Asymmetric Learning from Financial Information: A Replication

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Abstract

Replication is essential for scientific progress. Prior research by Kuhnen (2015) shows that investors update beliefs asymmetrically in response to gains and losses. The original evidence came from student samples drawn from Western university populations. We test the replicability of this result using data from 114 adults recruited via an experimental platform in India. We replicate the core finding: in the loss domain, individuals form overly pessimistic beliefs about available investment options. Our study provides robust evidence for the external validity of asymmetric belief updating in financial contexts. It also demonstrates the feasibility of conducting rigorous online experiments in resource-constrained settings.

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1. Introduction

We conduct a direct replication of Kuhnen (2015), who documented asymmetries in learning from financial information across the gain and loss domains. Kuhnen's results show that individuals, when evaluating available investment options, form beliefs that are overly pessimistic, overly sensitive to low outcomes, and further away from the objective Bayesian beliefs in the loss domain relative to the gain domain. These insights, obtained with U.S. university students and subsequently replicated in Romania, underscore the robustness of the pessimism bias in controlled settings and raise a natural follow-up question: Does the pessimism bias generalize beyond student samples and Western societies?

To test whether pessimism bias and related patterns persist in a non-WEIRD[1], culturally distinct context delivered online, we recruited 114 participants via the online platform BeSample[2] and administered the experiment online, closely following the original protocol (see Section 2). Our results confirm that pessimism bias is present in a general population sample from a non-WEIRD country. In fact, the magnitude of pessimism bias in our sample is roughly 3.85 times larger than in student samples, underscoring the importance of accounting for subjective beliefs in financial decision-making, especially among lay investors. These findings confirm the robustness and external validity of Kuhnen's findings.

As retail investing expands globally and financial decision-making increasingly occurs online, understanding the external validity of Kuhnen's mechanism is of growing importance. We replicate Kuhnen's protocol in a new country and an online setting that reflects how many financial decisions are made today. This design allows us to test whether asymmetries in belief updating persist across both institutional and technological contexts, and to evaluate the broader applicability of this empirical pattern in behavioral economics and finance. An additional benefit of the online design is that we reduce the cost of running the experiment thus, making this type of research more accessible. The study achieves substantial cost savings, with a 74% reduction in per-participant expenses compared to the original study ($8.07

[1]WEIRD stands for Western, Educated, Industrialized, Rich, and Democratic. It refers to populations commonly studied in psychological and economic research, which may not be representative of the global population (see Henrich et al., 2010).

[2]https://www.besample.app

vs. \$30.48).

Kuhnen's findings offer a compelling mechanism to explain several empirical regularities observed during economic downturns. In such periods, financial markets display stronger reactions to bad news, risk premia widen, executives issue more pessimistic forecasts, and economic recessions correspond with times of heightened sensitivity to news (see Andersen et al., 2007; Bollerslev and Todorov, 2011; Ben-David et al., 2013; García, 2013). Households exposed to recessions reduce equity holdings and adopt more pessimistic return expectations (Malmendier and Nagel, 2011), and individuals increase insurance purchases following natural disasters despite unchanged objective risks (Froot, 2001). Kuhnen's framework not only accounts for mechanisms contributing to these patterns but also links asymmetric learning to underinvestment in risky assets during bad times, consistent with models of counter-cyclical risk aversion (Routledge and Zin, 2010).

Scientific research faces growing scrutiny over its credibility, driven by concerns about low replication rates across disciplines—including psychology, economics, and finance (Collaboration, 2015; Camerer et al., 2016, 2018). Contributing factors include poor statistical practices, selective reporting, and underpowered designs that inflate false-positive rates (Ioannidis, 2005; Nosek et al., 2012; Button et al., 2013). These concerns have renewed attention to replication as a cornerstone of scientific self-correction (Maniadis et al., 2014; Ziliak, 2019).

In financial economics, many documented anomalies fail to replicate (Hou et al., 2018). In this spirit, we replicate an influential behavioral phenomenon: the pessimism bias in financial learning originally identified by Kuhnen (2015). Our replication confirms the external validity of this mechanism in a diverse sample and format, thereby contributing to the credibility and generalization of one of the most influential studies on investors' learning from financial information.

