

Research Article

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Failing Despite Knowing. Repeated Decision-Making During Binary Random Sequences with Asymmetric Probabilities

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Abstract: Previous research shows that people often misinterpret randomness, expecting short-term outcomes to balance out, known as negative recency. Most studies have focused on binary events with equal odds (1:1). This study uniquely examines risk-taking behaviour in an asymmetric setup with 2:1 odds. In two studies, we examined risk-taking behaviour of 178 and 55 participants, respectively, across two investment simulations, whereby individuals had to make sequential decisions (10×10 times) about how much money to invest in two kinds of risky shares, alternating randomly over 10 imaginary days: the winner type, with odds 2:1 of winning vs losing, and the loser type, with odds reversed. We analysed correlations of invested amounts with the signed run length and the posterior probability of trading with the "winner" type share, respectively. The first correlation captures the effect of the belief in the run continuing or reversing, and the second one is considered an indicator of economically rational decision-making. Despite the asymmetric setup, 29 and 31% of participants followed maladaptive strategies. Among them, 14 and 7 participants lost all their money before the simulation ended. These findings underscore the detrimental impact of negative recency, leading to significant financial losses and reduced gains.

Keywords: sequential decision-making, risk-taking, uncertainty

1 Introduction

Imagine that you flip a fair coin repeatedly. It has landed on heads four times in a row. On what would you bet next: heads or tails? Although the coin tosses are independent random events and the probability is always the base rate, $\frac{1}{2}$, we are still susceptible to choosing tails after several heads. This phenomenon is called the gambler's fallacy (GF) or negative recency: the belief that the same outcome cannot persist, and the longer a run continues, the more likely it is to end.

People tend to misinterpret random events in statistical terms (Falk et al., 2009; Nickerson, 2002; Oskarsson et al., 2009). Oskarsson et al. (2009) reviewed risk-taking after random or nearly random events in various areas. One of the most consistent findings is that people misinterpret random events in statistical terms. Two contradictory heuristics can be identified after consecutive random events. While "positive recency" believes in the continuation of the series, "negative recency" believes in its interruption. The latter

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is a manifestation of the law of small numbers: the belief that realisations of an independent and identically distributed random variable counterbalance each other even in the short term, hence longer positive or negative runs consequently discontinue and the subsequent outcome reverses. This belief in symmetric random binary events with a 50–50% chance is known as the GF.

Previous research consistently highlights the robustness of the GF across diverse contexts, including real financial markets, where investors frequently misinterpret random price sequences, incorrectly anticipating reversals after brief streaks and continuations after extended ones (Pelster, 2020). Empirical evidence for the GF emerges both from real-world scenarios (Chen *et al.*, 2016; Clotfelter & Cook, 1993; Terrell, 1994) and controlled laboratory experiments (Ayton & Fischer, 2004; Bar-Hillel & Wagenaar, 1991; Burns & Corpus, 2004; Rao & Hastie, 2023; Sun & Wang, 2010; Sundali & Croson, 2006).

In a foundational study, Leopard (1978) studied risk-taking over a series of independent decisions as a function of outcome history and financial situation. Specifically, she examined the choices of university students over 250 rounds of fair coin tosses in a computer simulation. However, participants were only able to choose the side of the coin and not the amount to be bet, as this was predetermined. It meant that they were not able to influence their risk-taking actively, and it also resulted in very different levels of wealth among participants. Ball (2012) developed Leopard's experiment further by manipulating the financial situation of the participants and keeping it within the same range. GF appeared in both studies: Leopard identified 8 individuals (from 40 participants), and Ball found 7 (from 60 participants) with negative recency. While Leopard only detected patterns of risk preferences through visual inspections, Ball managed to support results with significant statistical analyses as well.

What is the reason for this phenomenon? According to the representativeness heuristic, people consider small samples to be too similar to the entire population from which they are derived (Tversky & Kahneman, 1974). They also assume that small variations from the average in the samples balance each other out. The Law of Small Numbers (Rabin, 2002; Tversky & Kahneman, 1971) explains the belief in reversal by people's expectation that even short series should be representative of the population. For example, 5 consecutive heads during fair coin tossing are not representative of a 50–50% chance event, so people expect a tails to be followed to offset the occurrence ratio and to be more representative (Bar-Hillel & Wagenaar, 1991). Random processes follow their own laws, but longer time and larger sample size is necessary for them to be met. According to the law of large numbers, the relative frequency of the number of heads reaches 50% at infinity, but one expects the same from a much shorter series. However, the law of large numbers does not necessarily apply to small samples, as they are much more variable.

Previous research investigated negative recency during random events with a 50–50% chance (gamblers' fallacy). But what happens if we flip an unfair coin? It is biased to one side, and thus, the probability of heads or tails is not 1:1. We can then deduce which is the more likely side after more tosses. The longer the run of heads is, the more likely it is that the coin is biased to heads. Although the probability of heads is constant, the assessed probability of landing on heads changes depending on the previous outcomes. Rationally, one should bet on the side which has the higher assessed probability.

In the following simulation, we alter from the 1:1 odds and apply the biased coin-tossing design with 1:2 odds in the context of an investment simulation game. Thus, we examine sequential decision-making under uncertainty with not a 50–50% chance, but during asymmetric binary sequences. By deviating from 1:1 odds, it becomes evident that investing in the losing option is disadvantageous – in an extreme case, such as 1:10 odds, no one would invest after a decline. Conversely, in situations very close to 50–50 (e.g., 51:49), individuals struggle to discern the winning option. The choice of 2:1 odds allows a clear, yet challenging distinction from symmetric (1:1) scenarios.

