Proceedings of the 5th International Conference on Financial Technology and Business Analysis
DOI: 10.54254/2754-1169/2026.38556

After a Rare Extreme Loss: Experimental Evidence on Young Investors' Risk Allocation

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Abstract. Rare and severe market outcomes may influence subsequent financial decisions even when the objective probabilities of a new choice remain unchanged. However, the literature has not reached a consensus on whether extreme losses lead investors to avoid risk or engage in loss-chasing behavior. This study examines how a rare extreme-loss scenario affects subsequent risk allocation among young investors and whether an explicit reminder of outcome independence attenuates that response. A randomized online vignette experiment assigned 162 eligible investors aged 18–35 to a common-gain condition, an extreme-loss condition, or an extreme-loss-plus-reminder condition. Participants allocated RMB 10,000 of new hypothetical funds between a safe account and a risky asset. OLS models with HC3 robust standard errors estimated pre-specified group contrasts. Relative to the common-gain group, the extreme-loss group allocated 17.4 percentage points less to the risky asset (95% CI [−25.2, −9.5], $p < .001$; Hedges' $g = -0.84$). The reminder produced a small and statistically uncertain 3.7-point increase relative to loss alone. The results support immediate cautious carryover within the analyzed sample, but do not identify a unique psychological mechanism or establish that a brief reminder is effective.

Keywords: behavioral finance, extreme loss, risk allocation, randomized vignette experiment

1. Introduction

Rare and severe market losses are often discussed through the language of "black swans" because they can reshape attention to risk and influence behavior beyond the event itself [1]. The present experiment does not reproduce a literal black swan: the tail risk is known and quantified. Instead, it isolates a narrower behavioral question—whether a realized low-probability loss carries over to a separate investment decision whose objective probabilities have not changed. Research in behavioral finance suggests that personal experience can influence beliefs, risk perceptions, and portfolio choices. Poor lifetime market returns are associated with lower willingness to bear financial risk and reduced stock-market participation, with recent experiences receiving greater weight [2, 3]. Crisis-related fear and negative financial information may also promote more cautious financial behavior [4-6]. Yet the direction is not universal. Severe shocks have sometimes increased risk tolerance, and dynamic settings can produce loss chasing [7, 8]. Most existing research has focused on long-term life experiences or actual financial crisis shocks, with relatively little attention paid to brief, recent extreme tail losses and their immediate spillover effects on subsequent independent investment

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DOI: 10.54254/2754-1169/2026.38556

decisions. The literature therefore has not established whether a rare realized loss should reduce or increase risk in an immediately subsequent, independent choice.

This study addresses two questions. First, how does assignment to a rare extreme-loss scenario, compared with a common-gain scenario, affect the share of new funds allocated to a risky asset by investors aged 18-35? Second, does an explicit reminder that the two outcomes are independent attenuate this carryover? A three-group randomized online vignette experiment and pre-specified OLS contrasts are used to answer these questions. The study contributes evidence on immediate cross-decision carryover under unchanged probabilities and provides a bounded test of a simple probability reminder.

2. Literature review and theoretical framework

Standard models often treat risk preferences as stable, but research on experience effects shows that financial behavior depends partly on personally experienced outcomes. Evidence from crises and disasters also suggests that adverse events can lead to more cautious behavior. In financial settings, Cohn et al. primed financial professionals with boom or bust scenarios and reported lower risky investment and greater fear after the bust prime [4]. Guiso et al. using survey and portfolio data around the 2008 financial crisis, documented higher measured risk aversion and stock divestment after the crisis [5]. These studies establish that adverse experience can influence risk taking, but they do not imply one universal direction. Hanaoka et al. used panel data around the Great East Japan Earthquake and found that men exposed to greater earthquake intensity became more risk tolerant, an effect that persisted several years later; no comparable pattern was found for women [7]. The contrast with studies showing greater caution indicates that the nature of the shock, the population, the time horizon, and the decision frame can all matter.

