herd. Together, these results suggest that rational evaluation functions as a cognitive counteractive mechanism for social contagion.

Notwithstanding the abundant literature on the herding phenomenon, the evolution of risk preference itself under different degrees of transparency remains largely unexplored. The present study bridges this gap by investigating how public access to others' earnings shapes individual investment risk preferences in a controlled experimental setting. The core hypothesis posits that changes in risk preference are jointly driven by herding tendencies and rational assessments—and that the dominance of each depends on individuals' underlying risk tolerance.

2. Literature review

This section synthesizes prior theoretical and empirical research on herding behavior and risk preferences, with particular attention to the interplay between rational thinking and social influence in stock investment. We organize the review into four subsections: (i) foundational theories of informational cascades and herding, (ii) prospect theory and wealth effects, (iii) rational assessment of outcomes, and (iv) the presence of contrarian strategies.

2.1 Herding, informational cascades, and contrarian strategies

Herding describes the tendency of individuals to imitate others' actions, often with limited deliberation. Banerjee's (1992) sequential decision model illustrates how people may abandon private signals once enough prior choices accumulate, forming an informational cascade. Bikhchandani, Hirshleifer, and Welch (1992, 1998) expand this framework, showing how cascades produce conformity and even market fads. In such contexts, individuals act as though "the majority must know better," resulting in what Devenow and Welch (1996) term rational herding—though in practice it often becomes uncritical imitation.

The consequences are well documented: collective convergence amplifies volatility and contributes to bubbles and crashes (Hwang & Salmon, 2004; Ferreruela & Mallor, 2021). Laboratory studies echo these dynamics—Drehmann, Oechssler, and Roider (2005) show that public feedback alone can trigger cascades, and Jain and Gupta (1987) find that U.S. banks made clustered lending decisions under imitation pressure. These results illustrate how easily "mindless conformity" can dominate markets once social cues are visible.

Yet imitation is not inevitable. Some investors deliberately resist or invert social influence. Park and Sabourian (2011) model agents who profit by betting against the majority, while Drehmann et al. (2005) show that a minority consistently diverge despite equal information. Rejikumar et al. (2022) highlight the role of cognitive complexity in such contrarian behavior, and Guan et al. (2024) find that herders' land-transfer patterns can represent risk-accumulating contrarianism. The motivations for contrarianism could be self-confidence, advanced cognitive development, or high-risk propensity.

Baddeley (2010) extends this reasoning through a neuroeconomic lens. He posits that the need to conform while possessing contradictory private information derives from reward-related neural circuitry.Conformity thus reflects not only cognitive shortcuts but also reward-driven bias, diverting attention from rational evaluation toward the immediate satisfaction of alignment.

2.2 Prospect theory and wealth effects

Informational cascades clarify the concept of imitation, while Prospect Theory explains how people evaluate the potential rewards and losses when making a decision to take a risk. Kahneman and Tversky (1979), followed by Levy (1992) and Barberis (2013), contend that individuals assess outcomes in relation to a certain reference point. Investors who see themselves as a lower or losing median—which falls in the "loss domain"—are likely to take more risks to try and gain, while those who hold prior winnings are more likely to take a conservative approach in risk-taking in order to safeguard what they already have.

This framing directly connects to herding. When many participants recognize underperformance, a collective sense of being in the loss domain can push group behavior toward riskier decisions. Conversely, outperforming investors tend to protect their gains by reducing exposure. Ferreruela and Mallor (2021) similarly found that herding weakens during crisis peaks but re-emerges in high-volatility periods, consistent with the idea that reference-point divergence fragments investor behavior.

Recent research further shows that risk preference moderates susceptibility to social influence. Individuals with higher risk tolerance exhibit greater independence of judgment, while risk-averse individuals align with the majority to reduce uncertainty. Christoffersen and Stæhr (2019) and Menkhoff (2006) both demonstrate that higher risk tolerance corresponds to lower herding. From a cognitive standpoint, Rejikumar et al. (2022) find that risk-averse and less complex thinkers rely more on public cues, whereas risk-tolerant, cognitively complex individuals rely on self-assessment. Gemayel and Preda (2024) also show that risk-seeking investors are less prone to herd under collective market signals.