Sequential decision-making in uncertain environments typically requires individuals to adapt their behaviour based on past outcomes, an adaptive process extensively discussed in theories of dynamic decision-making (Gonzalez, 2022). This principle also applies here: analogous to the biased coin toss game, a quickly interpretable winning approach exists: to increase the investment amount to the extent to which you believe a winner's share is being traded. Bayes' theorem can be applied to calculate the exact likelihood, which is the posterior probability of trading with a winner share. This determines the rational strategy. This simulation design enables rational normative behaviour to be contrasted with actual risk-taking. However, if one believes that after several price declines, price increases would follow, and therefore one increases one's invested amount, or conversely, reduces the invested amount after price increases, one acts according to negative

recency. This clearly contradicts the dominant winning strategy. Therefore, we could expect no one or at least fewer individuals to follow negative recency in such a setting compared to previous 1:1 studies.

A close analogue to this shift from 1:1 to 2:1 odds is observed in Rao and Hastie's (2023) progression from Study 2A to 3A. In Rao and Hastie's (2023) study, participants encountered binary sequences generated by a random mechanical device, with explicit knowledge of the base rates. Initially, under symmetric conditions (0.50 base rate), the GF was evident. However, in a modified experiment with asymmetric base rates (0.25 and 0.75), the prevalence of GF significantly decreased, with only 4–14% of participants consistently exhibiting negative recency strategies. The observed reduction in GF prevalence under asymmetric conditions suggests that participants adjust their predictive strategies when provided with explicit, skewed base rate information. This modified experiment closely aligns with our simulation, which also employs skewed base rates (0.33 and 0.67).

Our study addresses the following core question: Do participants rely on the maladaptive heuristic of negative recency even in environments where the underlying probabilities are asymmetric (2:1 or 1:2)? Our hypothesis is that the proportion of individuals exhibiting negative recency behaviour under asymmetric (2:1) odds is equal to or less than the proportion observed in previous studies using symmetric (1:1) odds (15% did so in Leopard's and Ball's studies).

The following simulation was designed to grasp negative recency after asymmetric probability events by exploring the deviation from the normative economic models of rational decision-making. However, we will not analyse positive recency, as in this simulation it coincides substantially with normative rational behaviour, and thus, this simulation is not the proper tool for detecting this bias.

Previous research (Barberis et al., 1999; Thaler 1985; Thaler & Johnson, 1990) has already shown that gains and losses in previous periods influence risk-taking in consecutive periods. Making gains increases risk-taking (the “house money” effect) while making losses increases risk aversion (the break-even effect). When we raise our risk after a series of gains, it is difficult to make precise distinctions. Do we do so because we believe that the price increases will continue, or because it is harmless playing with “house money”? Which one influences our risk-taking – the previous period's outcomes or our new financial situation? In our study, we focus on the impact of previous price changes (outcome) on decision-making, and not on the effect of profits made (financial situation). In our interpretation, outcome refers to the history of events: on the financial markets, this means price increases or decreases, and not gains or losses that have been made.

The representativeness heuristic exists irrespective of how much people know about this phenomenon (Tversky & Kahneman, 1971). Williams and Connolly (2006) found that those who had learned about statistics and the calculation of probability provided significantly better answers to questions related to these areas, but when they had to apply them, there was no significant difference between the two groups in the performance of these tasks. Engländer (1999) also demonstrated that even mathematicians failed to bet an equal amount on the same probability game because the independent events were presented in a different order.

Empirical studies in financial settings provide consistent evidence of irrational decision-making patterns like the GF. Investors often increase their risk exposure based on incorrect beliefs about price reversals, even in professional trading environments (Pelster, 2020).

We also explore the extent of knowledge and the range of skills our participants possess that may contribute to this bias.

2 Method of Simulation 1 – Virtual Incentive Condition

2.1 Participants

In the first simulation, we examined the risk-taking of 178 volunteers (113 males) between the ages of 18 and 71, $M = 25.88$ ($SD = 8.90$). Individuals were not rewarded for participation, except for detailed individual feedback. The simulation was advertised on the campus of a University of Economics and on Facebook.

The rationale behind the sample size was shaped by both methodological and practical considerations. Based on prior findings from symmetric-odds studies (Ball, 2012; Leopard, 1978), which reported an approximate 15% prevalence of negative recency, we aimed to recruit 196 participants in order to estimate the expected proportion with 5% absolute precision at a 5% significance level. However, the largest feasible sample size within the allocated timeframe resulted in 178 participants.

The Institutional Review Board of Eötvös Loránd University approved the study design. Written informed consent was obtained from all participants before the simulation procedure began.

2.2 Questionnaire

Participants applied to take part in the simulation by filling out an online questionnaire. Apart from primary demographic data (age, gender, education), we asked applicants about the following usage behaviours: online trading, poker, strategic games (computer or board games), and sports betting. Questions were also asked about the number of semesters the respondents had spent studying statistics and probability theory.

2.3 Simulation Procedure

Our investment simulation represents a dynamic decision-making context, aligning with Gonzalez's (2022) characterization of environments where individuals repeatedly make interdependent decisions, adapting continuously based on outcomes. The procedure was based on Kuhnen and Knutson's simulation (2011) in which participants had to invest their money either in riskier equity or a risk-free bond and had to estimate the probability of whether a good or a bad share was being traded. As illustrated in Figure 1, our participants decided 10 times on 10 imaginary days how much to buy of an unknown kind of risky share, whose price was