The remainder of the paper proceeds as follows. Section 2 presents the experimental design. Section 3 reports the empirical results and contrasts them with those obtained in Kuhnen (2015). Section 4 concludes.

2. Experimental Design and Procedures

We closely replicate Kuhnen (2015)'s original experiment. In each trial, we present participants with a choice between a risky asset (i.e., a stock) and a safe asset (i.e., a bond). The stock can be either "*good*" (meaning achieving a high payoff with 70% probability and a low payoff with 30% probability) or "*bad*" (reversing the relation between probabilities and payoffs). Participants did not know the type of stock but could form beliefs about it by observing a sequence of payoff realizations across periods of 6 trials. The bond yielded a fixed, known payoff. We refer to a set of six trials as a *block*.

The experiment followed a within-participant design in that we presented participants with 6 blocks consisting of six trials each. In each block, the probability of having a good or a bad stock was the same (50%). Additionally, in each block the decision between the stock and the bond was randomly framed in terms of gains or losses. In gain blocks, participants faced positive payoffs, with high and low payoffs of $10 and $2, respectively. In loss blocks, the same magnitudes were presented, but this time as negative amounts (e.g., –$10 or –$2). Participants were informed in advance about the different framings, the magnitude of payoffs, and the fact that each block featured a new, independent stock with an equal chance of being good or bad. We instructed participants to make a choice in each trial. After the choice was made, we presented the realization of the outcome to participants, and we instructed them to estimate the probability (from 0 to 100) and indicate their confidence in that belief (from 1 to 9) that the stock was of the good type. Additionally, participants also completed another 6 blocks where they just saw the six realizations per block and had to report beliefs and their confidence on them, without making an investment decision between the stock and the bond. We refer to the six blocks where participants made investment decisions as *Active*, and the six blocks without decisions as *Passive*.

We depart from Kuhnen (2015) in three ways. First, we use 6 blocks of 6 trials in both Active and Passive tasks, rather than 10 blocks of 6 trials in Kuhnen (2015)'s original protocol. We do this to shorten the length of the experiment. Although this reduces the amount of data collected per participant, we recruit more participants than Kuhnen (2015)'s main experiment to compensate for loss of statistical power. This approach makes the experiment's length feasible for online implementation. Second, we calibrate incentives using purchasing power parity adjustments to ensure that payment amounts represent equivalent economic value to participants in India compared to participants in the original U.S. study.[3] Third, given the

[3]In Kuhnen (2015), the fixed payment was $23, and the variable payment was computed as 10% of the investment payoffs across all blocks and earnings from belief accuracy items.

greater socioeconomic diversity of our sample, we implemented a comprehension check to exclude participants who demonstrated poor understanding of the instructions. Specifically, we asked participants to report the correct prior probability that the stock was good before the first trial in each block. Participants who failed to provide at least 5 out of 6 correct priors did not pass the comprehension check and were therefore excluded from the final sample. In practice, this led to the exclusion of 138 participants, representing 54.8% of the initial sample. Descriptive statistics for both the final and excluded samples are presented in Tables A.5 and A.6 in the appendix.

Procedures. We ran the experiment online in June 2025. Our final sample includes 114 participants (average age = 25.8; 46.5% females) from India through the experimental platform BeSample.

3. Results

We replicate the main analysis conducted in Kuhnen (2015).[4] Specifically, we use our new experimental data to estimate and present the equivalents of Figure 3 (in the original study) and Tables II—V (our Figure 1 and Tables 1, 2, 3, and 4, respectively).

As in the original article, we find that subjective beliefs about the likelihood of the stock being "good"[5] differ significantly between the gain and loss conditions. Compared to the gain domain, participants form significantly more pessimistic beliefs about the stock being good in the loss domain. This replicates the pessimism bias reported in Kuhnen (2015). Also consistent with the target article, subjective beliefs deviate more from the objective Bayesian probability in the loss domain when the objective probability is high, and in the gain domain when it is low.

