Climbing the Social Ladder: How Rankings Shape Financial Risk-Taking

Wanqi Liang[1], Samir Huseynov*[1], and Fariz Huseynov[2]

[1]*Auburn University*

[2]*North Dakota State University*

Abstract

The availability of financial investment return rankings has increased with the proliferation of social trading platforms. We investigate the effects of ranking information on financial risk-taking with experiments. Investors choose riskier assets and hold them longer when presented with social ranking information. Using eye-tracking and mood state biometric measures, we find that participants display decreased attentiveness, reduced cognitive performance, and moderate drops in positive mood. These effects are more pronounced with ranking information. Our findings suggest retail investment platforms should recognize that sustaining investors' attention and replenishment of their mental resources help them avoid making premature investment decisions.

Keywords: Past performance, Risk Taking, Social Comparison, Emotions, Eye Tracking.

JEL: C93.

*Corresponding author: szh0158@auburn.edu

I Introduction

The efficient market hypothesis argues that investors make rational investment decisions based on all available information for unbiased estimation of an asset's intrinsic value (Fama, 1970; Brown and Cliff, 2005). However, the interaction of investor sentiment and asset valuation is the subject of a significant debate among financial economists. Several studies relate behavioral biases to investment sentiment, leading to systematic mispricing in the market. Brown and Cliff (2005) show that irrational sentiments of investors affect asset price levels, and sudden changes in sentiment may cause market bubbles. One of the behavioral factors that affect investor sentiment is social comparison (Kostopoulos and Meyer, 2018; Hu et al., 2014). This article studies how social comparison affects risk-taking in investment decisions.

Humans use comparisons to assess the outcomes of their financial performance. We make risky choices based on how different our situation is compared to others and how we can attain the desired relative outcome. When performance is shared transparently among peers, social reference points induce investors to take more risk, particularly when they fall behind in relative performance (Kirchler et al., 2018). Relatively weaker performance may lead to a greater willingness to take a risk, inconsistent with the investor's general risk tolerance. Several studies associate excessive risk-taking in finance with tournament incentives (Diamond and Rajan, 2009). These incentives include monetary gains, a positive self-image, and a desire for status. Some studies also document the diverse effects of social comparison and ranking on risk-taking, including how "bonus culture" and performance-based bonus schemes may lead to increased systemic risks and potential financial crises (Rajan, 2006; Kirchler et al., 2018; Dijk, 2017; Lindskog et al., 2022; Schwerter, 2023). For instance, in the recent Silicon Valley Bank run, the bank's managers were blamed for taking excessive risks to maximize their bonus earnings (Newsweek, 2023). Low-ranked tournament participants are more likely to choose riskier gambles even when they are risk-averse in terms of wealth (Dijk et al., 2014; Hopkins, 2018).

It has also been shown that under-performing firms tend to invest more in uncertain R&D projects to improve their market positions (Boudreau et al., 2016). Similarly, unfavorable ranking status leads to upward portfolio risk among professional investors (Kirchler et al., 2020). While previous studies have documented an inverse relationship between performance ranking and financial risk-taking, they have also found that low-ranked fund managers may decrease the risk exposure of their portfolio when facing employment uncertainties (Kempf et al., 2009). Taylor (2003) shows winning fund managers tend to take riskier bets instead of investing in safer indexing funds. Gill et al. (2019) find that top and bottom performers increase their effort after learning their performance ranking. Li et al. (2019) discuss the current body of evidence in the relevant literature and conclude that the relationship between status ranking and risk-taking is mixed and context-dependent.

Despite growing research on preferences for social status (Heffetz and Frank, 2011), there is still limited research on the role of social comparison for risk-taking in financial decisions. This strand of literature is more relevant today due to the technological advancements in financial brokerage services. Over the past decade, access to retail investment opportunities has significantly increased, enabling individuals with diverse educational backgrounds and financial asset management experience to actively trade various financial instruments (Yang et al., 2022). Their investment decisions are affected by how they gather and process information. Retail investors can invest based on their own analysis of fundamental factors or by learning from others, which requires social interaction. Investment platforms such as Etoro, ZuluTrade, and Alipay have lowered entry barriers in financial markets by offering social learning and interaction options (Wohlgemuth et al., 2016; Pelster and Hofmann, 2018; Gortner and van der Weele, 2019). These platforms allow individual investors to observe the portfolios of other members, their asset holding durations, and risk exposure levels, and mimic or copy successful investment strategies (Apesteguia et al., 2020). Some retail investment venues also provide individual asset-return ranking information in relation to fellow investors, fostering social comparison environments (Jin et al., 2019; Dorfleitner and Scheckenbach, 2022; Yang et al., 2022). Such investment environments present valuable learning opportunities regarding how investors adjust their investment decisions based on their performance ranking.

In this paper, we answer two research questions. First, we investigate how investors adjust their risk-return preferences when they are informed about how their financial performance compares to their peers. A growing literature shows that retail traders do not improve the quality of their investment decisions with social learning (Ammann and Schaub, 2021), and they increase platform-wide trading volume, elevating the overall market risk exposure level (Trautmann and Vieider, 2012; Andraszewicz et al., 2022; Gortner and van der Weele, 2019). As Shiller (2005) argues, news and narratives of price increases spur investor enthusiasm, which spreads from person to person, forming an asset bubble in the financial markets. Psychological factors that divert investors' focus from fundamentals to chasing outperforming peers may sustain such bubbles, increasing tail risks in stock prices. Thus, studying the impact of social comparison on financial risk-taking in a social trading setting is crucial for understanding the dynamics of emerging retail investment markets.

Second, we examine how the performance ranking information impacts investors' cognitive and affective states. For this purpose, we track investors' eye movements using eye-tracking technology and measure their mood states using cutting-edge facial expression analysis algorithms. Recent studies apply eye-tracking tools to explore learning and consumer behavior (Woller-Carter et al., 2012; Miloš et al., 2022; Huseynov et al., 2021). Due to the growing use of online resources to invest in the financial markets, it is important to understand how investors gather and react to financial information in an online investment environment that comes with social comparison. Several studies indicate that the format of portfolio-related information displayed in an online setting influences individual investors' decisions. Information acquisition becomes fast and almost automatic when portfolio performance summary and comparison with other retail traders' performance are displayed simultaneously. Shi et al. (2013) argue that eye-tracking methodology is suited to provide insights into investment decisions under these conditions. Academic studies that use eye-tracking technology focus on different eye movements and perceptual spans to analyze information processing and decision-making through human-computer interactions. We specifically focus on the eye movements, fixation time, fixation count, and blink rates of investors when they view the summary of their investment returns to infer attention and cognitive states.

Our use of emotional measures is motivated by a growing body of literature showing the interaction between cognitive deliberation and the mood states of investors in financial markets (Loewenstein, 2000; Nofsinger, 2005). Stock market upward trends can be associated with positive mood states, indicating asset valuations are driven by optimistic feelings (Nofsinger, 2005). Mood maintenance theory posits that happy investors tend to show a higher risk tolerance, leading to elevated financial risk-taking (Harding and He, 2016). However, the evidence is mixed, and relevant studies use different data sources and elicitation techniques. Goodell et al. (2023) survey studies and show that 78% of the literature uses secondary data sources and different methodologies for measuring emotional feelings. Previous studies relying on different psychological mood elicitation survey questions might bias the measured emotional states of investors. For example, Kassas et al. (2022) find that the relationship between emotional feelings and risk-taking is inconclusive. Our study provides additional evidence about this potential relationship using a controlled investment decision-making setting and employing the latest technological advancements in mood elicitation methodology.