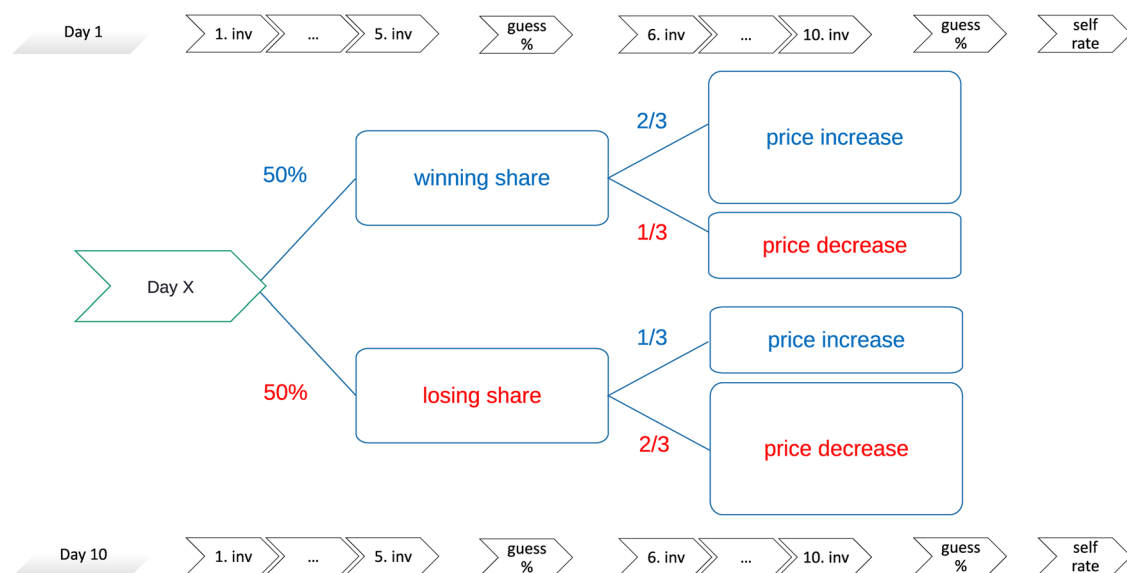


Figure 1: Process of the Investment Simulation with the probability of trading with a winner or loser share and the probability of the share's price changing. Note: inv = decision about the amount to be invested; guess = assessment of the probability of the winner or loser share being traded; self-rate = assessment of self-performance in the simulation.

more likely to increase (winner share) or more likely to decrease (loser share). If the share price went up, then the invested amount doubled; otherwise, the same amount was lost.

Throughout the day, either a “winner” or a “loser” share was traded. The odds of the “winner” share price increasing vs decreasing were 2–1, whereas the odds of the “loser” share changing in price were the opposite, 1–2 (price increase vs decrease), as can be seen in Figure 1. Over the whole day (10 investment decisions), the probability of the share price increasing or decreasing remained constant: either one-third or two-third. However, the winner and loser shares did change randomly (50–50%) day by day. All participants encountered the same price change sequence throughout the simulation (Section 2.5).

The participants received continuous, immediate feedback on the results of their investments and the share price changes in the previous period. The more frequently the share price increased on a given day, the higher the probability was that a winner share was being traded. This way, participants were able to learn whether the “winner”- or the “loser”-type share was being traded throughout the 10 decision days. Furthermore, the mathematical probability of trading with the winner share can be calculated from the number of price increases and decreases based on Bayes’ theorem.

In the middle of the day (after five decisions) and at the end of the day (after ten decisions), they assessed whether they had been trading with the “winner” or the “loser” share and at what probability. At the end of the day, they also assessed their own performance in the simulation on a 10-point Likert Scale, though these days were only virtual barriers for the different shares, and participants performed trading on each of the days jointly.

Our simulation incorporated continuous visual feedback about outcomes, consistent with findings that visual cues substantially impact probability learning and the chosen decision-making strategies in binary decision environments (Bagherzadeh & Tehranchi, 2023). All probabilities (1:2 and 2:1 price change odds, and 50–50% for the type of share) were explicitly presented to the participants who could thoughtfully examine them for as long as they needed. The simulation was not a zero-sum game; each participant’s returns were independent of others. Participants began with fixed initial assets and could either accumulate or lose wealth across trials. Investments were made continuously, allowing participants to freely choose any amount from zero up to their current assets. Participants received explicit information that each day’s trials involved fixed probabilities (either 2:1 or 1:2), clearly communicated before commencing the simulation. They were not informed of the share type (winner or loser) beforehand, requiring them to infer this through trial outcomes. They did not receive direct visual indications (e.g., arrows) but received textual feedback in red (loss) or blue (gain) following each decision, clearly illustrating outcomes. Complete participant instructions, including explicit statements provided before the simulation, are fully documented in Appendix 2.

Before the simulation, investors had the opportunity to test the program for 2×10 investments with both the winner and the loser share to ensure that they understood the instructions and could also address their questions to the instructors. The simulation was a computer program written using Visual Basic, which took approximately 20–35 min on average.

2.4 Motivation of the Participants

In the first simulation, the gains and losses were only virtual, and the final net profit was not paid to the 178 participants at the end of the game.

In the first simulation, people were introduced to a background story to think more thoroughly about their decisions. In the background story, the participant was living in modest conditions with a family of four, and the only opportunity to improve their living standards was to invest an inheritance of 20 million HUF (1 USD = 300 HUF). As no credit was available, bankruptcy could also occur, and the game could finish at any time. The living standards relating to investors’ actual wealth were continuously updated on the screen and broken down into detailed categories in HUF after each investment decision. At the end of the simulation, participants answered to what extent (1–7 Likert scale) they considered their living conditions during decision making.

2.5 The Price Change Sequence

To achieve a symmetrical distribution of price change frequencies across the simulation, we generated a 5-day random sequence under 1:2 odds and then inverted these outcomes for the subsequent 5 days. This method ensured that, overall, the frequency of price increases and decreases was balanced, thereby facilitating a controlled comparison between share types. Frequency distributions of price changes for winner- and loser-type shares are demonstrated in Table 1.

The signed run length of price change is the number of consecutive price increases or decreases. Thus -2 means two subsequent price decreases while $+3$ means three subsequent price increases. During the simulation, shorter runs occurred more frequently, and in only about a quarter of the cases did the run length exceed two. These longer runs occurred with the corresponding shares: price increases with winner shares and price decreases with loser shares (with only two exceptions, Table 1). As a result of the simulation setting, the price of the winner shares mostly increased, while that of the loser shares mostly decreased.

2.6 Measurement of Rational and Recency Heuristic Behaviour

To analyse the risk-taking behaviour of the individuals, we measured participants' invested amount (HUF). The more they invested, the more risk they took. The measure of risk-taking was defined as the invested amount.

In order to quantify the degree of rational and recency heuristic behaviour we used Pearson's linear correlation measure of the invested amount with posterior probability and signed run length, respectively.

