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

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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 could nudge investors to sustain their attention and replenish their mental resources, thereby helping to prevent premature investment decisions.

Keywords: Asset Market, Comparison, Emotions, Eye Tracking.

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I Introduction

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). 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-gain ranking information in relation to fellow investors, fostering social comparison environments (Jin et al., 2019; Dorfleitner and Scheckenbach, 2022; Yang et al., 2022). Understanding the impact of social comparison on financial risk-taking in a social trading setting is crucial for several reasons. 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). This article investigates the role of social comparison in risk-taking via a controlled asset market experiment. We also employ eye tracking and facial expression analysis biometric technologies to scrutinize how investment performance ranking information potentially changes retail investors' attention and mood states. 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).

A growing literature has documented 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).[1] It has

[1]For instance, in the recent Silicon Valley Bank run, the bank's managers were blamed for taking

been shown that 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), under-performing firms tend to invest more on uncertain R&D projects to improve their market positions (Boudreau et al., 2016), and unfavorable ranking status leads 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. 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. 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 conduct online and laboratory studies investigating asset market decisions in the face of social comparisons. Participants make asset decisions in two consecutive market cycles. In contrast to the *No Information* control group, participants in the *Ranking Information* condition receive information about their ranking status between the first and second market cycles. We find that ranking information induces a higher degree of risk-taking. Our analyses reveal that the effect of social comparison on asset choices is driven by low-ranked subjects, aligning 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 higher asset-holding times. Experiment subjects show fatigue effects in the second market cycle by diminishing their attention, cognitive activity, and positive mood states. 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.

Our contribution to the literature is threefold. First, most studies investigating

excessive risks to maximize their bonus earnings (Newsweek, 2023).

the role of social comparison in financial risk-taking employ tournament ranking, where individual ranking determines the final investment payoff (Li et al., 2019). However, 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. Second, we employ two asset market cycles capturing a social-comparison-free baseline for both experimental conditions. Third, eye tracking and facial expression analysis biometric measures enable us to understand the effect of social comparison on the decision process.

II Experimental Procedures and Estimation Methodology

We conducted an online study using the Prolific.co crowdsourcing platform and a follow-up laboratory experiment at a university in the United States. 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. Ensuring that our study subjects had high approval rates helped 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 across the campus. 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. Our design was built on Apesteguia et al. (2020). Participants were shown experimental assets, their gain and loss magnitudes, associated probabilities, and expected means and standard deviations of gains as described in Table 1. Asset A was risk and gain-free, mimicking a checking account. The risk and potential gain 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 should prefer riskier assets as they po-

Table 1: Experimental Assets

	Gain	Loss	Crash	$\mu(\sigma)$
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.

tentially yield higher gain levels. For instance, the expected mean of Asset C is lower than Asset B, but one could earn a higher gain with Asset C as the standard deviation of its expected gain distribution is larger compared to the same feature of Asset B. Before starting incentivized asset market cycles, subjects were shown 20 different simulation graphs based on asset features with an attention check task (see Figure S1 in Supplementary Materials). These simulated graphs ensured that subjects possessed sufficient information about the experimental assets' potential gain/loss paths.

Participants chose their preferred asset in two consecutive asset market cycles and were allowed to realize their asset in 20 periods. In each period, the software realized a gain or loss based on the asset features, and participants decided if they wanted to retain their asset and proceed to the next period or cash out and exit the market cycle. The starting value of all assets was 1000 Experimental Currency Units (ECUs), and gains and losses were accumulated throughout the market cycle periods.[2]

Before starting the market cycles, subjects were randomly assigned to the *No Information* and *Ranking Information* conditions. To establish our comparison sample, the No Information condition was conducted before the Ranking Information treatment. In the Ranking Information treatment, participants were shown their ranking after the first market cycle using the asset-earning data from the No Information sample.

[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.

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 tracking and facial expression mood measures in the lab study.[3]

II.A 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.