One account predicts cautious carryover. A rare loss is emotionally vivid and easy to retrieve, so it may make another loss feel more imaginable or the risky asset feel more dangerous. This availability-based response need not involve a deliberate numerical change in probability; salience and worry may be sufficient to reduce the willingness to bear risk. Under this account, exposure to an extreme loss should lower the allocation to the risky asset even though the new funds and the next draw are independent. Evidence for an availability response in market data is not guaranteed. Two competing accounts predict a higher risky allocation. First, the gambler's fallacy may lead a decision maker to believe that a rare loss is less likely to occur again immediately after it has occurred. Rabin and Vayanos formalized the mistaken expectation that independent random sequences should exhibit systematic reversals, and Pelster found evidence consistent with gambler's-fallacy and hot-hand predictions in retail trading data [9, 10]. Second, investors may seek extra risk to recoup prior losses. Later work underscores the role of decision framing. Loss chasing thus cannot be inferred from a prior loss alone; whether investors respond cautiously or aggressively depends on whether the loss is realized, whether choices are mentally integrated, and whether the setting is static or dynamic.

Existing research mainly examines cumulative lifetime experience, broad crises, natural disasters, market streaks, or continued positions. The present design addresses this gap by comparing a common prior gain with a realized prior loss, and by adding an independence reminder to the loss condition. Because theory is directionally ambiguous, the study evaluates competing predictions rather than presenting the observed direction as a pre-registered hypothesis:

H1a (cautious-carryover prediction). Participants assigned to the extreme-loss condition allocate a smaller share of new funds to the risky asset than participants assigned to the common-gain condition.

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H1b (aggressive-carryover prediction). Participants assigned to the extreme-loss condition allocate a larger share of new funds to the risky asset than participants assigned to the common-gain condition.

H2 (reminder prediction). An explicit reminder that the prior and current outcomes are independent shifts in allocation in the loss-plus-reminder condition closer to that in the common-gain condition than allocation in the loss-only condition.

3. Methodology

3.1. Design and procedure

The study used a randomized, between-subjects online vignette experiment hosted on Credamo. After reading the study information, respondents indicated informed consent and completed eligibility screening. Eligible participants were aged 18-35, had used real money to invest in at least one financial asset, and had personally made or participated in at least one investment decision. The survey randomly displayed one of three scenarios. In every scenario, participants were asked to imagine that they had invested RMB 5,000 in risky Asset X one week earlier. The asset offered a 95% probability of a 10% gain and a 5% probability of an 80% loss. In the common-gain condition (G0), the earlier investment gained 10%, increasing from RMB 5,000 to RMB 5,500. In the extreme-loss condition (G1), the earlier investment lost 80%, falling from RMB 5,000 to RMB 1,000. The current payoffs and probabilities were identical in all conditions. This structure isolates the effect of the assigned prior-outcome vignette relative to the common-gain comparison. Because G0 contains a positive prior outcome rather than no prior outcome, the design cannot distinguish an absolute loss effect from an absolute gain effect.

3.2. Recruitment, sample construction, and data quality

Data were collected on 28-29 July 2026. The Credamo platform hosted the questionnaire, but its proprietary panel service was not used. A third party distributed the survey link, and compensation was RMB 1.50 per completed response. The resulting sample was a paid convenience sample rather than a probability sample. The platform exported 184 raw responses. Ten respondents were outside the upper age limit and one reported not participating in personal investment decisions, leaving 173 responses that met the platform's core eligibility rules. One participant selected the 26-35 category but entered an exact age of 37 and was excluded from the main sample. Duplicate screening then identified nine clusters whose answers were identical across 29 substantive fields. The earliest completed response in each cluster was retained and ten excess records were removed. Repeated IP addresses alone were not used as an exclusion criterion because they may reflect shared or mobile networks. The final analysis sample contained 162 respondents: 55 in G0, 52 in G1, and 55 in G2. Response speed, comprehension errors, uniform answers across the six mechanism items, and inconsistencies between reported risky and safe amounts were not used as post hoc exclusions from the primary sample. Instead, they were flagged for pre-specified sensitivity analyses. The directly reported risky amount was complete and within range for all 162 observations. When reported risky and safe amounts did not sum to RMB 10,000, the risky amount was retained and the safe amount was reconstructed as RMB 10,000 minus the risky amount. The data were frozen and the statistical analysis plan was locked on 31 July 2026 before the group effects were inspected.

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3.3. Measures

The primary outcome was the share of the new RMB 10,000 allocated to the risky asset:

$$RiskShare_i = RiskAmount_i / 10,000 \quad (1)$$

Higher values indicate greater risk taking. Supporting outcomes included willingness to continue investing in Asset X, concern about another extreme loss, and confidence in the allocation decision, each measured from 0 to 10. Participants also entered their subjective probability, from 0 to 100%, that the asset would suffer the 80% loss in the current round. Six statements, each rated from 1 (strongly disagree) to 7 (strongly agree), measured candidate post-loss responses. Background variables included age group, gender, education, investment experience, review frequency, asset classes, prior substantial loss, self-rated investment knowledge, general financial risk willingness, and a numeracy question. Variables measured after the vignette, including self-rated knowledge and general risk willingness, were not included in the main covariate-adjusted model.