As there was no information about the previous price change at the start, the very first investment of each day was excluded from the analyses. Thus, out of 100 decisions, we only used 90 for correlation analysis. Given our sample size ($n = 90$), normality assumptions for Pearson correlations are asymptotically met. We also verified robustness using Spearman rank correlations, which yielded consistent findings. A power analysis indicated that using 90 decisions for the correlation analysis provided 83% power to detect a medium effect size ($r = 0.3$) with a two-tailed test at $\alpha = 0.05$. Thus, our sample was sufficiently powered to identify meaningful individual-level correlation differences. We used a significance level of 5% as a rule-of-thumb cut-off to identify potential negative recency individuals. The significance threshold is applied merely as a heuristic classification aid to group participants based on the strength and direction of their correlation.

2.6.1 Measurement of Rational Behaviour

We defined the normative risk-taking strategy according to economic rational behaviour. Our model is framed in utility maximization under limited wealth, assuming risk-averse propensity (see Appendix 1). This strategy explicitly models utility maximization under realistic constraints, incorporating a finite initial wealth and potential bankruptcy scenarios. The expected utility theory (EUT) with a logarithmic utility function inherently accounts for diminishing marginal utility and bankruptcy avoidance.

First, we calculated the mathematical probabilities for each round. Before the first investment of the days' probability of trading with the winner share, $P_{\text{prior}}(\text{winner})$ is 50%. The first prior is thus 50%, and by utilising

Table 1: Frequency of run length of the share price change in the investment simulation

Signed run length of share price change	-5	-4	-3	-2	-1	1	2	3	4	5	Total
Winner shares			1	2	12	14	10	6	3	2	50
Loser shares	2	3	6	10	14	12	2	1			50
Frequency	2	3	7	12	26	26	12	7	3	2	100

Note: Signed run length of price change = number of identical consecutive price increases or decreases.

the information from the price changes, the posterior probability can be calculated using Bayes' theorem. In case of a price increase (+), the posterior probability of trading with a winner share:

$$P_{\text{posterior}}(\text{winner}|+) = \frac{P_{\text{prior}}(\text{winner}) \times P(+|\text{winner})}{P(+)} = \frac{50\% \times 2/3}{(50\% \times 2/3) + (50\% \times 1/3)} = 67\%. \quad (1)$$

This formula can be applied to the rest of the series, retaining the posterior probabilities of trading with the winner share at each decision point.

We determined the normative risk-taking of the rational investor in the case of a commonly used risk-averse propensity. Assuming constant relative risk aversion and a utility function $\ln(x)$, the solution to the utility maximization of the investment decision is the function of the posterior probability of trading with the winner-type share (Appendix 1). This means that the higher the posterior probability, the more the investor should invest in the share according to the normative economic model. With the purpose of evaluating the similarity between the participant's actual risk-taking and the normative, economic rational investment strategy, we calculated the correlation between the invested amounts and the posterior probability. The more it correlated with the participant's invested amounts, the more rationally the participant behaved.

To control for the impact of wealth, we calculated the partial correlation between invested amounts and signed run length, removing the effect of wealth.

2.6.2 Measurement of Recency Heuristic Behaviour

Correlating the invested amounts with signed run length (−2 for two successive decreases) indicates how much the participant believes in the continuation or the reversal of the run. A positive correlation means that after several price increases, people will invest more, and after price decreases, they will take fewer risks. Owing to the simulation's design, this coincides reasonably with an optimal (rational) investment strategy. Conversely, negative correlation implies negative recency: once participants are faced with several price decreases, they will increase their investment, but after several price increases, they will take fewer risks. This is clearly not an optimal strategy.

To test whether someone is more susceptible to recency after price increases or decreases, we calculated the correlations for winner- and loser-type shares separately.

3 Results of Simulation 1 – Virtual Incentive Condition

3.1 Distribution of Participants Following Rational and Recency Heuristic Behaviour

One hundred and twenty-two participants succeeded in increasing their wealth from the starting account, but 25 participants (14%) had to finish the simulation before the end as they lost their entire wealth.

Different risk-taking strategies could be distinguished based on the sign and magnitude of the correlations of the invested amount with (1) signed run length and (2) posterior probability. Table 2 shows the number of individuals who followed either the heuristic of positive or negative recency (reflected in the correlations with the signed run length of the price change) and the rational investment strategy (reflected in the correlations with the posterior probability of trading with a winner share). The results of the two measurements partly overlap but also differ from each other to some extent.

While a significant negative correlation with signed run length revealed evidently negative recency, a significant positive correlation was unclear as to what extent it had been a sign of positive recency or investing in proportion to rational economic strategy, as mentioned before.

Table 2: Number of participants following the recency heuristic or rational behaviour based on different correlation measurements in the first simulation

Pearson linear correlations of risk-taking	r	Partial r	r_{winner}	r_{loser}
With signed run length: indicates recency heuristic				
Significant negative	51 (29%)	57	54	70
Insignificant	69 (39%)	80	112	91
Significant positive	58 (32%)	41	12	17
With posterior probability: indicates normative rational behaviour				
Significant negative	21 (12%)	26	12	41
Insignificant	51 (29%)	58	118	89
Significant positive	106 (59%)	94	48	48