III Results

We start our discussion by scrutinizing general trends in our data. Table 2 presents asset choice proportions, the average number of asset holding periods, and final earnings in both market cycles across experimental conditions. We observe that the first market cycle asset decisions are identical in both experimental conditions, as the ranking information was only introduced before the second market in the treatment. Participants increasingly choose Asset D in the second market cycle. We also note that trends

[3]See Supplementary Materials Figure S2 for biometric measures.

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	5%	6%	5%	4%
Asset B	30%	32%	30%	26%
Asset C	30%	21%	30%	24%
Asset D	35%	41%	35%	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 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.

in asset holding times vary based on experimental conditions and asset types.

Figure 1 illustrates the relationship between asset holding duration and asset earnings, using the complete study data from both market cycles. Riskier assets yield higher earning levels as participants hold their assets longer. However, holding Assets C and D for longer durations also increases the chances of a crash, leading to an abrupt decrease in earnings.

Table 3 Panel I presents the results of statistical tests comparing asset decisions, earnings, and holding times across experimental conditions. We find that, overall,

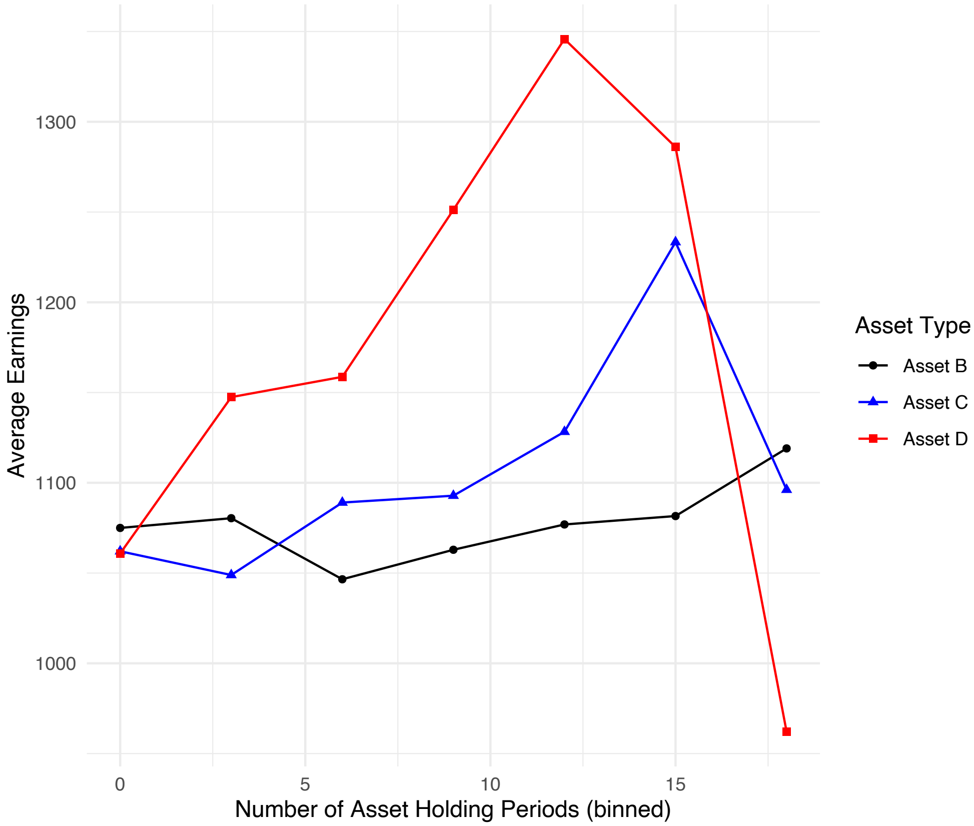


Figure 1: Relationship between Number of Asset Holding Periods and Average Earnings

participants choose riskier assets in the second market cycle and reduce their asset holding duration. However, the increase in asset risk profiles in the second market cycle is driven by the Ranking Information treatment $(0.17, p < 0.01)$. 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. Figure 2 also confirms this conclusion using empirical CDFs, showing that the Ranking Information group has a longer asset holding duration. We do not detect any changes in asset earnings in the second market cycle for either experimental condition.