Figure 1 captures these results. The horizontal axis of each panel represents the objective Bayesian probability that the stock is good, and the

For India, we offered a fixed payment of $1.50, and the variable payment was computed as a fixed part of $1.45, to ensure no losses as the platform does permit negative bonuses, and 1% of the investment payoffs on all blocks plus a total sum of what they earned from belief accuracy items.

[4]When discussing the results, we follow Dreber and Johannesson (2025)'s recommendation to report relative effect sizes when conducting replication studies.

[5]From now on, we use the term "good stock" to refer to the stock that yields the most attractive dividend with higher probability.

vertical axis represents the participants' subjective belief about that same probability. The left (resp., right) panel presents the data for the Active (resp., Passive) tasks. The 45º line in both panels depicts the locus of points where subjective beliefs coincide exactly with the objective Bayesian posterior probability.

Our data, plotted with solid lines for the gain domain and dashed lines for the loss domain, show that the average posterior beliefs deviate substantially from the objective probability line. The most notable difference compared to Kuhnen (2015)'s original experiment is that the pessimism bias — i.e., the distance between the subjective posterior belief curves in the gain and loss domains — is substantially larger in our sample.

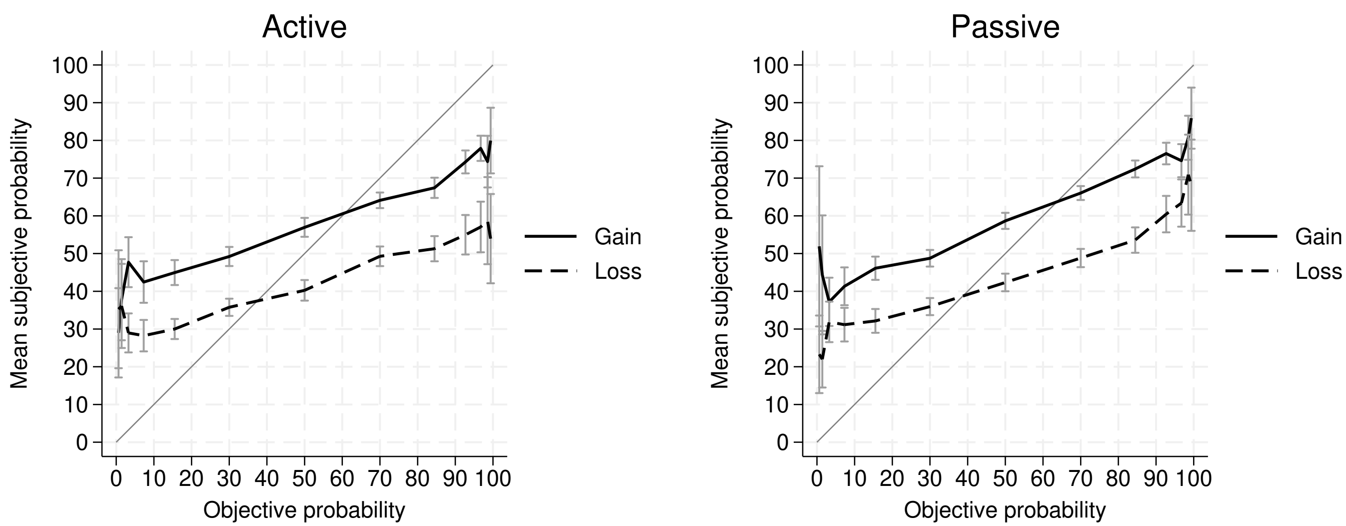
These effects are also replicated in the regression analyses reported in Table 1. Controlling for the objective Bayesian probability, subjective beliefs about the good stock in the loss condition are, on average, 15.17% ($p < 0.01$) lower (i.e., more pessimistic) than in the gain condition. Notably, the effect size in our sample is 3.85 times larger ($\frac{15.17}{3.94} = 3.85$) than that reported in the original study. Participants in our sample exhibit a substantially higher degree of pessimism bias. This result remains robust even after controlling for participant fixed effects (column 2). However, contrary to Kuhnen (2015)'s findings, we do not observe a sizable difference between the loss condition coefficients for the Active and Passive tasks (columns 3 and 4). Taken together, these results suggest that our experimental investors exhibit stronger deviations from rational updating than those in Kuhnen (2015), highlighting the joint influence of online environments and culture in shaping behavioral regularities.