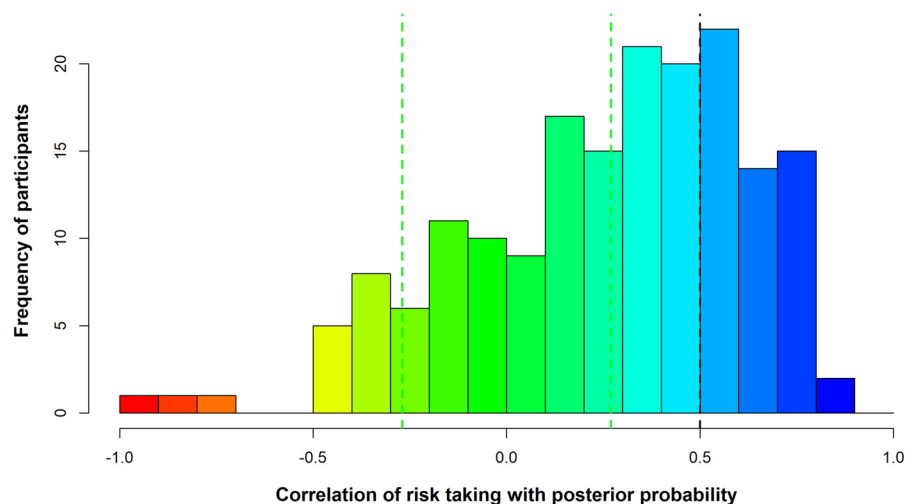
Notes: r = Pearson linear correlation between risk-taking (invested amount) and second variable; Partial r = Partial correlation controlling for wealth; $r_{\text{winner}} = r$ calculated when the winner share type was being traded; $r_{\text{loser}} = r$ calculated when the loser share type was being traded.

The negative correlation between the invested amount and the signed run length indicates that 51 participants followed negative recency. These 29% (95% CI: 22–36%) of the participants invested according to negative recency. Of these, 14 lost all their money before the end of the simulation. When monitoring for the effect of wealth, we identified a total of 57 investors who followed negative recency. More people were prone to the heuristic with winner-type shares than with loser-type shares.

The 57 participants' investment showed significant positive correlations with the signed run length, and 41 did so after monitoring for wealth. This was more common in the case of loser-type shares than in the case of winner-type shares.

Between those with significant negative and positive correlations, there were 69 people who either followed the recency heuristic but with less intensity or whose strategy was independent of both principles.

Apart from the 21 (12%) participants who invested in the opposite way to the normative model, the behaviour of most people was not particularly irrational. Almost half of them invested according to the rational economic model to some extent ($r > 0.3$). However, correlation with the posterior probability was moderate; for only 30% of the participants did it exceed 0.5, and for no more than 1% of participants was it above 0.8 (Figure 2). After controlling the effect of wealth, irrational behaviour was revealed by 26 (15%) participants, mainly when trading with the loser share.

**Figure 2:** Frequency distribution of correlation of risk taking with posterior probability in Simulation 1. Notes: green line indicates significant positive correlation ($r = 0.27$) on a 5% level; black line indicates stronger correlation ($r = 0.5$).

3.2 Risk Taking of Participants Followed Negative Recency

As can be seen in Figure 3, negative recency individuals invested more after price decrease runs, but less after price increase runs. The longer the consecutive price increases continued, the more the invested amount decreased.

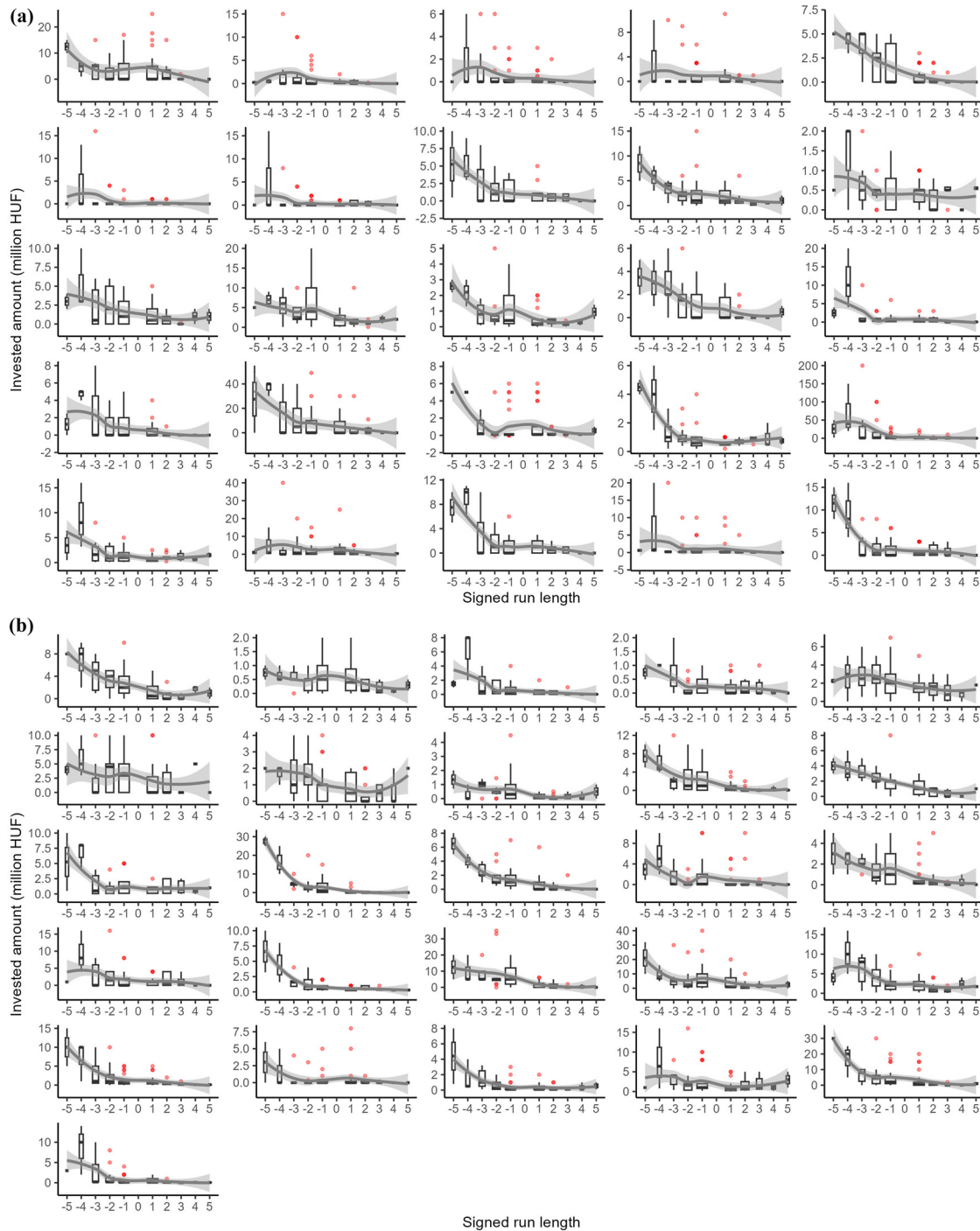


Figure 3: Negative recency participants' invested amount after signed run length of share price changes (in million HUF) on the individual level in Simulation 1. (a) First 25 participants; (b) second 26 participants.