We examine the role of social comparison in risk-taking via a controlled asset market experiment. We conduct laboratory and online studies investigating asset market decisions in the face of social comparisons. Participants make asset decisions in two consecutive market cycles. Participants in the *Ranking Information* receive information about their ranking status between the first and second market cycles, whereas the *No Information* control group does not receive such information. For each group, we examine asset choices, the average number of asset holding periods, and final earnings in both market cycles. We employ eye tracking and facial expression analysis biometric technologies to scrutinize how investment performance ranking information potentially changes retail investors' attention and mood states across experimental asset markets. Our biometric measures speak to recent studies highlighting the significance of emotions and attention in financial decision-making (Breaban and Noussair, 2018; Miloš et al., 2022). Our paper provides a further investigation of this relationship and also explores attention and mood aspects of risk-taking behavior when the social comparison is salient, potentially informing more effective retail investment platform designs.

We find that ranking information induces a moderately higher degree of risk-taking. In the first market cycle, participants make similar asset allocation decisions in both experimental conditions. However, when the ranking information is introduced in the second market, low-ranked participants increasingly allocate more investment into riskier assets. The results are consistent with the findings of previous studies (Kirchler et al., 2018; Apesteguia et al., 2020; Andraszewicz et al., 2022). We also find that social comparison induces longer asset-holding times. Eye-tracking measures indicate that experiment subjects show fatigue effects in the second market cycle by diminishing their attention and cognitive activity. However, this effect is more pronounced in the Ranking Information condition, suggesting social comparison might strain investors' attention and cognitive bandwidth, leading to impulsive financial risks. We also note a moderate decrease in the average number of positive mood frames in the second market cycle across both experimental conditions. However, we do not detect any causal effect of the Ranking Information on mood states. Our results are aligned with the general conclusions of Goodell et al. (2023) and show that the role of emotions in financial decisions is multifaceted and context-dependent.

Our contribution to the literature is threefold. First, most studies investigating the role of social comparison in financial risk-taking employ tournament ranking, where individual ranking determines the final investment payoff (Li et al., 2019). It is very challenging to tease out the causal impact of social comparison on financial risk-taking when investment performance ranking is also part of the earning function. In our study, the ranking information does not have any bearing on returns; thus, any detected causal change in financial risk-taking is attributed to the effect of social comparison. Moreover, ranking in social trading platforms does not directly affect one's earnings (Andraszewicz et al., 2022; Apesteguia et al., 2020). In our study, ranking information only creates social comparison without impacting individual payoffs, increasing our findings' practical implication value. Second, we employ two asset market cycles capturing a social-comparison-free baseline for both experimental conditions, offering robust benchmarks for both experimental conditions. Third, eye tracking and facial expression analysis biometric measures enable us to understand the effect of social comparison on the cognitive and affective decision processes.

The remainder of the paper is organized as follows. Section 2 presents experimental procedures. Section 3 provides estimation methodology, and in Section 4, we discuss the results. Section 5 connects our findings with relevant literature. Finally, we provide concluding remarks in Section 5.

II Experimental Procedures

We conducted an online study using the Prolific.co crowdsourcing platform and a follow-up laboratory experiment at a university in the United States with IRB-approved protocols. We utilized Qualtrics survey software and the same study instruments in both experiments. In the online study, we recruited 478 US resident Prolific.co members with a 95% or higher approval rate, offering a $4.00 participation compensation. We ensure that our study subjects had high approval rates to maintain the quality of our participant pool in terms of attentiveness to study protocols. Participants were also provided with $1.00 in seed money to make investment decisions. We had 67 participants in the lab experiment, recruited from Economics and Finance courses offered in a land-grant university. The participation reward and seed money fund were $10.00 and $5.00 for the lab study, respectively.

The study started with a consent form outlining general rules. Then, participants received detailed information about the study procedures and incentive structures. We constructed our experiment design based on Apesteguia et al. (2020). Participants were shown experimental assets, their return and loss magnitudes, associated probabilities, and expected return and standard deviations of returns as described in Table 1. Asset A was risk and return-free, mimicking a checking account. The risk and

Table 1: Experimental Assets

	Gain % (Prob)	Loss % (Prob)	Crash % (Prob)	$\mu(\sigma)$
Asset A	0% (0%)	0% (0%)	0% (0%)	1000 (0)
Asset B	+5% (50%)	-4% (50%)	0% (0%)	1104.9 (223.4)
Asset C	+5% (49.5%)	-3% (49.5%)	-50% (1%)	1102.7 (331.4)
Asset D	+8.2% (48%)	-3% (48%)	-50% (4%)	1104 (615.6)

The table shows asset gain, loss, and crash percentage changes and associated probabilities (in parentheses). The last column indicates the expected means and standard deviations of asset earnings.

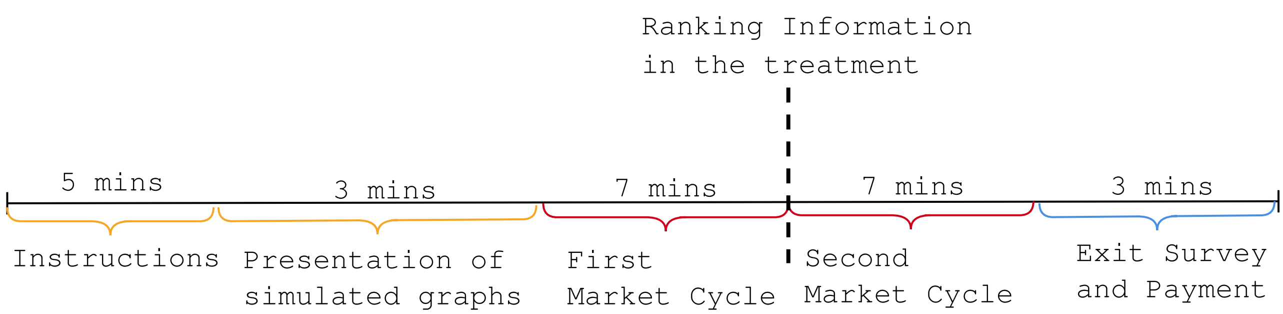


Figure 1: Timeline of Experimental Procedures.

potential return profiles of assets increased from Asset B to peak in Asset D. Assets C and D had crash probabilities but better earning potentials. A risk-seeking agent may prefer riskier assets as they can potentially yield higher return levels. For instance, the expected return of Asset C is lower than Asset B, but one could earn a higher return with Asset C as the standard deviation of its expected return distribution is larger compared to the same feature of Asset B. Specifically, the potential uptick return of Asset C (331.4) was larger than Asset B (223.4).

Figure 1 describes our online and laboratory experiments' experimental procedures and average duration times. Before starting the incentivized asset market cycles, subjects were shown 20 different simulated graphs based on asset features, reflected in Table 1 (see Figure 2). Study subjects were required to maintain their attention on the presented graphs. Each graph was shown for seven seconds, and participants could not skip this stage. They were also informed in the Instructions stage that we would randomly show a two-digit number during the presentation, and participants would have to enter the number in the provided box. Failure to enter the shown two-digit number resulted in the termination of participation status.[1] The box was prompted immediately after the two-digit number to prevent the potential cognitive taxing of memorizing the number.

These simulated graphs ensured that subjects possessed sufficient information about the experimental assets' potential gain/loss paths. As one can observe from Figure 2, riskier assets can potentially yield larger returns than relatively safer assets. However, they may also cause significant losses as they have crash probabilities.