3.4. Statistical analysis

The primary model was an unadjusted OLS regression with G0 as the reference group:

$$\mathrm{RiskShare}_i = \alpha + \beta_1 \mathrm{G1}_i + \beta_2 \mathrm{G2}_i + \varepsilon_i \quad (2)$$

In this parameterization, β_1 estimates G1−G0 and β_2 estimates G2−G0; the reminder contrast G2-G1 is β_2-β_1. HC3 heteroskedasticity-robust standard errors were used. The three-group omnibus test, planned contrasts, 95% confidence intervals, two-sided p values, and Hedges' g are reported. A robustness model added pre-treatment age, gender, education, investment experience, prior substantial loss, asset count, and numeracy, using complete cases.

Secondary outcomes were analyzed with OLS and HC3 standard errors, with Benjamini-Hochberg false-discovery-rate correction across 33 planned secondary contrasts. Ordered logit models were used as supporting checks for ordinal outcomes. Spearman correlations and group-adjusted partial Spearman correlations were exploratory, with false-discovery-rate correction across 36 variable pairs. Exploratory indirect effects were estimated using 5,000 bootstrap resamples. Pre-specified sensitivity analyses excluded responses completed in less than 120 seconds, respondents who failed an applicable comprehension check, respondents who gave identical ratings to all six mechanism items, and records with inconsistent allocation totals. Additional analyses restored the age-inconsistent record, used IP-clustered standard errors, and applied Kruskal-Wallis and Wilcoxon rank-sum tests.

4. Results

4.1. Sample characteristics and comprehension

Table 1 describes the 162 respondents. Most were aged 21-25 (74.7%), male (75.3%), and undergraduates or bachelor's degree holders (72.2%). Investment experience was concentrated between six months and three years (84.6%). Funds or ETFs were the most frequently reported asset class (66.0%), followed by stocks (50.6%) and bonds (45.7%).

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Table 1. Sample characteristics (N = 162)

Characteristic	Category	n	%
Age	18–20	19	11.7
	21–23	52	32.1
	24–25	69	42.6
	26–35	22	13.6
Gender	Male	122	75.3
	Female	39	24.1
	Prefer not to say	1	0.6
Education/status	Undergraduate / bachelor's	117	72.2
	Postgraduate	28	17.3
	Secondary/vocational	10	6.2
	Working/other	7	4.3
Investment experience	< 6 months	12	7.4
	6–12 months	70	43.2
	1–3 years	67	41.4
	> 3 years	13	8.0
Asset class	Stocks	82	50.6
	Funds / ETFs	107	66.0
	Bonds	74	45.7
	Cryptocurrency	26	16.0

Note. Asset classes were multiple-response items; percentages therefore do not sum to 100%.

Recall of the previous outcome ranged from 80.0% to 84.6% across the three groups, while recall of the stated 5% loss probability ranged from 72.7% to 80.0%. Only 28 of 55 G2 participants (50.9%) correctly indicated that the previous outcome had not changed the current objective probability. The loss and gain scenarios were therefore generally recalled, but the independence reminder was not consistently understood. Observed background characteristics were also checked across conditions. Any chance imbalance is addressed as a robustness issue rather than an eligibility rule: the primary estimate remains the unadjusted contrast implied by random assignment, while the complete-case model adds the pre-treatment covariates specified in Section 3.4.

4.2. Primary risk allocation

Table 2 shows a clear reduction in risky allocation after the extreme-loss scenario. The mean risky share was 52.3% in G0 (SD = 20.3), 34.9% in G1 (SD = 20.6), and 38.6% in G2 (SD = 22.2). The corresponding medians were 55%, 30%, and 40%, and the groups' interquartile ranges overlapped. A robust omnibus test nevertheless rejected equality across the three means, $F(2, 159) = 10.57$, $p <$

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.001, R^2 = .114. The confidence intervals around the G1 and G2 means were both below the G0 mean, while the G1 and G2 intervals overlapped substantially.