Together, these findings support the theoretical expectation that herding behavior is stronger among risk-averse individuals, while risk-seeking investors display more stable and self-directed decision patterns—an asymmetry empirically examined in the present experiment.

2.3 Rational assessment and learning from outcomes

Not all observed behavior constitutes blind imitation. Growing evidence shows that reasoned judgment can counteract social pressure. Stanovich (2016) and Stanovich and West (2014) argue that individuals with stronger rational thinking styles resist conformity and make more independent choices. In financial contexts, rational assessment involves interpreting others' outcomes as data rather than instructions—evaluating whether superior performance reflects skill, information, or luck.

Knowledge and analytical ability further foster rationality. Black and Ellis (2010) show that critical thinking training enables investors to separate signal from noise, while Kantarelis (2018) demonstrates that systematic stock screening helps avoid speculative fads. This research supports and broadens the application of important behavioral and rational-choice theories and provides valuable new evidence that performance transparency operates as a two-way mechanism—it can deepen imitation and encourage independent assessment, depending on the cognitive style and context. By demonstrating this dichotomy, the study enhances the theoretical scope around the behavior of finance and provides practical contributions to encourage more rational and resilient markets.

While much of the literature documents the prevalence of herding, recent studies explore how risk preference and rationality jointly shape responses to social information. Baddeley et al. (2010) show that risk-averse or conformity-prone individuals are more likely to imitate peers, whereas Christoffersen and Stæhr (2019) observe that this inverse link between risk tolerance and herding weakens when peer disagreement is low. Hon-Snir et al. (2012) and Kudryavtsev et al. (2013) also suggest that rational investors are less susceptible to imitation.

Nevertheless, herding often overrides rational judgment in practice. Devenow and Welch (1996) describe "rational herding," in which imitation can be justified if others possess valuable information. Lin (2013) similarly argues that whether herding is rational or irrational depends on context: sometimes it represents informed inference, while at other times it stems from fear or panic. Hence, herding exists along a continuum—from information aggregation to mindless conformity.

3. Proposed model and experimental design

This section outlines the main behavioral assumptions and experimental setup used to test both the Main and Alternative Hypotheses. The design examines whether participants "go with the flow" by mimicking others' investment choices—exhibiting herding behavior—or whether visibility of peer earnings prompts a rational reassessment of personal strategies. By comparing decisions across phases, the experiment measures both the extent of imitation and whether performance transparency alters the group's average risk preference. It also explores how these dynamics vary with individuals' prior wealth and performance, capturing conformity pressures and rational recalibration within one framework.

At the heart of this design is the recognition that financial decision-making does not always follow a single pathway. Some individuals may default to imitation under uncertainty, while others may critically reinterpret peer outcomes and adjust their behavior rationally. By structuring the experiment around these dual possibilities, the study seeks to capture the coexistence of herding tendencies and rational adjustment mechanisms, thereby providing a richer picture of how performance transparency shapes investment risk preferences.

3.1 Key hypothesis

For our consideration and testing we define the following hypothesis:

Hypothesis : Risk-tolerant investors tend to be less influenced by herding tendencies and more influenced by rational thinking compared to risk-averse investors

Prior studies show that risk-averse investors are more likely to rely on social cues and follow the crowd as a way to reduce uncertainty, whereas risk-tolerant investors display greater independence of judgment (Banerjee, 1992; Baddeley et al., 2010; Christoffersen & Stæhr, 2019). Rational thinking research further suggests that higher risk tolerance is associated with a stronger tendency to critically evaluate others' outcomes rather than blindly imitate them (Stanovich, 2016; Kudryavtsev et al., 2013). Hence, risk-tolerant investors are expected to be less influenced by herding tendencies and more guided by rational assessment

4. Experimental design

4.1 Environment: participants and set-up

Participants: Each session involved around 30 undergraduate students, randomly assigned to terminals under conditions of full anonymity. All participants had a basic understanding of stock market concepts but limited or no real-world investment experience. This ensured they could follow the tasks while still reflecting relatively inexperienced investor behavior.