In line with Kuhnen (2015), our Table 2 shows that learning in the loss condition not only induces greater pessimism but is also associated with larger probability estimation errors. These errors, measured as the distance between the objective Bayesian posterior probability and participants' subjective reports, are 2.537% ($p < 0.01$) larger in the loss condition relative to the gain condition — an effect 1.38 times larger ($\frac{2.537}{1.86} = 1.38$) than the one reported in the original study.

Contrary to the original findings, however, the difference in estimation errors is not significantly greater in the Active (2.368%; $p < 0.1$) than in the Passive task (2.707%; $p < 0.01$), as reported in columns 2 and 3. The effect sizes of these two estimates are 0.925 ($\frac{2.368}{2.56} = 0.925$) and 2.33 ($\frac{2.707}{1.16} = 2.33$) times the size of those reported in the original paper.

Columns 4, 5, and 6 of Table 2 suggest that participants make smaller

Figure 1: **Average subjective beliefs that the stock is good, as a function of the objective Bayesian probability.**



Notes: This figure replicates Kuhnen (2015)'s Figure 3. The left panel presents the data for the Active task, while the right panel presents the data for the Passive task. The 45-degree line depicts the objective posterior Bayesian probability. Perfect Bayesian learners would report subjective posterior beliefs that align perfectly with this line.

Table 1: **Differences in Probability Estimates in the Loss and Gain Conditions**

Dependent Variable	*Probability Estimates*$_{it}$ (Subjective Posterior Belief)			
	All Trials	All Trials	Active Trials	Passive Trials
Loss trial$_{it}$	-15.17***	-15.17***	-15.50***	-14.90***
	(-7.47)	(-7.47)	(-6.76)	(-6.67)
Objective posterior$_t$	0.351***	0.351***	0.323***	0.378***
	(10.95)	(10.92)	(8.63)	(10.08)
Constant	40.34***	40.33***	41.26***	39.49***
	(17.58)	(18.26)	(16.19)	(15.67)
Adjusted R^2	0,248	0.260	0.243	0.275
Observations	8208	8208	4104	4104

Notes: This table directly replicates the regression analyses reported in Kuhnen (2015)'s Table II. The dependent variable (*Probability Estimate*$_{it}$) is the subjective posterior belief (of participant i in trial t) that the stock is good. Independent variables include a dummy for the loss domain (*Loss trial*$_{it}$) and the objective Bayesian probability of the stock being good given the history of observed realizations until time t (*Objective Posterior*$_t$). Subscript i refers to the participant and subscript t refers to the trial. The last three specifications include subject fixed effects. Standard errors are robust to heteroskedasticity and are clustered by subject. t statistics in parentheses.* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$.

estimation errors in the Passive task relative to the Active task, although this result is only marginally significant at the 10% level (column 4). This effect appears to be entirely driven by the gain domain ($p < 0.1$ for the gain domain; no significance in the loss domain), contrary to the findings in Kuhnen (2015). The coefficients in columns 4, 5, and 6 are 1.5 ($\frac{-1.593}{-1.06} = 1.5$), 4.9 ($\frac{-1.763}{-0.36} = 4.9$), and 0.81 ($\frac{-1.424}{-1.76} = 0.81$) times the size of the corresponding coefficients in the original paper.

Finally, the regression models in the last two columns of Table 2 show that subjective posterior probabilities under losses are closer to the objective Bayesian posteriors for objective probabilities below 50% (8.258% smaller estimation errors in the loss domain; $p < 0.01$) but further away for objective probabilities above 50% (10.24% greater estimation errors in the loss domain; $p < 0.01$), replicating the pattern reported in Kuhnen (2015). However, our coefficients are 5.86 ($\frac{-8.258}{-1.41} = 5.86$) and 2.38 ($\frac{10.24}{4.31} = 2.38$) times larger than the corresponding ones in the original study. This, alongside our earlier findings of a substantially greater pessimism bias, reinforces the conclusion that online environments and cultural factors significantly influence the degree of irrationality in financial decision-making. The results remain virtually unchanged when controlling for participant fixed effects (bottom panel).