Depending on where the negative correlation stems from, different patterns can be grasped. The majority of individuals increased their risk taking after price decreases more than they decreased their risk taking after price rises; thus, the reversal after price increases was less pronounced. However, since investors could not buy shares for less than zero, negative recency behaviour after price increases was constrained.

When the negative association between risk taking and signed run length is similar both after the price increase and decrease runs, the smooth line is a negative straight line, and its steepness depends on the degree of the correlation. Nevertheless, few individuals increased the invested amount linearly with the number of price decreases. In most of the cases there was a spike after three.

3.3 Comparing Negative Recency Participants to the Rest

First, we tested whether individuals perceived the occurrences correctly and whether they assessed the type of share adequately. We examined how participants observed the probability of trading with the winner type of share (“Which type of share was being traded? 100% to winner share, 0% to loser share – by 10%”). As can be seen in Table 3, investors assessed the probabilities quite well on average. Except for four cases, there was no significant difference in assessed probabilities between those who showed the fallacy of negative recency and the rest ($p > 0.05$) (Table 4). As this group was not less accurate at estimating the shares’ type, the differences in risk-taking strategy between these groups could not be explained by different assessment abilities.

Table 3: Posterior and mean assessed probabilities of trading with the winner share at the middle and end of the day

Day	Number of price increases (mid)	Number of price increases (end)	Posterior P (mid) [%]	Posterior P (end) [%]	Mean assessed P (mid) [%]	Mean assessed P (end) [%]
1	4	7	89	94	84	86
2	3	6	67	80	60	71
3	1	3	11	6	14	10
4	2	5	33	50	32	38
5	1	1	11	0	16	4
6	2	4	33	20	36	20
7	4	9	89	100	80	94
8	3	5	67	50	60	45
9	1	3	11	6	15	11
10	4	7	89	94	81	87

Notes: mid = middle of the day; after five investment decisions; end = at the end of the day; after ten investment decisions; P = probability.

Table 4: Independent sample t -tests comparing assessed probabilities between participants exhibiting negative recency and the rest

Day	p (mid)	p (end)	t (mid)	t (end)	df (mid)	df (end)	d (mid)	d (end)
1	0.21	0.23	−1.24	−1.19	176	175	−0.21	−0.20
2	0.65	0.01	−0.46	−2.62	175	175	−0.08	−0.43
3	0.45	0.72	−0.75	0.36	175	173	−0.12	0.06
4	0.18	0.03	−1.34	−2.15	171	171	−0.23	−0.37
5	0.94	0.73	−0.08	0.35	170	164	−0.01	0.06
6	0.74	0.27	0.33	1.11	159	157	0.06	0.20
7	0.19	0.31	−1.33	−1.01	157	157	−0.24	−0.19
8	0.01	0.00	−2.64	−4.59	157	155	−0.49	−0.85
9	0.62	0.61	0.50	−0.51	155	153	0.09	−0.10
10	0.50	0.64	−0.67	−0.47	153	151	−0.13	−0.09

Notes: mid = middle of the day; after five investment decisions; end = at the end of the day; after ten investment decisions; p = p -value of t -statistic, t = test statistic, df = degrees of freedom, d = Cohen’s d effect size.

We found no gender ($\chi^2(2) = 3.11, p = 0.08, N = 178$), age ($F(1,176) = 0.61, p = 0.44$) or education ($\chi^2(3) = 2.62, p = 0.45$) differences between those who followed the heuristic of negative recency and those who did not; neither was there any difference in how many courses they completed in statistics or probability theory ($r_s = 0.04, p > 0.05$). There was no relationship between how much someone read about statistics or probability in his/her free time and how well they performed in the simulation – as enumerated by the correlation between run length and risk-taking ($r_s = 0.05, p > 0.05$).

There was a weak relationship between engaging in poker ($r_s = 0.30, p < 0.05$) and sports betting ($r_s = 0.21, p < 0.05$), and negative recency. Those who were more susceptible to negative recency played more poker or bet more on sports than those who were not. We did not find any significant differences in the use of online trading or strategic games ($p > 0.05$).

3.4 Motivation and Self-Assessment of the Participants

The majority of the participants (82 or 46%), however, weren't influenced by their living conditions at all; they just considered the sole value of gains and losses. This was even more so the case with the negative recency group. They considered the gains and losses more than the rest of the participants and valued less their standard of living. ($r_s = 0.15, p < 0.05$). Only a few participants (12 or 7%) indicated a higher preference for the background story. Those who behaved more irrationally during the simulation were more dissatisfied ($r_s = 0.27, p < 0.01$) and felt less good ($r_s = 0.27, p < 0.01$) at the end.

This suggests that the background story did not influence participants' decision-making, as they only considered the actual value of gains and losses. However, reported unpleasant feelings (sadness and dissatisfaction) among those who performed poorly in the simulation can support the assumption that they nevertheless took the simulation seriously. To dispel such doubts, we repeated the simulation without the background story but with real money.

4 Method of Simulation 2 – Real Incentive Condition

To address concerns about whether participants took the simulation seriously in the absence of real stakes in Simulation 1, we conducted Simulation 2 with actual financial incentives, removing the hypothetical narrative scenario. This confirmed that negative recency effects observed initially were not artefacts of low participant motivation.

In the second simulation, 55 volunteers (24 males, 15 females, 16 NA) participated between the ages of 18 and 63, $M = 26.81$ ($SD = 10.04$).