Investment Horizon: The experiment adopts a short-term, repeated horizon, where participants make decisions across ten consecutive rounds. This design reflects the reality of frequent trading in financial markets and highlights how individuals adjust their risk preferences in response to peer outcomes within a compressed timeframe. Such short horizons have also been widely used in experimental finance (e.g., Drehmann, Oechssler, & Roider, 2005), which show that repeated rounds are effective in capturing immediate behavioral responses to social information.

Pre-Test: Prior tests, including the questionnaires with 5, 8 and 10 questions, are made to set the question number at an optimal level where participants have the highest consistency of risk preference in their choices.

Experimental Institution:"In this experiment, you will make a series of investment decisions. In each round, you'll choose one of three risk options in the five questions. Your earnings will depend on the risks you take and chance. At the first round, you'll make investment on your own. At the second phase, you'll see how the number of investors for each option. At the third phase, you'll see others total earning and rank from Phase I and the subsequent choices of others in real time. Please read all instructions carefully."

Investment Options:

Investment options are designed to represent different levels of risk preference, including high (with expected utility of 5), medium (with expected utility of 10) and low (with expected utility of 5) risk levels(Figure 1). The portfolios of options in each question are different, but keeping the expected utility constant at each risk level. To avoid the potential bias in option selection, the order of the options is random, with no revelation of the risk level.

$$\mathrm{H}\Big(\mathrm{gain}\Big) = \mu + \sqrt{\sigma^2 * (1-\mathrm{p})/\mathrm{p}} \tag{1}$$

$$\mathrm{L}(\mathrm{loss}) = (\mu - \mathrm{p} * \mathrm{H})/(1-\mathrm{p}) \tag{2}$$

$$\text{where } \mu = 5,\ \mathrm{p} = 0.2,\ \sigma = 20 \text{ for high risk,} \tag{3}$$

$$\mu = 10,\ \mathrm{p} = 0.6,\ \sigma = 10 \text{ for medium risk,} \tag{4}$$

$$\mu = 5,\ \mathrm{p} = 0.9,\ \sigma = 2 \text{ for low risk} \tag{5}$$

Examples (a set of investment choices)

High Risk: 20% chance of +50.83, 80% chance of -7.42

Medium Risk: 60% chance of +16.83, 40% chance of 0.06

Low Risk: 90% chance of +5.28 , 10% chance of -0.49

Each choice with possible outcome and possibility of each choice will be labeled for each single choice, their real-time outcome will not come at the time they choice immediately, which make this experiment more real-life connected. That's to said that, they only able to see their outcome after each phase, and the risk preference measured index will only visible to the terminal of the experiment holder, which can reveal the change of each people's risk performance.

Example:

The expected utility was 5 points for both the high-risk and low-risk options, and the medium-risk option also produced 5 points. This confirms that variations in behavior arose from the exposure and social comparison of performance, and not from any differences in the value of the money involved. Each round, participants select one of the above. The risk preference score is recorded as +3, +2, or +1 per round.

Phase I: No Disclosure of Information

Participants make 5 investment decisions, with their initial risk preference being computed and recorded.

Phase II: Disclosure of Number of Options Chosen (Statistics, Rank)

Intervention: Disclosure of Other People's Choices

The amount of person of each investment is shared during this phase— earnings are private. Participants are given chance to change their investment decisions after knowing others' options. Finally, each participant's risk preference and total earnings from Phase II are computed and recorded.

Phase III : Disclosure of Individual Earnings

Intervention: Disclosure of Other People's Earnings

Each participant gets to see the total earnings of every other player in Phase II. Then participants chose the options again based on new figures. Lastly, the risk preferences in Phase III are re-calculated and compared with those in Phase II.

5. Experiment outcome

5.1 Descriptive statistics

Across the three experimental stages, participants' average risk preference scores exhibited a clear and systematic shift as performance transparency increased.

In Stage 1 (No Disclosure), participants' choices reflected their inherent risk preferences, with a mean total risk score of 10.20 (SD = 1.88). Once peer choices were visible during Stage 2, the mean increased slightly to 11.03 (SD = 1.19), along with a significant decrease in standard deviation. This convergence suggests that the participants began to align their choices with the modal risk level most frequently selected, indicative of the initial stages of informational herding.