We now turn our attention to Table 3. As in the original study, the first three columns of Panel A show that the effect of the loss versus gain condition on probability estimation errors persists when we examine separately the first three trials and the last three trials of each learning block. However, contrary to Kuhnen (2015)'s findings, we do observe a difference when examining separately the trials in the first and second halves of the Active and Passive tasks. This difference suggests that, in our sample, the effect of the loss condition is primarily driven by choices made in the first half of the Active and Passive tasks. Panel B replicates the same analysis as Panel A but considers only Active trials. Panel B yields a very similar pattern to Panel A, although the results are only marginally significant ($p < 0.10$).

Lastly, in Table 4 we examine how probability estimates evolve trial-by-trial separately for the loss and gain conditions. The table reports the average change in subjective probability estimates that the stock is good. In contrast to the original findings, we observe significant differences only when belief updating follows a high dividend.

4. Discussion

Our replication strongly supports the main findings of Kuhnen (2015), though we observe differences in the magnitude and significance of certain effects. As in the original study, we find that subjective beliefs about the likelihood that the stock is good differ markedly between the gain and loss conditions. In the loss domain, participants form significantly more pessimistic beliefs about the stock being good, on average, compared to the gain domain.

Also consistent with the original study, subjective beliefs deviate more from the objective Bayesian probability in the loss domain than in the gain domain. The most notable difference is that the pessimism bias — defined as the distance between the subjective posterior belief curves in the gain and loss domains — is substantially larger in our sample. Another exception is that we do not replicate the learning dynamics reported in Table V of Kuhnen (2015) (our Table 4).

Table 2: **Differences in Probability Estimation Errors in the Loss and Gain Conditions**

Dependent Variable	*Absolute Probability Error*$_{it}$							
	All Trials	Active Trials Only	Passive Trials Only	All Trials	Gain Trials Only	Loss Trials Only	Trials with Objective Posterios $< 50\%$	Trials with Objective Posterios $\geq 50\%$
				Main Specification				
Loss trial$_{it}$	2.537***	2.368*	2.707***				-8.258***	10.24***
	(3.24)	(1.96)	(2.86)				(-4.57)	(7.18)
Passive trial$_{it}$				-1.593*	-1.763*	-1.424		
				(-1.75)	(-1.66)	(-1.11)		
Constant	21.72***	22.60***	20.84***	23.79***	22.60***	24.97***	29.18***	16.59***
	(21.31)	(18.53)	(19.40)	(21.02)	(18.53)	(18.59)	(16.55)	(21.08)
Adjusted R^2	0.003	0.003	0.004	0.001	0.002	0.001	0.033	0.058
Observations	8208	4104	4104	8208	4104	4104	3458	4750
				Subject fixed effects specification				
Loss trial$_{it}$	2.537***	2.368*	2.707***				-7.731***	9.825***
	(3.24)	(1.96)	(2.86)				(-4.62)	(7.19)
Passive trial$_{it}$				-1.593*	-1.763*	-1.424		
				(-1.75)	(-1.66)	(-1.11)		
Adjusted R^2	0.004	0.004	0.006	0.002	0.002	0.001	0.040	0.070
Observations	8208	4104	4104	8208	4104	4104	3458	4750

Notes: This table directly replicates the regression analyses reported in Kuhnen (2015)'s Table III. The dependent variable (*Absolute Probability Error*$_{it}$) captures the difference between the subjective and the objective Bayesian probabilities of the stock being good. Independent variables include a dummy for losses (*Loss trial*$_{it}$) and a dummy for passive trials (*Passive trial*$_{it}$). Subscript i refers to the participant and subscript t refers to the trial. Bottom panels replicate the same analyses including subject fixed effects. Standard errors are robust to heteroskedasticity and are clustered by subject. t statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: **In-Sample Robustness Checks**