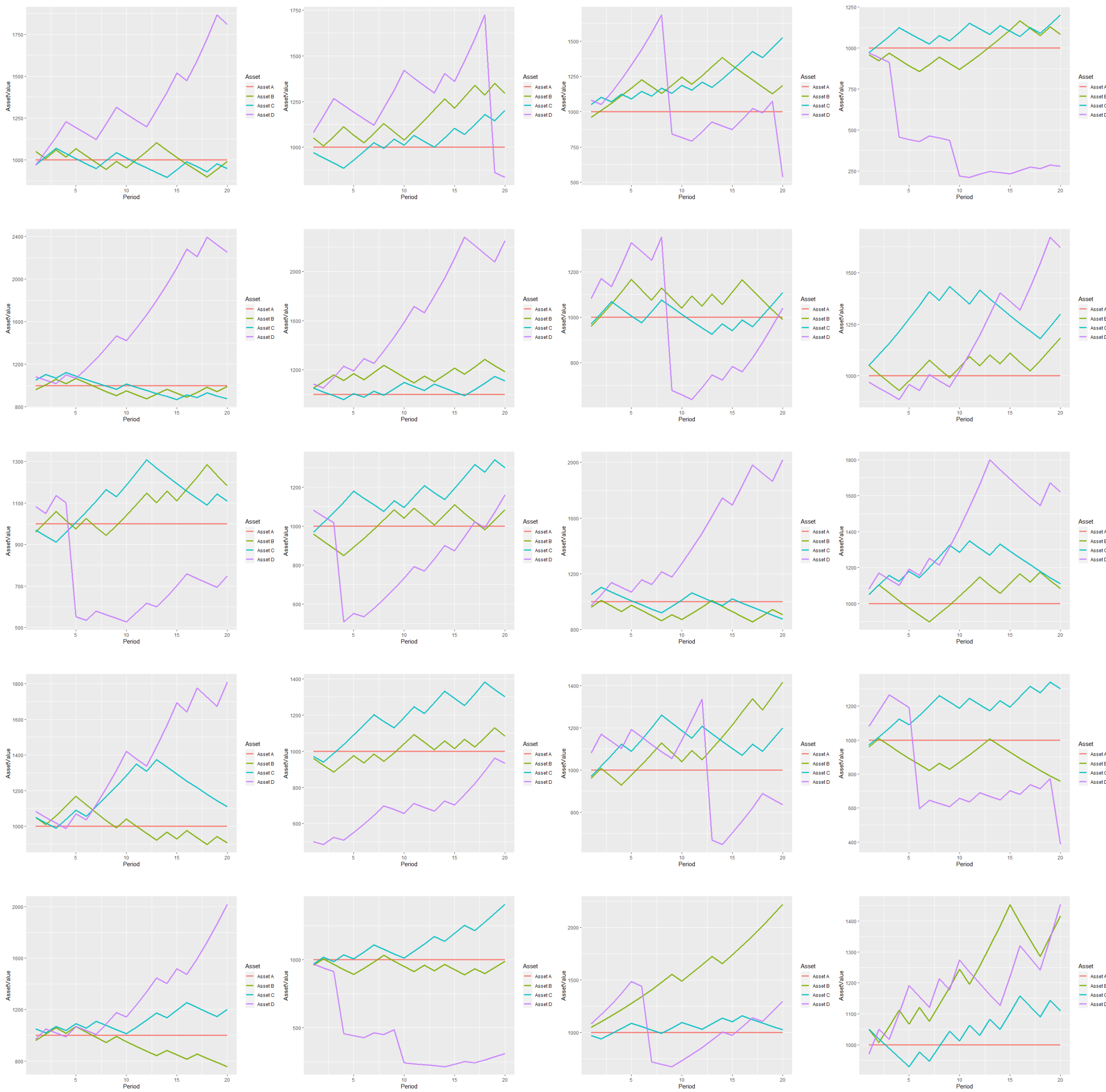
Study subjects proceeded to the market cycles after maintaining their attention on the presented simulated asset return graphs and passing the attention check. Participants chose their preferred asset out of four available assets at the beginning of the First Market Cycle. Then, they started realizing their chosen asset over up to 20 market periods. We randomized the display order of financial assets during the asset choice stage to avoid any confounding effect stemming from the presentation order.

The starting value of all assets was 1000 Experimental Currency Units (ECUs), and gains and losses were accumulated throughout the market cycle periods.[2] In each period, the computer randomly realized the chosen asset based on the features shown in Table 1. The asset realization could be *gain* or *loss* depending on the features of the chosen asset and luck. Figure 3 shows an example from one subject's decision from the laboratory experiment. In each period, after the realization of the asset, participants had to make a trade-off between continuing their market cycle by proceeding to the next asset market period or cashing out their earnings and quitting the market. This design feature enabled us to measure asset holding duration preferences of experimental subjects.

Before starting the market cycles, subjects were randomly assigned to the *No Information* and *Ranking Information* conditions. In the No Information condition, subjects

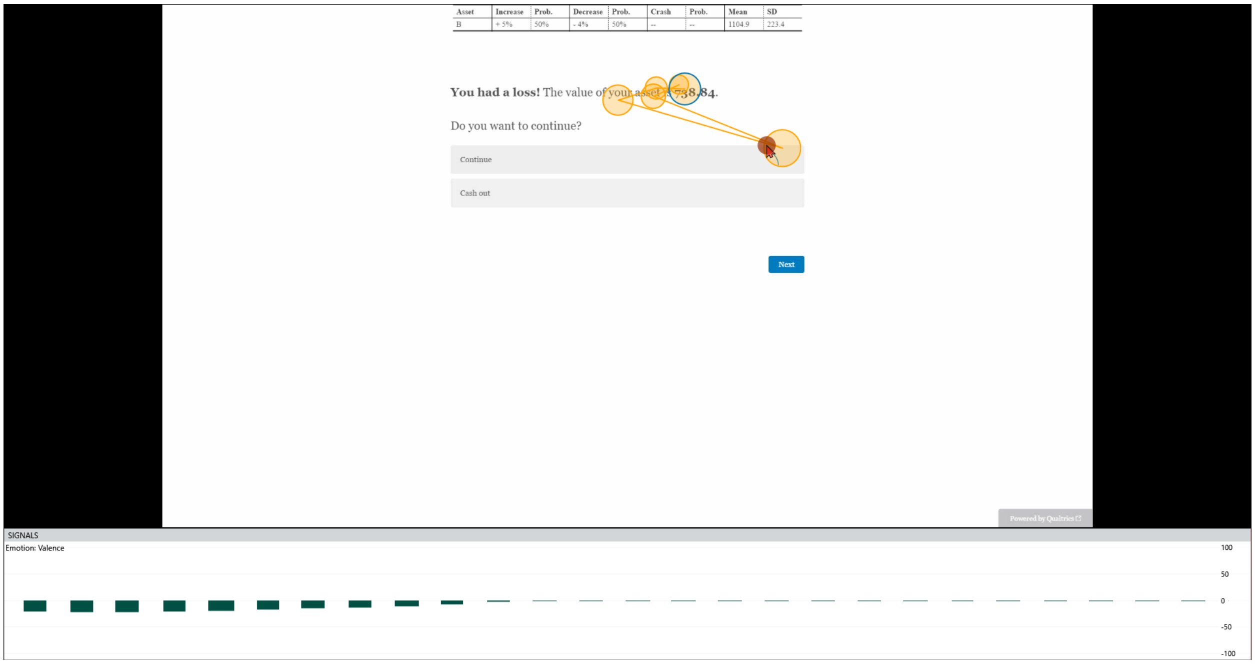
[1] Two subjects were dismissed from the online study for failing to enter the two-digit number. In our laboratory study, all subjects passed this attention test.

[2] The exchange rate between ECU and USD was 1 ECU = 0.001 USD and 1 ECU = 0.005 in the online and lab studies, respectively.