After participant peer earnings were disclosed in Stage 3, the mean score increased again to 12.37 (SD = 1.77) in Stage 3, but variance increased once more, indicating a period of rational diversification. The mean being so much higher suggests that, on average, participants became more risk-seeking, while the increased variance suggests that rational reassessment took place with the outcome transparency peer earnings, in relation to position-taking.

5.2 Statistical analysis

Paired-sample t-tests confirm that the changes in risk preference between stages were statistically significant(Figure 1):

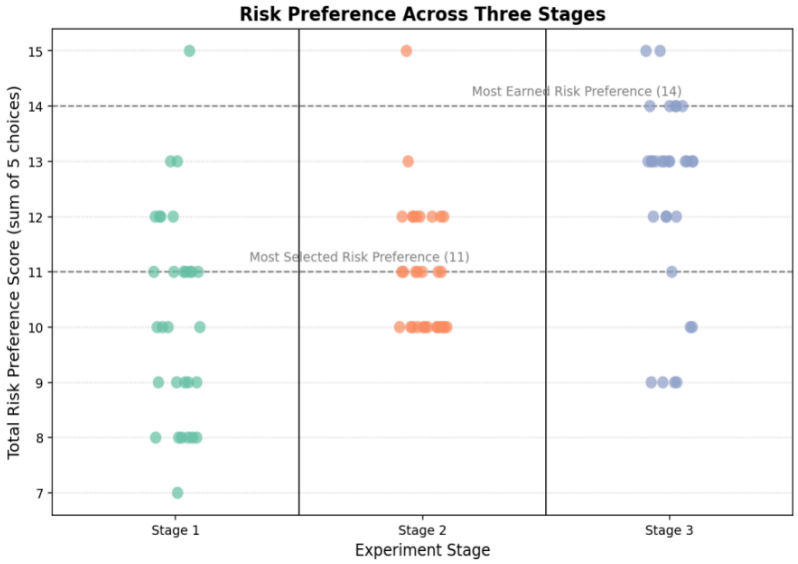

Figure 1. Evolution of risk preference under increasing transparency

Table 1.

Comparison	t(29)	p value	Significance
Stage 1 → Stage 2	–2.65	0.013	Significant
Stage 2 → Stage 3	–3.92	< 0.001	Highly Significant
Stage 1 → Stage 3	–4.79	< 0.001	Highly Significant

These results indicate that each incremental increase in information transparency triggered a significant shift in participants' risk-taking behavior. The most pronounced change occurred between Stages 2 and 3, suggesting that visibility of others' earnings exerts a stronger influence than visibility of choices alone.

5.3 Behavioral interpretation

The quantitative results support the study's central hypothesis: performance transparency significantly shapes individual risk preferences by interacting with both herding tendencies and rational assessment mechanisms.

The convergence of scores from Stage 1 to Stage 2 validates the presence of herding behavior as predicted by Banerjee (1992) and Bikhchandani et al. (1992). In the absence of direct performance signals, participants inferred value from social frequency cues, forming an informational cascade.

The divergence observed from Stage 2 to Stage 3 suggests that rational evaluation re-emerges once credible performance data are available. Participants no longer imitated blindly but assessed others' outcomes analytically, confirming Stanovich's (2016) argument that rational thinking moderates social influence.

The asymmetric direction of change also mirrors Prospect Theory (Kahneman & Tversky, 1979). Participants perceiving themselves in the loss domain (below the median return) exhibited compensatory risk-seeking to "catch up," while those in the gain domain adopted more defensive strategies to protect accumulated gains. In addition, the greater variance seen in Stage 3 may point to the development of contrarian tendencies, given that a subset of participants purposely chose to go against the dominant trend, even when performance signals were the same for all (Park & Sabourian, 2011; Drehmann et al., 2005). This indicates that transparency can not only fuel imitation but also encourage strategic divergence.