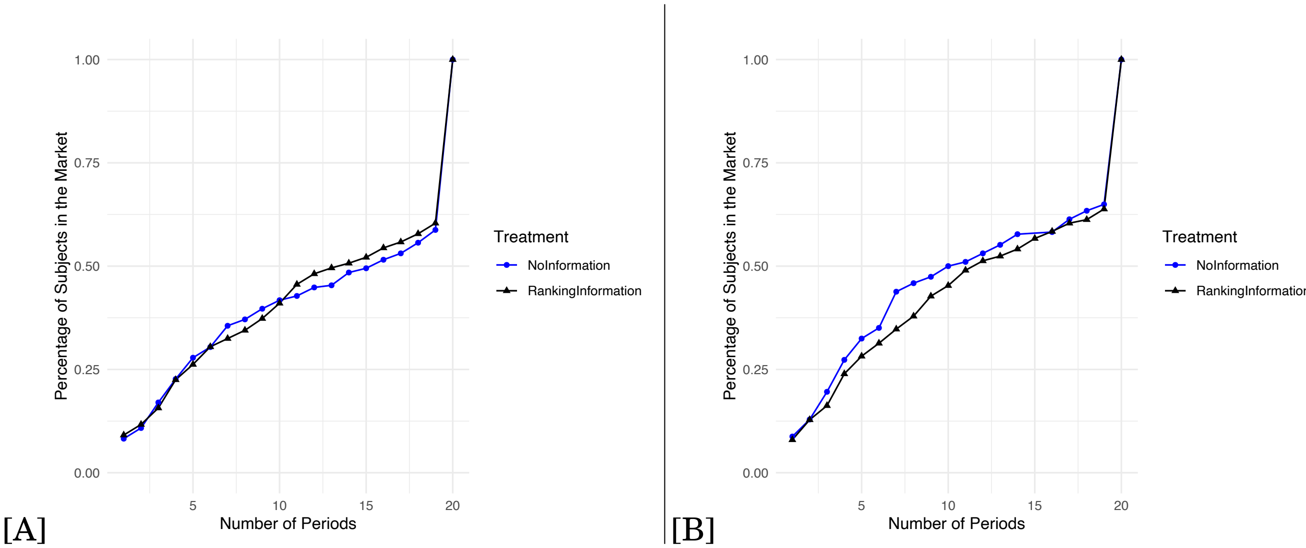
Table 4 Column 1 examines the causal effect of ranking information on risk-taking, while Columns 2-5 employ various model specifications in line with Equation 1. We corroborate our primary test result in Table 3 and find that subjects in the Ranking

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 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.

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 1-4. 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



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

Figure 2: Empirical CDF of Asset Holding Periods

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.

Table 3 Panel II reports the test results comparing biometric performance metrics of subjects along Fixation Time, Fixation Count, Blinks, Positive and Negative Mood frames. Overall, participants become 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 reduce cognitive activity and mental workload (Fogarty and Stern, 1989; Van Orden et al., 2001). Table 3 Panel III shows that the reduction of attention and cognitive performance is stronger in the Ranking Information treatment compared to the No Information control. Table 3 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

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

conditions.[4]

IV Conclusion

We examine the influence of social comparison on financial risk-taking using controlled online and lab studies. 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.

We observe that participants become less attentive, experience diminished cog-

[4]Table S1 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 deteriorates across the market cycle periods, not in the initial asset choice stage.

nitive 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.

References

Ammann, M. and Schaub, N. (2021). Do individual investors trade on investment-related internet postings? *Management science*, 67(9):5679–5702.

Andraszewicz, S., Kaszás, D., Zeisberger, S., and Hölscher, C. (2022). The influence of upward social comparison on retail trading behavior.

Apesteguia, J., Oechssler, J., and Weidenholzer, S. (2020). Copy trading. *Management Science*, 66(12):5608–5622.

Boudreau, K. J., Lakhani, K. R., and Menietti, M. (2016). Performance responses to competition across skill levels in rank-order tournaments: field evidence and implications for tournament design. *The RAND Journal of Economics*, 47(1):140–165.