Table 2. Risky allocation by experimental condition

Condition	n	Mean %	SD	Median %	IQR %	95% CI
G0: Common gain	55	52.3	20.3	55.0	32.5–65.0	46.8–57.8
G1: Extreme loss	52	34.9	20.6	30.0	20.0–50.0	29.2–40.6
G2: Loss + reminder	55	38.6	22.2	40.0	20.0–57.5	32.6–44.6

Note. The outcome is the percentage of the hypothetical RMB 10,000 allocated to the risky asset. Confidence intervals refer to group means.

The primary planned contrast, G1-G0, was -17.4 percentage points (95% CI [-25.2, -9.5], p < .001), equivalent to RMB 1,737 less allocated to the risky asset. The standardized difference was large (Hedges' g = -0.84). This result supports the cautious-carryover prediction H1a over the aggressive-carryover prediction H1b for the average respondent in this sample. The reminder contrast, G2-G1, was +3.7 percentage points (95% CI [-4.5, 12.0], p = .372; Hedges' g = 0.17). Although the point estimate moved toward G0, the interval included both a moderate decrease and a meaningful increase. The result therefore provides insufficient evidence that the brief reminder attenuated the behavioral carryover predicted in H2. G2 remained 13.6 percentage points below G0 (95% CI [−21.7, −5.6], p = .001).

The covariate-adjusted model used 157 complete cases and produced the same pattern. The adjusted G1−G0 difference was −16.4 points (95% CI [−25.3, −7.6], p < .001), while G2−G1 was +4.8 points (95% CI [−4.3, 13.9], p = .294). Because the unadjusted model directly reflects the randomized assignment, it remains the primary estimate.

Table 3. OLS estimates for planned contrasts in risky allocation

Contrast	Unadjusted Δ pp [95% CI]	p	Hedges' g	Adjusted Δ pp [95% CI]	p
G1 − G0	−17.4 [−25.2, −9.5]	< .001	−0.84	−16.4 [−25.3, −7.6]	< .001
G2 − G1	+3.7 [−4.5, 12.0]	.372	0.17	+4.8 [−4.3, 13.9]	.294
G2 − G0	−13.6 [−21.7, −5.6]	.001	−0.64	−11.6 [−20.2, −3.0]	.009
Model N	162			157	

Note. G0 is the reference condition. Estimates are percentage-point differences from OLS models with HC3 robust standard errors. The adjusted model includes pre-treatment age, gender, education, investment experience, prior substantial loss, asset count, and numeracy. Unadjusted omnibus test: F(2, 159) = 10.57, p < .001, R^2 = .114.

4.3. Supporting outcomes and exploratory associations

Supporting outcomes were consistent with a cautious average response. Relative to G0, G1 reported substantially lower willingness to invest in the asset (mean difference -3.18 on the 0-10 scale, 95% CI [-4.04, -2.32], FDR p < .001), greater worry (+2.66, 95% CI [1.67, 3.65], FDR p < .001), and lower decision confidence (-2.13, 95% CI [-3.13, -1.12], FDR p < .001). G1 also reported more vivid loss imagery (+0.73 on the 1-7 scale, FDR p = .019) and greater perceived danger (+1.19, FDR p < .001). By contrast, gambler's-fallacy endorsement did not clearly differ between G1 and G0,

DOI: 10.54254/2754-1169/2026.38556

while loss-chasing endorsement was lower in G1 (-0.83, FDR p = .010). Thus, the secondary outcomes do not support a generalized shift toward aggressive recovery behavior.

Compared with G1, G2 respondents reported lower subjective loss probabilities, worry, and perceived danger in the unadjusted models, but these differences did not remain below the 5% threshold after correction across the full family of secondary contrasts. Behavioral allocation also did not change appreciably. The pattern is compatible with a reminder that affects some stated perceptions without producing a reliably detectable allocation response, but the low reminder-comprehension rate limits this interpretation.

The three-item availability score had modest reliability (Cronbach's alpha = .644 overall and .517 in G0), so it was not treated as a validated mediator. After controlling for the experimental group, risky allocation was positively correlated with investment willingness (partial Spearman ρ = .302, FDR p < .001) and more weakly with gambler's-fallacy endorsement (ρ = .232, FDR p = .011). The partial association with loss-chasing endorsement was borderline after correction (ρ = .183, FDR p = .054), and worry, perceived danger, subjective loss probability, and the availability mean had no stable partial correlations with allocation. All pre-specified bootstrap indirect-effect intervals crossed zero. These analyses provide evidence of associations rather than establishing causal mechanisms.