5.4 Risk preference and susceptibility to herding trends

In the experimental data demonstrate considerable variation in the social information response of participants with differing underlying risk preferences. Over the three stages of the experiment, risk-seeking participants demonstrated structured decision-making with consistent levels of risk exposure even when social and performance information was available. In contrast, risk-averse participants were more adaptive in behavior. They became closely aligned with the majority when peer choices were visible in Stage 2 and more strongly imitated high earners in Stage 3. This explains the imitative response. These differences in behavior can be explained with Prospect Theory and the dual-process reasoning model. The risk-averse decision maker, who is more likely to stay in a loss-avoidance frame, will stick to rule-externals in risk-avoidance situations, as loss minimization is a dominant strategy (Baddeley et al., 2010; Rejikumar et al., 2022). In contrast, risk-seeking participants more likely to frame situations as opportunities and will be more processed. Hence, there will be more rational calibration in the risk-averse cohort while the risk-seeking regulate their rational processes.

5.5 Synthesis

Together, the data and statistical tests provide strong evidence that transparency functions as a dual mechanism: partial visibility (peer choice disclosure) amplifies conformity and social imitation, whereas full performance visibility (peer earnings disclosure) fosters analytical comparison and individual differentiation.

Crucially, this process varies across individuals. Risk preference moderates conformity, as risk-seeking participants maintained stable, self-directed choices and showed greater resistance to social influence. In contrast, more cautious participants were prone to imitate majority actions under uncertainty. This is also consistent with Christoffersen and Stæhr (2019) and Menkhoff (2006), who state that higher risk tolerance is associated with lower herding susceptibility. This type of behavioral asymmetry demonstrates how risk attitudes associated with certain personality traits interact with information environments to drive particular decisions. This dual mechanism bridges Informational Cascade Theory and Rational Thinking Theory, showing that cascades are reversible through feedback and evaluation. It also extends Prospect Theory by revealing how reference-dependent framing interacts with transparency, determining whether individuals imitate, recalibrate, or diverge.

In short, as transparency deepened, participants moved from herding hearts to rational minds. The findings highlight that imitation and independent reasoning coexist dynamically, governed by cognitive framing, information context, and individual risk disposition.

6. Discussion

This research contributes to the understanding of herding behavior by differentiating between rational adjustment and irrational imitation when transparency of performance is present. The refinement of the Informational Cascade Theory (Banerjee, 1992; Bikhchandani et al., 1992) is evidenced by the findings where performance disclosure not only triggers imitation but also permits the imitation to rationally recalibrate. While informational cascades are mostly perceived as unidirectional conformity, the results indicate herding behavior can also be limited, under certain social conditions investors pay attention to and amplify herding behavior. The results are also congruent with Prospect Theory (Kahneman & Tversky, 1979) in that social responses to others' earnings are reference dependent. Participants in the loss domain perceived themselves as having lost something and took excessive risks to recover, while those in the gain domain were defensive to the loss of their earnings. The results additionally validate Rational Thinking Theory (Stanovich, 2016; Stanovich & West, 2014) by showing the rational evaluation of console position, as social influence operates freely. The more analytical the rational thinker, the less he/she ascribes to herding,

indicating the coexistence, and probable competition, of rational recalibration and imitation under transparency. Together, these findings offer a more complete picture of the dual approaches to decisions.

Practical insights can be gathered for the use of findings by businesses, consumers, and policymakers. For businesses and their financial arms, the influence of transparency on imitation behavior can be a determinant of communication and disclosure policies to be averse to excessive communication. Visibility of data during a certain period of time can ensure the data's informational efficiency and mitigate speculative herding. Educating consumers by targeting susceptibility to social proof and fake popularity can help mitigate irrational imitation. For policymakers, stabilizing markets and excessive conformity can be achieved with integrated policies on transparency and staggered performance disclosure.

This research supports and broadens the application of important behavioral and rational-choice theories and provides valuable new evidence that performance transparency operates as a two-way mechanism—it can deepen imitation and encourage independent assessment, depending on the cognitive style and context. By demonstrating this dichotomy, the study enhances the theoretical scope around the behavior of finance and provides practical contributions to encourage more rational and resilient markets.

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