Simulated Assets: Asset A (red), Asset B (green), Asset C (blue), and Asset D (purple).

Figure 2: Simulated Gain/Loss Paths for Experimental Assets



This figure presents a screenshot from one subject's decision in the first market cycle. The features of the selected asset were always displayed at the top of the screen to prevent decision confusion due to not remembering the asset's gain and loss properties. **Eye tracking:** The circles show fixation points, where larger circles are correlated with fixation time. The fixation count measures the number of fixation points/circles during the decisions. **Affdex Facial Expression analysis:** The bottom panel shows positive and negative mood frames during the decision.

Figure 3: A representative Screenshot from a Market Cycle period with Biometric Measures

repeated two market cycles before the exit survey and the payment stages. However, in the Ranking Information treatment, participants were informed about their relative performance ranking based on the First Market Cycle asset returns with respect to other participants. To establish our comparison sample, the No Information condition was conducted before the Ranking Information treatment. In the Ranking Information treatment, participants were informed either they were in the top 50 percentile of the baseline sample or in the bottom 50 percentile of the benchmark group.[3] At the end of the study, we randomly selected one of the market cycles as binding. Participants' final asset earning in the binding market was their bonus payoff. The study concluded with a basic survey on demographic characteristics. We only collected eye

[3]Specifically, we used *less 10%*, *better than 10%*, *better than 25%*, *better than 50%*, *better than 60%*, *better than 80%*, and *better than 90%* ranking information messages before the Second Market cycle in the Ranking Information condition.

tracking and facial expression mood measures in the lab study.[4]

We utilized eye tracking and facial expression analysis technologies in our laboratory studies. Eye fixation counts and times were measured with the Tobi Pro Fusion eye tracker (120 Hz) using iMotions software. This technology utilizes near-infrared light directed toward the center of participants' eyes (the pupils), generating visible reflections in the cornea. Fixation counts (i.e., the number of circles in Figure 3) show the number of attention points until the conclusion of the decision. In its turn, Fixation times measure the total time the subject spent fixating during this decision. For each subject, we find the average number of Fixation counts and times (in milliseconds) across decision periods in a market cycle. Our eye-tracking technology also enables us to measure blink rates, indicating the cognitive bandwidth or engagement level of study participants

The bottom panel in Figure 3 shows emotional mood measures, where 0 is neutral. Positive and Negative mood states are represented by above and below-zero activation, respectively. In this example, the subject incurs a loss in the 14^{th} period of the first market cycle, they exhibit a Negative mood stage in the first part of their decisions. Notice that the participant does not fixate on the return message "You had a loss!" and they only track the value of their asset in that period. This suggests that after spending some time in our asset markets, participants just fixated on the part of the screen showing their chosen asset's return. We use the iMotions Affdex module and capture 30 frames per second. The collected data indicates the total number of Positive and Negative mood frames in each decision period. For each subject, we find the average number of Positive and Negative Mood Frames for 1) the asset choice screens and 2) decision periods in a market cycle. We follow the same approach in constructing our eye-tracking measures, focusing on asset choice screens and decision periods in market cycles.

[4]See Supplementary Materials for screenshots of the key survey instruments.

III Estimation Methodology

Our primary outcome measure is the difference in asset choice behavior between the No Information and Ranking Information experimental conditions in the second market cycle. We estimate the following linear regression model:

$$Asset_{i,M2} = \alpha_0 + \alpha_1 T_i + \alpha_2 Earning_{i,M1} + \alpha_3 NPeriods_{i,M1} + \alpha_4 * \mathbf{\Gamma_i} + \epsilon_i \tag{1}$$

where $Asset_{i,M2}$ is a categorical variable indicating asset choices in the second market cycle (it takes 1, 2, 3, and 4 for Assets A, B, C, and D, respectively). In Equation 1, T_i is a binary variable and equals one for the Ranking Information treatment, and zero otherwise; $Earning_{i,M1}$ and $NPeriods_{i,M1}$ represent the first market cycle individual earnings and asset holding periods, respectively. The vector $\mathbf{\Gamma_i}$ contains control measures, such as the first market cycle individual asset choices $Asset_{i,M1}$ and a dummy variable indicating whether the data is from the online study.

IV Results

Result 1: Study Participants mostly prefer risky assets to risk-free Asset A, and they increase their overall asset risk exposure levels in the second market cycle.

We start our discussion by scrutinizing general trends in our data. Figure 4 illustrates the relationship between asset holding duration and asset earnings, using the complete study data from both market cycles. On average, riskier assets yield higher earning levels if participants hold their assets longer than five and less than 15 periods. However, holding Assets C and D for longer duration also increases the chances of a crash, leading to an abrupt decrease in earnings. Figure 4 also validates our experimental design logic. Notice that, per Table 1, assets' risk profiles (i.e., standard deviations) increase starting with Asset B and peak in Asset D. A risk-tolerant subject will be more likely to choose an asset with a higher standard deviation, although the

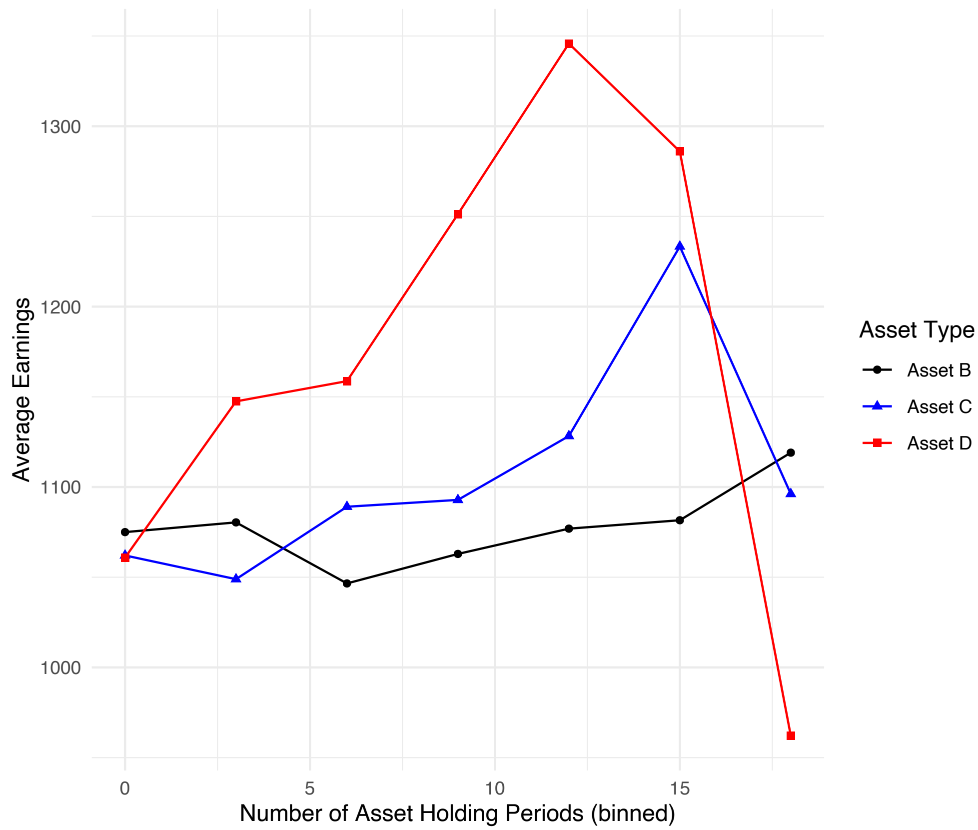


Figure 4: Relationship between Number of Asset Holding Periods and Average Earnings

chosen asset does not necessarily promise a better average return. Assets with higher standard deviations may also potentially yield higher returns if the investor does not experience a crash. However, the crash probability increases as the investor holds the asset longer. It is exactly what we observe in Figure 4. Study participants exiting the asset markets between the 5th and 15th periods, on average, earn higher returns by betting on riskier assets. But this trend breaks after the 15th period due to crashes, generating significantly lower returns.