Panel A: All Trials

Dependent Variable	*Absolute Probability Error$_{it}$*				
	All Trials	First Three Trials of Each Learning Block	Last Three Trials of Each Learning Block	Trials in First Half of Active and Passive Tasks	Trials in Second Half of Active and Passive Tasks
Loss trial$_{it}$	2.537***	2.133***	2.941***	4.315***	0.697
	(3.24)	(2.84)	(2.89)	(3.65)	(0.53)
Constant	21.72***	18.46***	24.99***	21.89***	21.56***
	(21.31)	(19.23)	(21.17)	(19.07)	(17.52)
Adjusted R^2	0.003	0.003	0.004	0.009	0.000
Observations	8208	4104	4104	4104	4104

Panel B: Active Trials Only

Dependent Variable	*Absolute Probability Error$_{it}$*				
	All Trials in Active Task	First Three Trials of Each Learning Block of Active Task	Last Three Trials of Each Learning Block of Active Task	Trials in First Half of Active Task	Trials in Second Half of Active Task
Loss trial$_{it}$	2.368*	1.885*	2.850*	4.748***	-0.108
	(1.96)	(1.73)	(1.84)	(2.70)	(-0.06)
Constant	22.60***	19.09***	26.12***	22.40***	22.79***
	(18.53)	(16.94)	(18.09)	(16.75)	(14.56)
Adjusted R^2	0.003	0.002	0.003	0.010	-0.000
Observations	4104	2052	2052	2052	2052

Notes: This table reproduces the regression analyses reported in Kuhnen (2015)'s Table IV. The dependent variable is the *Absolute Probability Error$_{it}$t*, a measure of the distance between the objective Bayesian posterior probability and participants' subjective reports. The independent variable is a dummy for the loss condition (*Loss trial$_{it}$*). t statistics in parentheses.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: **Differences in Probability Updating in the Loss and Gain Conditions**

	Probability Estimate$_{t+1}$ − *Probability Estimate*$_t$					
	High Dividend in Trial $t+1$	Low Dividend in Trial $t+1$	Low Dividend in Trial $t+1$, *Probability Estimate*$_t < 50\%$	Low Dividend in Trial $t+1$, *Probability Estimate*$_t \geq 50\%$	Low Dividend in Trial $t+1$, *Probability Estimate*$_t \geq 50\%$ Passive Trials	Low Dividend in Trial $t+1$, *Probability Estimate*$_t \geq 50\%$ Active Trials
Loss condition	5.23%	−8.18%	−18.59%	−7.17	−6.66%	−7.68%
Gain condition	10.26%	−7.76%	−25.13%	−7.20	−7.75%	−6.64%
Loss − Gain	−5.03%***	−0.42%	6.54%	0.03%	1.09%	−1.04%

Notes: This table reproduces the analyses reported in Kuhnen (2015)'s Table V. The table reports the average change in subjective probability estimates that the stock is good in both the loss and gain domains, as well as the difference between them.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix A. Descriptive Statistics of the final sample and excluded participants

Table A.5: **Sample Descriptive Statistics**

Variable	N	Mean	Median	Std. Dev.	Min	Max	Distribution
Panel A: Demographics							
Age (years)	114	25.8	25	6.2	18	40	
Gender (%)	114			—			Female: 46.5% Male: 53.5%
Education (%)	114			—			High School or lower: 13.2% Bachelor's: 44.7% Master's: 18.4% Other: 27.2%
Panel B: Experimental Measures							
Risk Aversion	114	5,128	5,000	2,224	0	10,000	Amount invested in stock fund ($)
Financial Literacy Score	114	2.16	2	0.87	0	3	Perfect (3): 41.2% One error (2): 38.6% Two errors (1): 14.9% Three errors (0): 5.3%
Comprehension Check	114	5.91	6	0.28	5	6	Correct prior beliefs
Correct Beliefs	114	30.7	26	16.5	8	81	Accurate estimates (max = 84)
Bonus Payoffs	114	0.03	0.00	0.24	-0.56	0.64	Total payoff from investment and evaluation tasks ($)
Panel C: Technical Controls							
Device Type (%)	114			—			Computer: 75.4% Mobile: 24.6%
Recaptcha Score	114	0.95	1	0.09	0.4	1	Bot detection score