Table 4. Group-adjusted partial Spearman correlations with risky allocation

Variable	n	Partial Spearman	Raw p	FDR p	Interpretation
Investment willingness	162	.302	< .001	< .001	Positive
Gambler's-fallacy endorsement	162	.232	.003	.011	Positive
Loss-chasing endorsement	162	.183	.020	.054	Borderline
Perceived danger	162	.111	.161	.348	Uncertain
Availability mean	162	.110	.164	.348	Uncertain
Decision confidence	162	.089	.259	.491	Uncertain
Worry	162	−.025	.752	.873	Uncertain
Subjective loss probability	155	−.009	.907	.933	Uncertain

Note. Partial correlations control for G1 and G2 indicators. FDR p values use Benjamini–Hochberg correction across 36 variable pairs. Correlations are exploratory and do not identify mediation.

4.4. Sensitivity analyses

The main loss-versus-gain contrast was stable across the pre-specified checks. Excluding responses completed in less than 120 seconds produced an estimate of -19.4 points (N = 143), and excluding respondents who failed an applicable comprehension check produced an estimate of -27.3 points (N = 93). Excluding uniform mechanism responses or inconsistent allocation totals produced estimates of -17.3 and -18.8 points, respectively. The estimate remained -17.4 points with IP-clustered inference and was -16.4 points after covariate adjustment. In every case, the 95% interval for G1-G0 remained below zero.

Rank-based tests told the same substantive story: the Kruskal-Wallis test showed a three-group difference (p < .001), and the Wilcoxon comparison between G1 and G0 was also significant (p < .001). In contrast, G2-G1 remained positive but statistically uncertain in every sensitivity analysis; the rank-sum p value was .375. Table 5 summarizes the principal robustness results.

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Table 5. Sensitivity of the two principal contrasts

Analysis	N	G1 − G0 Δ pp [95% CI]	p	G2 − G1 Δ pp [95% CI]	p
Primary	162	−17.4 [−25.2, −9.5]	< .001	+3.7 [−4.5, 12.0]	.372
Covariate adjusted	157	−16.4 [−25.3, −7.6]	< .001	+4.8 [−4.3, 13.9]	.294
Exclude <120 seconds	143	−19.4 [−27.9, −10.9]	< .001	+5.0 [−3.9, 13.9]	.268
Exclude check failures	93	−27.3 [−37.1, −17.5]	< .001	+10.6 [−1.4, 22.6]	.082
Exclude uniform items	158	−17.3 [−25.3, −9.3]	< .001	+4.4 [−3.9, 12.6]	.297
Exclude inconsistent totals	132	−18.8 [−27.5, −10.0]	< .001	+7.1 [−2.4, 16.5]	.140
IP-clustered inference	162	−17.4 [−27.8, −6.9]	.001	+3.7 [−4.5, 11.9]	.371

Note. Estimates are percentage-point differences. Exclusion rules were not applied to the primary sample. Rank-based checks also supported G1 − G0 (Kruskal–Wallis $p < .001$; Wilcoxon $p < .001$), while G2 − G1 remained uncertain (Wilcoxon $p = .375$).

5. Conclusion

This study examined whether a rare extreme-loss scenario affects subsequent investment allocation when the objective probabilities of the new decision remain fixed. Among 162 investors aged 18–35 with real-money investment experience, participants assigned to the extreme-loss condition allocated 17.4 percentage points less to the risky asset than those assigned to the common-gain condition. The estimate remained negative and similar across covariate-adjusted, exclusion-based, clustered, and non-parametric analyses. The average response therefore favored cautious behavioral carryover over generalized loss chasing in this sample. The independence reminder did not produce a clearly detectable behavioral correction. Its 3.7-point positive estimate was imprecise, and only 50.9% of reminder-group participants demonstrated correct understanding. The result should be interpreted as insufficient evidence for the effectiveness of this specific brief message, rather than evidence that all probability communication is ineffective. Likewise, post-vignette measures and correlations cannot establish whether availability, worry, probability beliefs, or another process caused the allocation response. The contribution is therefore narrower than a general theory of responses to "black swan" events. The experiment shows that a quantified tail-loss scenario can change an immediate independent allocation, but it does not recreate an unforeseeable market event or determine how long the response persists. It nevertheless helps distinguish a concrete short-run behavioral effect from broader claims about stable preferences and responses to market-wide shocks. Two priorities follow for future research. To improve identification, a replication should include a neutral prior-outcome condition and a stronger, pilot-tested reminder, allowing loss, gain, and debiasing effects to be separated more cleanly.

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