Table 2 presents asset choice proportions, the average number of asset holding periods, and final earnings in both market cycles across experimental conditions. Table 2 Panel I shows that around 5% of study participants preferred risk-free investment, choosing Asset A. This small proportion is almost stable across market cycles and

Table 2: Aggregate Asset Decisions Data

	No Information		**Ranking Information**	
	First Market Cycle	Second Market Cycle	First Market Cycle	Second Market Cycle
	Panel I: *Asset Choice Proportions*			
Asset A	9 (5%)	11 (6%)	17 (5%)	13 (4%)
Asset B	59 (30%)	63 (32%)	105 (30%)	93 (26%)
Asset C	59 (30%)	40 (21%)	106 (30%)	83 (24%)
Asset D	67 (35%)	80 (41%)	123 (35%)	162 (46%)
Total	100% (N=194)	100% (N=194)	100% (N=351)	100% (N=351)
	Panel II: *Average Asset Holding Periods*			
Asset A	1 (0)	1 (0)	1 (0)	1 (0)
Asset B	12.9 (7.40)	13.6 (7.09)	13.0 (7.25)	12.4 (7.38)
Asset C	13.1 (6.89)	11.8 (7.62)	12.0 (7.18)	12.3 (7.13)
Asset D	14.0 (7.30)	11.2 (7.10)	14.5 (6.51)	12.7 (6.96)
	Panel III: *Average Realized Asset Earnings*			
Asset A	1000 (0)	1000 (0)	1000 (0)	1000 (0)
Asset B	1125 (182)	1123 (217)	1083 (179)	1063 (137)
Asset C	1095 (259)	1110 (207)	1092 (223)	1083 (229)
Asset D	1020 (445)	1139 (407)	1099 (484)	1085 (455)

Note: This table displays the aggregate performance in both market cycles across No Information and Ranking Information experimental conditions. Panel I reports asset choice sample frequencies (proportions). Panel II shows the average number of holding periods for each experimental asset. Panel III displays the average final realized earnings (in ECUs). Standard deviations are reported in parentheses for Panels I and II.

experimental conditions, indicating that a great majority of our study participants chose risky assets. We observe that asset decisions in the first market cycle are identical in both experimental conditions, as the ranking information was only introduced before the second market in the treatment. Study participants' Asset B and C choice proportions are very close. Interestingly, Asset D is the most popular choice in the first market cycle. Participants increasingly choose Asset D while Asset B and C proportions decrease in the second market cycle. Therefore, we detect a general trend of choosing riskier assets across experimental conditions in the second market cycle. The discussed general trends in our data resemble some findings of Apesteguia et al.

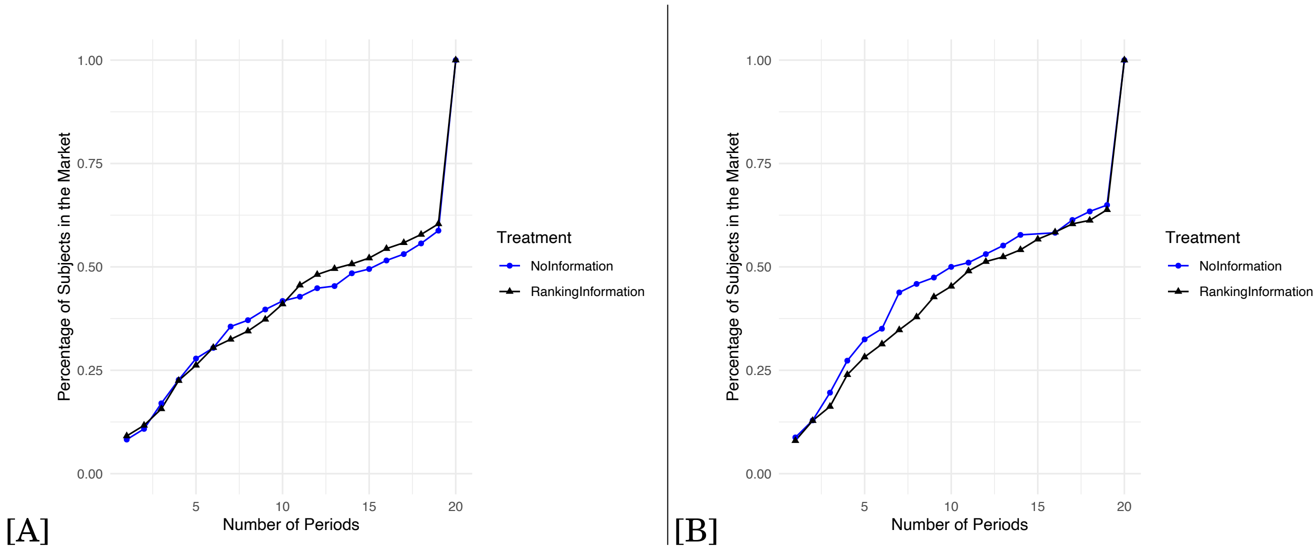
(2020). They report that a very small proportion of experimental subjects prefer risk-free asset choice in their study, and participants increase their asset risk exposure levels in the second market cycle.

Result 2: We find that study participants usually exhibit longer asset duration. The Ranking Information condition induces a longer asset holding time.

Table 2 Panel II notes that general trends in asset holding times vary based on experimental conditions and asset types. The average length of asset holding periods is between 12 and 14, suggesting that subjects exhibit long positions in both market cycles. Figure 5 depicts empirical CDFs of asset holding times comparing the NO Information and Ranking Information conditions in the first (panel A) and the second (Panel B) market cycles. As expected, asset holding times are the same in the first market cycle, as the Ranking Information condition was introduced in the second cycle. However, average holding times in the Ranking Information treatment stochastically dominate the No Information control condition. As additional evidence, Table 3 Panel I presents the results of statistical tests comparing asset decisions, earnings, and holding times across experimental conditions. We also find that subjects in the No Information condition reduce their asset holding times $(-0.79, p < 0.01)$, while participants in the treatment do not change their behavior. This finding hints that the difference in asset holding times between experimental conditions stems from reduced asset holding times in the No Information control condition, while subjects in the treatment maintained their holding times.

Result 3: The Ranking Information moderately increases asset risk-taking. The effect is primarily driven by low-ranked participants.

Table 3 Panel I shows that study participants chose riskier assets in the second market cycle in the Ranking Information treatment $(0.17, p < 0.01)$. However, we do not observe any change in the risk profiles of the chosen assets in the No Information control. Table 4 Column 1 further examines the causal effect of ranking information on risk-taking, while Columns 2-5 employ various model specifications in line with



Panel A (Panel B) shows the empirical CDFs of the number of periods for experimental conditions in the first (second) market cycle.

Figure 5: Empirical CDF of Asset Holding Periods

Equation 1. We corroborate our primary test result in Table 3 and find that subjects in the Ranking Information treatment choose riskier assets in the second market cycle than participants in the No Information condition. Our findings are robust to different model specifications, as shown in Table 4, Columns 1-5. Higher earning levels in the first market cycle also contribute to an increased risk profile of chosen assets in the second market. Asset duration and asset choices in the first market cycle do not affect risk-taking in the subsequent market. Additionally, we do not detect behavioral differences between our online and lab samples. Table 4 Column 6 reports the estimation outcomes of OLS regression when we replace the treatment dummy with two binary variables representing top-50% and bottom-50% performers in the Ranking Information condition. The estimation results reveal that the asset choice differences between the Ranking Information treatment and No Information control in the second market cycle are primarily driven by low-ranked participants. As a robustness check, we replicate Table 4 using ordinal probit model regressions and show results in Table S1 in the Supplementary Materials.