Breaban, A. and Noussair, C. N. (2018). Emotional state and market behavior. *Review of Finance*, 22(1):279–309.

Dijk, O. (2017). For whom does social comparison induce risk-taking? *Theory and Decision*, 82(4):519–541.

Dijk, O., Holmen, M., and Kirchler, M. (2014). Rank matters–the impact of social competition on portfolio choice. *European Economic Review*, 66:97–110.

Dorfleitner, G. and Scheckenbach, I. (2022). Trading activity on social trading platforms–a behavioral approach. *The Journal of Risk Finance*.

Fogarty, C. and Stern, J. A. (1989). Eye movements and blinks: their relationship to higher cognitive processes. *International journal of psychophysiology*, 8(1):35–42.

Gortner, P. J. and van der Weele, J. J. (2019). Peer effects and risk sharing in experimental asset markets. *European Economic Review*, 116:129–147.

Hopkins, E. (2018). Inequality and risk-taking behaviour. *Games and Economic Behavior*, 107:316–328.

Jin, X., Zhu, Y., and Huang, Y. S. (2019). Losing by learning? a study of social trading platform. *Finance Research Letters*, 28:171–179.

Kempf, A., Ruenzi, S., and Thiele, T. (2009). Employment risk, compensation incentives, and managerial risk taking: Evidence from the mutual fund industry. *Journal of Financial Economics*, 92(1):92–108.

Kirchler, M., Lindner, F., and Weitzel, U. (2018). Rankings and risk-taking in the finance industry. *The Journal of Finance*, 73(5):2271–2302.

Kirchler, M., Lindner, F., and Weitzel, U. (2020). Delegated investment decisions and rankings. *Journal of Banking & Finance*, 120:105952.

Li, Z., Wang, C., Wang, Q., and Luo, B. (2019). A review on risk-taking in tournaments. *Journal of Modelling in Management*, 14(2):559–568.

Lindskog, A., Martinsson, P., and Medhin, H. (2022). Risk-taking and others: Does the social reference point matter? *Journal of Risk and Uncertainty*, 64(3):287–307.

Miloš, B., Loreta, C., and Riccardo, P. (2022). Eye-tracking for the study of financial decision-making: A systematic review of the literature. *Journal of Behavioral and Experimental Finance*, page 100702.

Newsweek (2023). Svb ceo greg becker's pay was doubled for making risky bets: Report.

Pelster, M. and Hofmann, A. (2018). About the fear of reputational loss: Social trading and the disposition effect. *Journal of Banking & Finance*, 94:75–88.

Rajan, R. G. (2006). Has finance made the world riskier? *European financial management*, 12(4):499–533.

Schwerter, F. (2023). Social reference points and risk taking. *Management Science*.

Taylor, J. (2003). Risk-taking behavior in mutual fund tournaments. *Journal of Economic Behavior & Organization*, 50(3):373–383.

Trautmann, S. T. and Vieider, F. M. (2012). Social influences on risk attitudes: Applications in economics. In *Handbook of risk theory*, pages 575–600. Springer Verlag.

Van Orden, K. F., Limbert, W., Makeig, S., and Jung, T.-P. (2001). Eye activity correlates of workload during a visuospatial memory task. *Human factors*, 43(1):111–121.

Wohlgemuth, V., Berger, E. S., and Wenzel, M. (2016). More than just financial performance: Trusting investors in social trading. *Journal of Business Research*, 69(11):4970–4974.

Yang, M., Zheng, Z., and Mookerjee, V. (2022). How much is financial advice worth? the transparency-revenue tension in social trading. *Management Science*, 68(7):5252–5268.