Notes: This table reports descriptive statistics for the experimental sample. The sample consists of 114 participants who completed the experimental task obtaining at least 5 correct responses in the *Comprehension Check* administered during their second task. In the comprehension check, participants had to state the prior belief about the likelihood of the stock being the good one. *Age* is measured in years. *Risk Aversion* represents the dollar amount (out of $10,000) that participants chose to invest in a risky stock index fund versus a risk-free savings account. The risky asset offers returns of +40% or −20% with equal probability, while the risk-free asset provides a certain 5% return. *Financial Literacy Score* ranges from 0 to 3, where 3 indicates no errors in calculating expected portfolio returns, 2 indicates one type of error, 1 indicates two types of errors, and 0 indicates all three types of errors. The three error types are: (1) misunderstanding probability statements, (2) confusing net versus gross returns, and (3) confusing stock versus risk-free asset investments. *Correct Beliefs* counts the number of accurate posterior estimates (within 5 p.p. of the Bayesian value, maximum = 84). *Bonus Payoffs* represent dollar earnings from performance in both the investment and belief tasks (theoretical bounds from –$1.80 to +$1.80). *Device Type* indicates whether participants used a computer (Windows, macOS, Linux) or mobile device (iOS, Android) based on their operating system. *Recaptcha Score* is a measure of bot detection quality ranging from 0 to 1, with higher scores indicating more human-like behavior.

Table A.6: **Excluded Participants Descriptive Statistics**

Variable	N	Mean	Median	Std. Dev.	Min	Max	Distribution
Panel A: Demographics							
Age (years)	151	27.5	28	6.4	18	42	
Gender (%)	151			—			Female: 52.3% Male: 47.7%
Education (%)	151			—			High School or lower: 14.6% Bachelor's: 53% Master's: 17.9% Other: 14.6%
Panel B: Experimental Measures							
Risk Aversion	151	4,622	5,000	2,425	0	10,000	Amount invested in stock fund ($)
Financial Literacy Score	151	1.75	2	0.96	0	3	Perfect (3): 28.5% One error (2): 25.8% Two errors (1): 37.7% Three errors (0): 7.9%
Comprehension Check	151	0.96	0	1.24	0	4	Correct prior beliefs
Correct Beliefs	151	11.3	11	5.3	1	35	Accurate estimates (max = 84)
Bonus Payoffs	151	0.01	0.00	0.25	-0.72	0.60	Total payoff from investment and evaluation tasks ($)
Panel C: Technical Controls							
Device Type (%)	151			—			Computer: 68.2% Mobile: 31.8%
Recaptcha Score	151	0.95	1	0.11	0.2	1	Bot detection score

Notes: This table reports descriptive statistics for the experimental sample. The sample consists of 151 participants who completed the experimental task but did not obtain at least 5 correct responses in the *Comprehension Check* administered during their second task. In the comprehension check, participants had to state the prior belief about the likelihood of the stock being the good one. *Age* is measured in years. *Risk Aversion* represents the dollar amount (out of $10,000) that participants chose to invest in a risky stock index fund versus a risk-free savings account. The risky asset offers returns of +40% or −20% with equal probability, while the risk-free asset provides a certain 5% return. *Financial Literacy Score* ranges from 0 to 3, where 3 indicates no errors in calculating expected portfolio returns, 2 indicates one type of error, 1 indicates two types of errors, and 0 indicates all three types of errors. The three error types are: (1) misunderstanding probability statements, (2) confusing net versus gross returns, and (3) confusing stock versus risk-free asset investments. *Correct Beliefs* counts the number of accurate posterior estimates (within 5 p.p. of the Bayesian value, maximum = 84). *Bonus Payoffs* represent dollar earnings from performance in both the investment and belief tasks (theoretical bounds from –$1.80 to +$1.80). *Device Type* indicates whether participants used a computer (Windows, macOS, Linux) or mobile device (iOS, Android) based on their operating system. *Recaptcha Score* is a measure of bot detection quality ranging from 0 to 1, with higher scores indicating more human-like behavior.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) used Grammarly, ClaudeAI, and chatGPT in order to improve the readability and language of the manuscript. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

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