Simulation 2 was designed as a real-stakes replication to test whether negative recency effects persist under monetary incentives. Due to financial and logistical constraints inherent to incentivized research, the sample size was limited to 55 participants.

Participants could invest 2 USD in their home currency, which had been given to them in advance. At the end of the simulation, the final net profit was paid. Apart from removing the background story (Section 2.4) simulation procedure (Section 2.3) and the price change sequence (Section 2.5) were identical to those in Simulation 1.

5 Results of Simulation 2 – Real Incentive Condition

5.1 Distribution of Participants Following Rational and Recency Heuristic Behaviour

The distribution of participants indicating rational and recency heuristic behaviour shows a very similar shape to that in the first simulation (Figure 4).

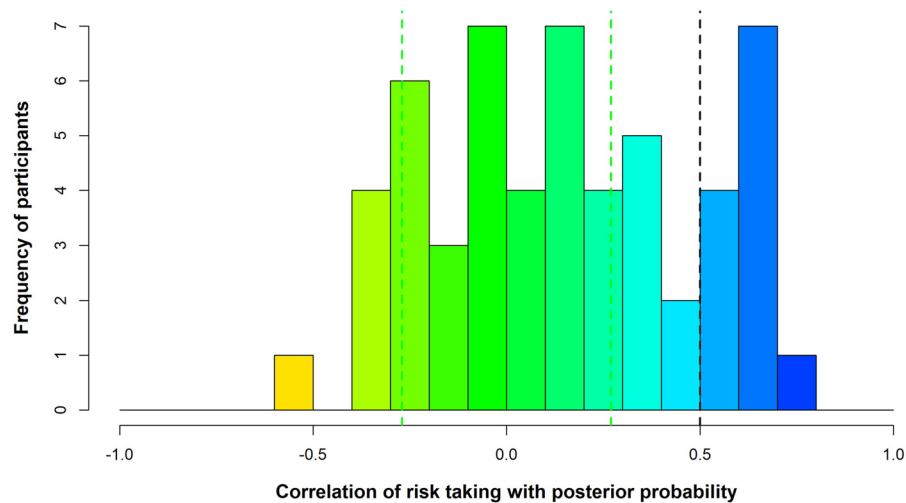


Figure 4: Frequency distribution of correlation of risk taking with posterior probability in Simulation 2. Notes: *green line* indicates significant positive correlation ($r = 0.27$) on a 5% level; *black line* indicates stronger correlation ($r = 0.5$).

Seventeen participants (31%; 95% CI: 19–45%) exhibited the negative recency, and 7 (13%) lost their entire fortune before the end of the simulation (Table 5).

5.2 Risk Taking of Participants Followed Negative Recency

Despite the increased probability of winning, these participants failed to exploit the low-risk profit opportunities following price increases. They also raised their risk-taking after several share price decreases in the losing series, which then led to severe losses owing to the increased probability of losing (Figure 5).

5.3 Comparing Negative Recency Participants to the Rest

Interestingly, they were again aware that they had invested in the “loser-type” share.

Table 5: Number of participants following the recency heuristic or rational behaviour based on different correlation measurements in the monetised investment simulation

Pearson linear correlations of risk-taking	r	Partial r	r_{winner}	r_{loser}
With signed run length: indicates recency heuristic				
Significant negative	17 (31%)	20	19	23
Insignificant	27 (49%)	26	36	29
Significant positive	11 (20%)	9	0	3
With posterior probability: indicates normative rational behaviour				
Significant negative	9 (16%)	11	3	14
Insignificant	24 (44%)	23	43	33
Significant positive	22 (40%)	21	9	8

Notes: r = Pearson linear correlation between risk-taking (invested amount) and second variable; Partial r = Partial correlation controlling for wealth; $r_{\text{winner}} = r$ calculated when the winner share type was being traded; $r_{\text{loser}} = r$ calculated when the loser share type was being traded.

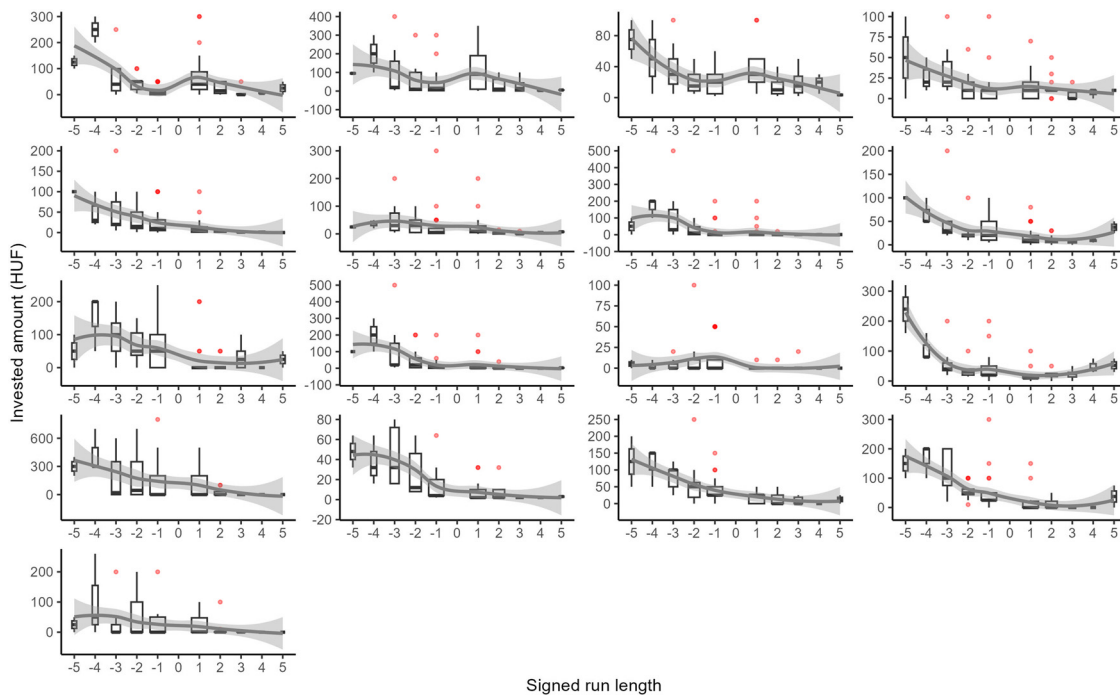


Figure 5: Negative recency participants' invested amount after signed run length of share price changes (in HUF) on individual level in Simulation 2.