Supplementary Materials

Table S1: Comparing The Second and First Asset Market Cycles along Biometric Process Data (Only Lab Sample, N=66)

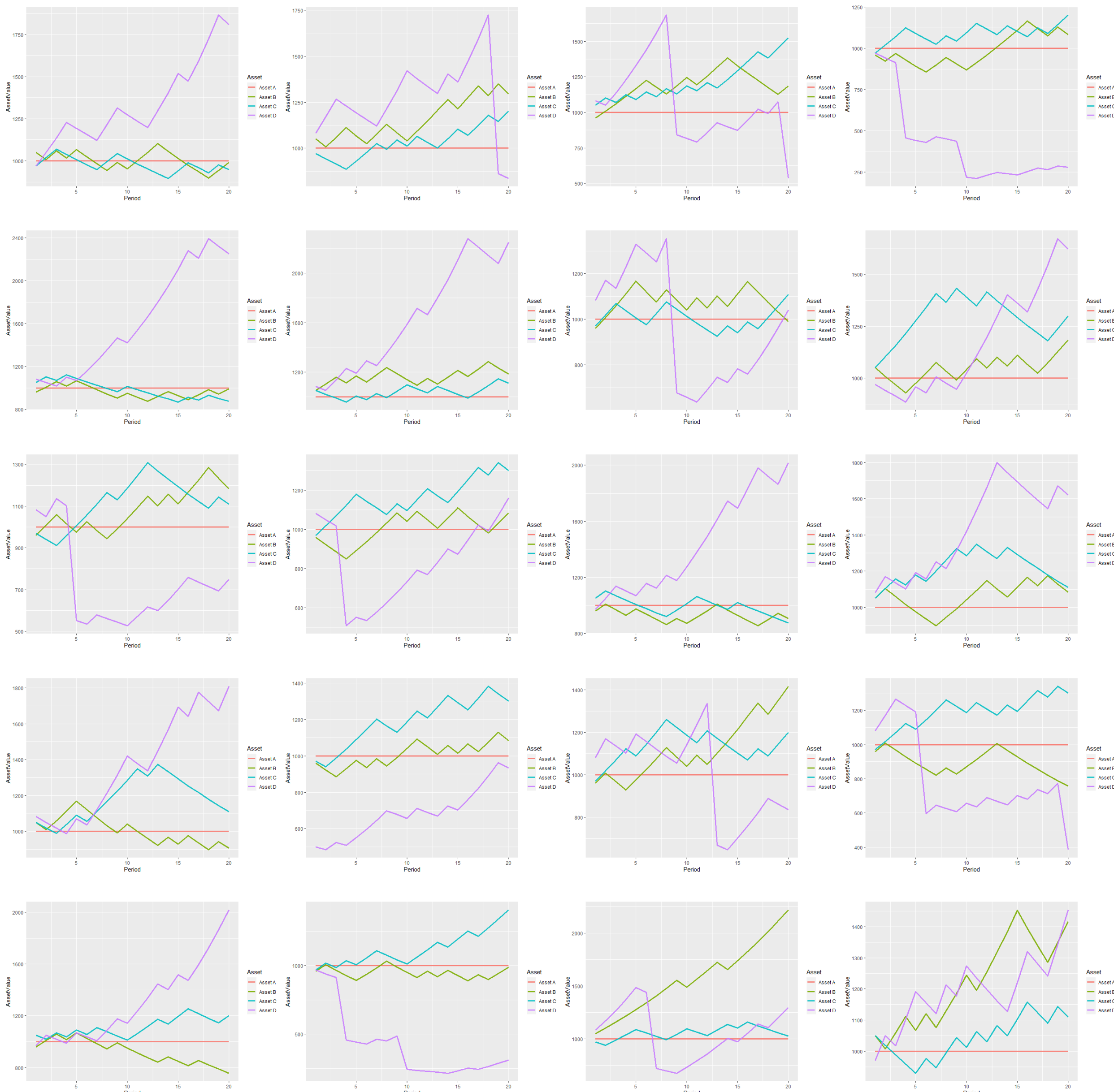
	Δ_{Overall}	$\Delta_{\text{No Information}}$	$\Delta_{\text{Ranking Information}}$
Asset Decision Stage			
Fixation Time	−1.35 (1.51)	−2.09 (2.51)	−0.81 (1.88)
Fixation Count	−10.14 (6.10)	−2.14 (9.20)	−8.66 (8.25)
Blinks	−0.87 (0.87)	0.52 (1.17)	−1.92 (1.24)
Positive Mood Frames	0.42 (1.42)	0.97 (0.93)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