Result 4: Biometric measures show that study participants reduce their

Table 3: Comparing The Second and First Asset Market Cycles

	Δ_{Overall}	$\Delta_{\text{No Information}}$	$\Delta_{\text{Ranking Information}}$
Panel I: *Asset Decision Outcome Data*			
Asset Choices	0.12^{**} (0.05)	0.03 (0.09)	0.17^{***} (0.06)
Holding Periods	-0.79^{***} (0.29)	-1.25^{***} (0.48)	−0.53 (0.37)
Earnings	8.92 (19.38)	45.60 (31.40)	−11.25 (24.54)
Panel II: *Asset Decision Process Biometric Data*			
Fixation Time	-1.06^{***} (0.18)	-0.58^{***} (0.20)	-1.42^{***} (0.27)
Fixation Count	-4.89^{***} (0.77)	-2.41^{**} (1.01)	-6.72^{***} (1.02)
Blinks	-0.58^{***} (0.13)	-0.32^{***} (0.10)	-0.76^{***} (0.21)
Positive Mood Frames	-0.17^{*} (0.10)	−0.11 (0.15)	−0.22 (0.13)
Negative Mood Frames	−1.59 (1.05)	−0.78 (1.61)	−2.19 (1.39)
Panel III: *Asset Decision Process Biometric Data and Rankings*			
	$\Delta_{\text{No Information}}$	$\Delta_{\text{Bottom50\%-Message}}$	$\Delta_{\text{Top50\%-Message}}$
Fixation Time	-0.58^{***} (0.20)	−0.49 (0.36)	-1.32^{**} (0.51)
Fixation Count	-2.41^{**} (1.01)	-3.02^{*} (1.60)	-6.08^{***} (1.94)
Blinks	-0.32^{***} (0.10)	-0.69^{*} (0.35)	−0.10 (0.19)

Note: Results have been obtained using OLS regressions with HC1 robust standard errors. Reported values are compared against zero in Panels I and II (*p<0.1; **p<0.05; ***p<0.01). In **Panel I**, the change (Δ) is calculated as follows: $\Delta X_i = X_{i,M=2} - X_{i,M=1}$, where M represents a market cycle, and i denotes individuals. In **Panel II**, the change (Δ) is calculated as follows: $\Delta X_i = \frac{1}{T}\Sigma_1^T X_{i,t,M=2} - \frac{1}{T}\Sigma_1^T X_{i,t,M=1}$, where M represents a market cycle, t indicated the market period, and i denotes individuals. In **Panel III**, the changes in biometric measures are calculated following Panel II. The first column shows changes in process variables in the No Information control while statistically comparing it to zero. However, the second and third columns show process data changes in the bottom and top-ranked groups with respect to the No Information control.

attention intensity and cognitive engagement in the second market cycle, and these changes are more pronounced in the Ranking Information treatment.

Table 3 Panel II reports the test results comparing biometric performance metrics of subjects along Fixation Time, Fixation Count, Blinks (i.e., blink rates or average number of blinks), Positive and Negative Mood frames. Overall, participants become

Table 4: Asset Decisions In Second Market Cycle

	Dependent variable: Asset Choice					
	(1)	(2)	(3)	(4)	(5)	(6)
Ranking Treatment	0.15*	0.15*	0.15*	0.15*	0.15*	
	(0.09)	(0.09)	(0.09)	(0.08)	(0.09)	
1st Market Cycle: Earning		0.22*	0.22**	0.19*	0.19*	0.25*
		(0.12)	(0.11)	(0.11)	(0.11)	(0.13)
1st Market Cycle: N Periods			0.02***	0.01	0.01	0.01
			(0.01)	(0.01)	(0.01)	(0.01)
Online Sample					0.01	0.01
					(0.11)	(0.11)
Bottom50%-Message						0.19*
						(0.11)
Top50%-Message						0.11
						(0.10)
Constant	2.97***	2.73***	2.53***	1.89***	1.88***	1.80***
	(0.07)	(0.15)	(0.16)	(0.26)	(0.28)	(0.30)
1st Market Cycle: Asset Choice FE	*No*	*No*	*No*	*Yes*	*Yes*	*Yes*
$\beta_{AssetB} = \beta_{AssetC}$					$p = 0.69$	
$\beta_{AssetB} = \beta_{AssetD}$					$p = 0.39$	
$\beta_{AssetC} = \beta_{AssetD}$					$p = 0.64$	
N	545	544	544	544	544	544
R^2	0.01	0.01	0.03	0.06	0.06	0.06

OLS regression results with HC1 robust standard errors are reported. The outcome variable is asset choice decision in the second market cycle, where it takes 1,2,3,4 for Asset A, Asset B, Asset C, and Asset D, respectively. *p<0.1; **p<0.05; ***p<0.01

less attentive in the second market cycle as they exhibit reduced fixation times and fixation counts. The number of average blinks also went down in the second market cycle in both experimental conditions, indicating reduced cognitive activity and mental workload (Fogarty and Stern, 1989; Van Orden et al., 2001). However, we find that these changes are stronger in the Ranking Information condition. Average Fixation Time $(-0.84, p < 0.01)$, Fixation Counts $(-4.31, p < 0.1)$, and Blinks $(-0.44, p < 0.01)$ are reduced significantly more in the Ranking Information condition compared to the No Information control. Panel II also shows the change in positive and negative mood states in the second market cycle across experimental treatment conditions. We detect a moderate decrease in the average number of positive mood frames in the second market cycle. However, we do not observe differences between experimental conditions.

Table 3 Panel III shows that the reduction in Fixation Time and Fixation Count attention values primarily come from the top-50% participants compared to the No Infor-

Table 5: Comparing The Second and First Asset Market Cycles along Biometric Process Data (Only Lab Sample, N=66)

	Δ_{Overall}	$\Delta_{\text{No Information}}$	$\Delta_{\text{Ranking Information}}$
Asset Decision Stage			
Fixation Time	−1.35 (1.51)	−2.09 (2.51)	−0.81 (1.88)
Fixation Count	−10.14 (6.10)	−2.14 (9.20)	−8.66 (8.25)
Blinks	−0.87 (0.87)	0.52 (1.17)	−1.92 (1.24)
Positive Mood Frames	0.42 (1.42)	0.97 (0.93)	−0.00 (2.41)
Negative Mood Frames	−0.99 (4.11)	−2.00 (8.74)	−0.21 (2.98)

Note: This table is based on collected biometric measures on the asset choice stage. Results have been obtained using OLS regressions with HC1 robust standard errors. Reported values are compared against zero (*p<0.1; **p<0.05; ***p<0.01). The change (Δ) is calculated as follows: $\Delta X_i = X_{i,M=2} - X_{i,M=1}$, where M represents a market cycle, and i denotes individuals.

mation control. However, in terms of the Blink rate measure, we find that the bottom-50% performance group exhibits significantly lower cognitive engagement than the No Information condition. We conclude that top performers reduce their attention in the second market cycle if provided with the ranking information. However, bottom performers reduce their cognitive engagement. We also show that bottom performers exhibit a higher reduction in average Fixation Count values than the control condition.

Table 5 conducts the same analyses for the asset choice stage and reports no difference in the second market cycle. This indicates that attention and cognitive function only deteriorate across the market cycle periods, not in the initial asset choice stage.