Table S2: Asset Decisions In First Market Cycle

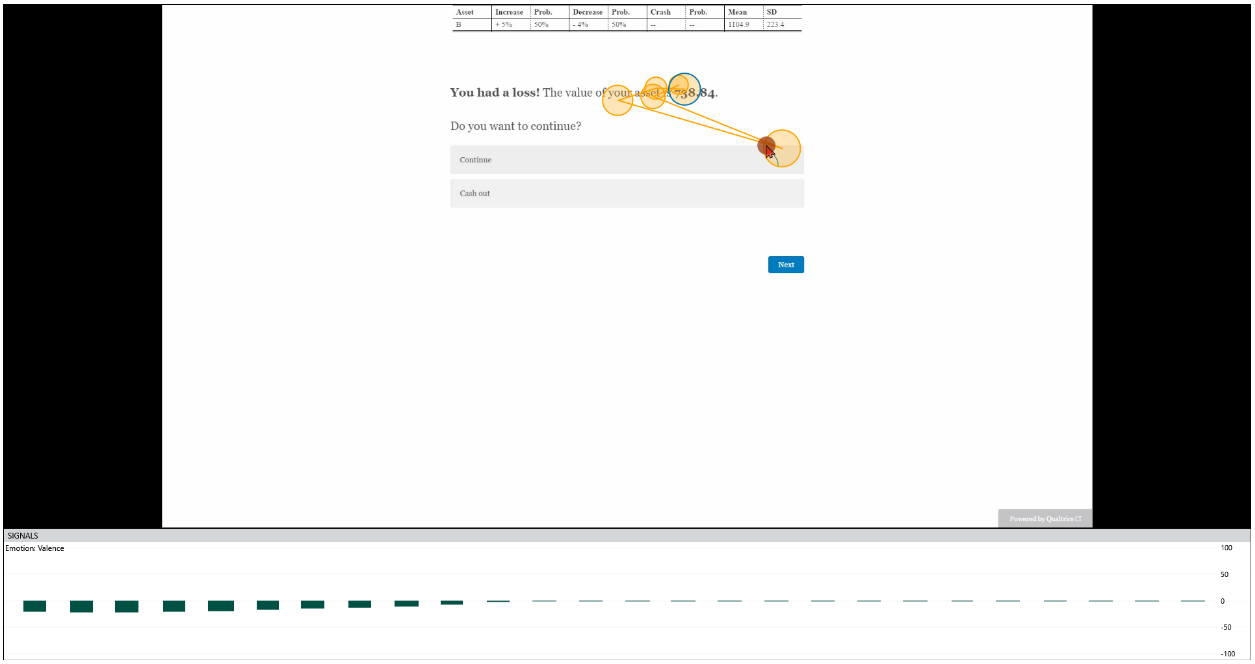
	Asset Choice	Asset Choice	Periods	Periods	Earnings	Earnings
Ranking Treatment	0.01	0.01	−0.08	−0.22	0.01	0.02
	(0.08)	(0.08)	(0.66)	(0.66)	(0.03)	(0.03)
Online Sample	−0.04	−0.01	−1.46	−1.51	−0.02	−0.02
	(0.11)	(0.12)	(0.91)	(0.95)	(0.05)	(0.05)
Male		0.16*		1.19*		−0.01
		(0.08)		(0.68)		(0.03)
1yr-Trading 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



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

Figure S1: Simulated Gain/Loss Paths for Experimental Assets



This figure presents a representative screenshot from one subject's decision in the first market cycle. Fixation counts (i.e., the number of circles) 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. Fixation counts and times were measured with the Tobi Pro Fusion eye tracker (120Hz) using iMotions software. For each subject, we find the average number of Fixation counts and Times (in milliseconds) across decision periods in a market cycle.

The bottom panel 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. 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 across decision periods in a market cycle.

Figure S2: A representative Screenshot for Biometric Measures