Result 5: We detect heterogeneous asset choice decisions in the first market cycle. Males tend to choose riskier assets and hold longer in the first market cycle. We also find that previous trading experience affects first-market cycle asset choices and holding times.

Table 6 scrutinizes how different individual characteristics affect asset choices, asset holding times, and earnings in the first market cycle. We use the first market cycle to investigate heterogeneous individual behaviors, as we introduced the information treatment after the first market cycle, and our primary results rely on the difference between first and second market decisions. The first column of Table 6 serves as a robustness check, showing that our random treatment assignment was successful, and we do not detect any differences in asset choices between the Ranking Information and No Information control conditions in the first market cycle decisions. We also find that there are no behavioral differences between our online and lab samples. The third and fifth columns conduct similar analyses for holding times and earnings, yielding the same conclusion.

Table 6: Asset Decisions In First Market Cycle

	Asset Choice	Asset Choice	Periods	Periods	Earnings	Earnings
Ranking Treatment	0.01	0.01	−0.08	−0.22	0.01	0.02
	(0.08)	(0.08)	(0.66)	(0.66)	(0.03)	(0.03)
Online Sample	−0.04	−0.01	−1.46	−1.51	−0.02	−0.02
	(0.11)	(0.12)	(0.91)	(0.95)	(0.05)	(0.05)
Male		0.16^{*}		1.19^{*}		−0.01
		(0.08)		(0.68)		(0.03)
1yr-Trading Exp		0.13		0.69		0.02
		(0.11)		(0.96)		(0.04)
2yr-Trading Exp		0.33^{**}		2.75^{**}		0.06
		(0.14)		(1.08)		(0.06)
3yr-Trading Exp		0.17		0.99		0.01
		(0.20)		(1.55)		(0.07)
4yr-Trading Exp		0.17		4.91^{***}		−0.06
		(0.23)		(1.43)		(0.09)
5yr-Trading Exp		−0.09		-4.13^{*}		0.05
		(0.37)		(2.15)		(0.08)
More than 5yr-Trading Exp		0.17		2.50^{**}		0.005
		(0.13)		(1.03)		(0.05)
LotteryChoice 2		−0.14		0.61		−0.06
		(0.19)		(1.49)		(0.06)
LotteryChoice 3		0.02		0.68		−0.01
		(0.19)		(1.48)		(0.06)
LotteryChoice 4		0.26		0.28		−0.001
		(0.20)		(1.54)		(0.06)
Constant	2.98^{***}	2.78^{***}	14.03^{***}	12.25^{***}	1.09^{***}	1.11^{***}
	(0.12)	(0.21)	(0.91)	(1.65)	(0.04)	(0.07)
N	545	545	545	545	544	544
R^2	0.00	0.05	0.00	0.05	0.00	0.01

OLS regression results with HC1 robust standard errors are reported. *p<0.1; **p<0.05; ***p<0.01

Table 6 demonstrates that male participants tend to choose riskier assets and hold longer in the first market cycle. However, male study participants do not achieve higher returns than non-male subjects. We also detect heterogeneous effects of prior trading experiences on asset decisions and holding times. However, this relationship is not unidirectional, preventing us from making any conclusions. For instance, study participants with a 2-year trading experience prefer riskier assets and longer positions than those with no trading experience. However, participants with five years of trading experience prefer staying in the first market cycle shorter than subjects with no trading experience. *LotteryChoice* variable indicates hypothetical lottery choices designed using Eckel and Grossman (2008). We do not find any correlation between asset choices and other related decisions in the first market cycle and hypothetical lottery decisions.

V Discussion of findings and related literature

How do our findings square with financial industry realities and relevant literature? Our study participants generally prefer risky assets and exhibit long asset holding times. This finding is compatible with the average behavior of U.S. financial management industry executives. Brenner (2015) calibrates risk attitudes of 7,000 U.S. financial executives liking estimated risk aversion parameters to their asset holding times. Their paper reports an inverse relationship between risk aversion and the number of asset long-holdings, showing that risk-tolerant executives prefer longer investment positions. Brenner (2015) also presents some evidence that financial executives' risk preferences might be affected by reference points. Interdisciplinary studies show that risk-seeking behavior is more prevalent among pro-social and sensation-seeking individuals, hinting that social desirability wants can drive risk preferences (Zhang et al., 2023; Mishra and Lalumière, 2011).

In recent years, the increasing accessibility of social trading platforms to individuals and households has elevated the need for understanding the causal relationship between social reference points and financial risk preferences (Yang et al., 2022). Theoretical models and controlled studies document that high network connectivity and social learning do not necessarily improve welfare, leading to increased risk takings and spread-seeking trades (Gong and Diao, 2023; Apesteguia et al., 2020; Yang et al., 2022). Our contribution to this growing literature is that we isolate social learning from social reference points/ranking and show that merely revealing one's relative investment performance can lead to elevated risk-seeking tendencies and longer asset-holding times. Our ranking information is *passive*, meaning it does not affect earnings, and there is no reputation loop. Our findings reveal that performance ranking impacts risk preferences, even with a minimal social context.

Previous studies also highlight the need to understand the effect of social comparison on affective and cognitive decision functions (Eisenbach and Schmalz, 2016). One might expect risk decisions to have some antecedents stemming from emotional states or cognitive abilities (Loewenstein et al., 2001). Our design enables us to establish the baseline cognitive and affective states of study participants (i.e., first market cycle) and control for fatigue and resource depletion effects (i.e., comparing the second and first market cycles differences between experimental conditions). Using biometric measures, we find that social comparison negatively influences attention and cognitive engagement. However, we do not detect any changes in mood states due to social comparison.

Our study offers robust evidence regarding the role of social comparison in financial risk-taking decisions. Using two different participant pools, we show that social cues affect risk decisions, and low-ranked decision-makers mostly drive this effect. We also document that the student population and general participant pool show the same decision tendencies, hinting that controlled experiments have plausible external validity. Finally, utilizing eye tracking and facial expression non-invasive technologies allows us to capture affective and mood states, providing insights into the "black box" of financial decision-making.

VI Conclusion

We examine the influence of social comparison on financial risk-taking using controlled online and lab studies. Participants make asset choice decisions across two consecutive market cycles. Our experimental design also enables us to measure asset duration. In the treatment condition, we introduce ranking information after the first market cycle, establishing both within-condition (i.e., first vs. second market cycle) and across-condition (i.e., No Information vs. Ranking Information) baselines. This framework allows us to causally determine the effect of social comparison on financial risk preferences.

Participants select riskier assets and demonstrate longer asset holding times in the Ranking Information treatment compared to the No Information control. However, we do not observe a difference in asset earnings. Our analysis indicates that low-ranked decision-makers drive the impact of social comparison.

Using biometric measures, we observe that participants become less attentive, experience diminished cognitive performance, and exhibit moderate reductions in positive mood in the second market cycle. The decline in attention and cognitive performance is more pronounced in the Ranking Information treatment compared to the No Information control, suggesting that social ranking strains the attention and mental bandwidth of decision-makers. Our findings imply that presenting ranking information may raise the risk-exposure level of the market by promoting riskier asset choices. Retail investment platforms might nudge investors to be more attentive and replenish their mental resources to help prevent premature investment decisions.

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Supplementary Materials

Table S1: Asset Decisions In Second Market Cycle
(Ordinal Probit Regressions)

	Dependent variable: Asset Choice					
	(1)	(2)	(3)	(4)	(5)	(6)
Ranking Treatment	0.170*	0.173*	0.177*	0.183*	0.182*	
	(0.099)	(0.100)	(0.100)	(0.100)	(0.100)	
1st Market Cycle: Earning		0.267*	0.282*	0.250	0.251	0.325*
		(0.152)	(0.153)	(0.155)	(0.155)	(0.185)
1st Market Cycle: N Periods			0.020***	0.009	0.009	0.009
			(0.006)	(0.007)	(0.007)	(0.007)
Online Sample					0.027	0.035
					(0.145)	(0.145)
Bottom50%-Message						0.235*
						(0.124)
Top50%-Message						0.127
						(0.125)
1st Market Cycle: Asset Choice FE	*No*	*No*	*No*	*Yes*	*Yes*	*Yes*
N	545	544	544	544	544	544

Ordinal probit regression results are reported. The outcome variable is asset choice decision in the second market cycle, where it takes 1,2,3,4 for Asset A, Asset B, Asset C, and Asset D, respectively. *p<0.1; **p<0.05; ***p<0.01

Screenshots of the Experiment

Welcome to our "Investment Decisions" study!

You will be compensated with $10 for participating in this study and completing all instructed tasks.

The study involves making a series of investment decisions in two investment market cycles.

The investment decisions are real and you have an opportunity to earn additional rewards (up to $25.00) depending on your decision and luck.

This study consists of three parts:

Part 1: 20-period investment market cycle
Part 2: 20-period investment market cycle
Part 3: Short survey

The setup of the Investment decisions:
Before starting your investment decisions, you will be endowed with 1000 ECU (Experimental Currency Unit). Then you will be offered 4 different financial assets: A, B, C, and D. You will be required to choose one of the four assets (A, B, C, and D) to invest your 1000 ECU in the market.

The exchange rate between ECU and USD is:

200 ECU = 1.00 USD

Please click Next button to learn more about each financial asset!

Next

Asset A:
If you invest your 1000 ECU in Asset A, the value of your asset won't change across market cycle periods. You will surely receive 1000 ECU at the end of the investment market cycle.

Asset B:
If you invest your 1000 ECU in Asset B, in each market period, there is a 50% chance of gaining a 5% return on your investment. There is also a 50% chance of losing 4% of your investment.

Asset C:
If you invest your 1000 ECU in Asset C, in each market period, there is a 49.5% chance of gaining a 5% return on your investment. There is also a 49.5% chance of losing 3% of your investment. Assets C has a 1% crash probability. Asset C will lose 50% of its value when the crash happens.

Asset D:
If you invest your 1000 ECU in Asset D, in each market period, there is a 48% chance of gaining an 8.2% return on your investment. There is also a 48% chance of losing 3% of your investment. Assets D has a 4% crash probability. Asset D will lose 50% of its value when the crash happens.

This table summarizes the attributes of each financial asset:

Asset	A	B	C	D
Increase	--	+ 5%	+ 5%	+ 8.2%
Prob.	--	50%	49.5%	48%
Decrease	--	- 4%	- 3%	- 3%
Prob.	--	50%	49.5%	48%
Crash	--	--	- 50%	- 50%
Prob.	--	--	1%	4%
Mean	1000	1104.9	1102.7	1104
SD	0	223.4	331.4	615.6

Please click Next button to learn more about how financial assets are realized!

Next

After you choose your preferred financial asset, the investment market cycle will start. The market cycle will function for 20 periods. In each period, the computer will randomly determine whether your financial asset had a gain or loss, (or crash if Asset C or D is selected). Gains or losses (or crash if Asset C or D is selected) will be realized based on the asset probabilities. Please consult the table below to refresh your memory on financial asset attributes.

Asset	A	B	C	D
Increase	--	+ 5%	+ 5%	+ 8.2%
Prob.	--	50%	49.5%	48%
Decrease	--	- 4%	- 3%	- 3%
Prob.	--	50%	49.5%	48%
Crash	--	--	- 50%	- 50%
Prob.	--	--	1%	4%
Mean	1000	1104.9	1102.7	1104
SD	0	223.4	331.4	615.6

There are 20 periods in each investment market cycle. In each period, the computer will also calculate your earning or loss (or the crash value if Asset C or D is selected) values.

At the end of each period, you can check the current net value of your asset and decide whether to continue to the next period or to cash out. If you choose to cash out, then the current net value of your asset will be your final earning for this investment market cycle. If you continue to hold your asset, you will move to the next market period and the computer will realize your asset based on the attributes presented in the table above.

Remember!

In each period, the starting value of your asset will be the net value of your asset from the previous period.

The second investment market cycle will start after you complete the first investment market cycle. Similar to the first cycle, you will be endowed with 1000 ECU before making investment decisions in the second market cycle.

You will be presented with the same 4 financial assets (A, B, C, D) in the second market, and the market will function with the same rules.

At the end of the study, the computer will randomly select one of the investment market cycles and your earning from the selected cycle will be your study bonus payoff.

Since neither you nor we know which investment market cycle will be randomly selected by the computer, it is in your best interest to try your best in each market to increase your study payoff.

Please click Next button to learn more about study details!

Next

Now you will be presented with 20 graphs showing randomly generated investment market cycles. This will help you to understand the potential gain and loss paths of each financial asset.

Please pay attention! The graphs will progress automatically. You will need to visually examine each graph to improve your knowledge of the financial assets (A, B, C, and D) so that you can increase your study payoffs.

We will have one attention-check question during the display of the 20 graphs.

Your participation in this study will be immediately terminated if you fail in the attention check question! You won't be compensated with the study participation reward if you fail the attention test!

Please click Next button to start the display of 20 graphs!

Next

You have successfully passed the attention test and now you have more knowledge about the gain and loss potentials of each financial asset!

Please, click Next button to start the first Investment Market Cycle!

Next

Asset	A	B	C	D
Increase	--	+ 5%	+ 5%	+ 8.2%
Prob.	--	50%	49.5%	48%
Decrease	--	- 4%	- 3%	- 3%
Prob.	--	50%	49.5%	48%
Crash	--	--	- 50%	- 50%
Prob.	--	--	1%	4%
Mean	1000	1104.9	1102.7	1104
SD	0	223.4	331.4	615.6

Please select your preferred financial asset to start the investment market cycle.

- Asset C
- Asset A
- Asset D
- Asset B

Next

Asset	Increase	Prob.	Decrease	Prob.	Crash	Prob.	Mean	SD
D	+ 8.2%	48%	- 3%	48%	- 50%	4%	1104	615.6

You chose Asset D. Click Next to see your earnings in period 1!

Next

Asset	Increase	Prob.	Decrease	Prob.	Crash	Prob.	Mean	SD
D	+ 8.2%	48%	- 3%	48%	- 50%	4%	1104	615.6

You had a gain! The value of your asset is **1082.00**.

Do you want to continue?

Continue

Cash out

Next

Asset	Increase	Prob.	Decrease	Prob.	Crash	Prob.	Mean	SD
D	+ 8.2%	48%	- 3%	48%	- 50%	4%	1104	615.6

Click next to see your earnings in Period 2!

Next

Asset	Increase	Prob.	Decrease	Prob.	Crash	Prob.	Mean	SD
D	+ 8.2%	48%	- 3%	48%	- 50%	4%	1104	615.6

You had a loss! The value of your asset is **1049.54**.

Do you want to continue?

Continue

Cash out

Next

Asset	Increase	Prob.	Decrease	Prob.	Crash	Prob.	Mean	SD
D	+ 8.2%	48%	- 3%	48%	- 50%	4%	1104	615.6

Your final earning is **1049.54**, we round it to **1050** as your reward.

Next

You already finished the first investment market cycle!

Please click Next button to start the second investment market cycle!

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