6 Discussion

Sequential risk taking was examined in a dynamic, learning environment where participants empirically experienced uncertainty while actively making decisions based on the immediate feedback of their investments. Despite the perceivable asymmetric probabilities, in the first simulation, altogether 51 of the total 178 participants, and in the second simulation, 17 out of the total 55 followed the heuristic of negative recency. Even though participants were aware of the type of shares being traded, they made a financially disadvantageous choice. Among the 25 investors who lost all their money in the first simulation, 14 invested along with this heuristic, which highlights the noteworthy negative consequences of this maladaptive behaviour.

Previous research focused mainly on symmetric random events such as coin tosses or casino events. Ball (2012) and Leopard (1978) applied random-like coin tosses with explicit 50–50% balanced probabilities. In their experiments, 11 and 20% respectively of the participants showed signs of the GF. In these cases, GF was only a misbelief and did not necessarily lead to an increased risk of losing. Betting on tails after several heads does not decrease our chances of winning compared to betting on heads. However, when the coin is biased, acting in line with negative recency turns out to be much more harmful. It was therefore surprising that in our simulation, where asymmetric probabilities were applied (1:2 odds), still 29% (95% CI: 22–36%) of the 178 participants and 31% (95% CI: 19–45%) of the 55 participants invested according to this maladaptive strategy. Thus, we rejected the hypothesis that in binary games with asymmetric odds such as 1:2, fewer or none of the participants exhibit negative recency behaviour compared to previous studies with 1:1 odds, where 15 out of 100 did so (as observed in Leopard's and Ball's studies). In such an asymmetrical situation, negative recency contradicts rationality even more.

Thaler and Sunstein (2008) argue that real-world decision-making often occurs in environments of asymmetrical risk. Asymmetric probability distributions capture better decisions in real life under risk and uncertainty and have higher ecological validity. They can also model better stock price trends, when the market is either bullish or bearish (rising and falling market prices). In the current simulation, we used constant

asymmetric probabilities for increasing and decreasing price changes (1/3–2/3), which represents odds of 1:2. Such uneven distribution allowed investors to learn whether the winner or the loser type share was being traded. The more frequently the share price increased on a given day, the higher the probability was that a winner share was being traded. Investors could have even calculated the exact posterior probabilities from the provided information, but at best intuitively identified it through the continuous immediate feedback after each investment decision.

On average, participants identified the type of share correctly both at the end of the day and in the middle of the day (Table 3). This implies that participants were aware of the situation throughout the trading period. Thus, the disadvantageous decisions cannot be attributed to a misperception of winning probabilities. There was no significant difference in 80% of the cases between how negative recency participants assessed the probabilities of trading with the winner share and the rest (Table 5).

When they knew that a loser type of share was being traded, why did a substantial number of people still increase their invested amounts after a price decrease runs? Furthermore, why did they fail to exploit low-risk opportunities when a winner-type share was being traded? It appears that they still believed that the price decrease or increase runs would reverse, and this misbelief overrode the dominant winning strategies. This is in line with Kahneman and Tversky's work on the law of small numbers (Tversky & Kahneman, 1971), which demonstrated that people often believe in reversals in independent random sequences, even when these beliefs lead to maladaptive financial behaviours. The belief in the law of small numbers proved to be stronger than rational behaviour.

So why cannot people tolerate long runs in random sequences? Longer identical outcomes do occur also in random processes: five coin tosses, for example, result in five consecutive heads once in 32. Since such series are deemed to be rare and unique, this may explain why their occurrence is not considered representative enough. Yet a series of five heads is just as probable to occur as any other series of five. It's just more striking, it is more organised, it's easier to remember as the information can be compressed. We do not remember or differentiate alternating sequences (Sun & Wang, 2010).

Then we can address the question as to whether those who are more experienced in probability theory and statistics and have learned about randomness, may understand it better and can perform better in related tasks. If we compare the formal education of the negative recency group to that of others, our results support research by Tversky and Kahneman (1971), Williams and Connolly (2006), Engländer (1999), which states that knowledge of statistics and probability theory does not stop people from behaving according to this heuristic. It did not matter how many such courses participants had completed, nor how much they had read about the topic in their free time; education did not prevent them from exhibiting negative recency in their choices. The persistence of such biases, despite education and experience, indicates that simply informing individuals about probability and risk is insufficient to alter behaviour in real-world contexts (Gonzalez, 2022; Thaler & Sunstein, 2008).

Gender, age, or other usage differences were not revealed between negative recency participants and the rest, either. However, those who were more susceptible to negative recency played more poker and bet more on sports. It is possible that people who like games of chance are more prone to misinterpreting random, chance events and to holding unsupported beliefs about randomness. Another explanation could be that it is not a cognitive mistake, but a proof of unsuccessful inhibitory functions. Despite knowing that the loser share is traded and as such the chance of losing is higher, one cannot resist entering a possibly rewarding – “It is now turning” – game, because one needs stimulation. One can experience excitement by raising one's bet – in an investment simulation, in poker, or sports betting. Is impulsive sensation seeking and a lower level of MAO-B in the background? (Zuckerman & Kuhlman, 2000).

Zaleskiewicz (2001) distinguished between Instrumental and Sensational risk-taking. The Sensational risk taker is present-oriented and engages in risks in order to experience immediate excitement. He does not care about the consequences, nor is he affected by the size of the losses. His decisions and actions are characterized by speed, effortlessness, and automaticity. He deems investment as more of a gamble. In contrast, the Instrumental Risk-taker is future-oriented and takes risks to achieve a future goal. Control is important for him to influence the outcomes of his actions merely against luck. Complex cognitive thinking, intentionality, and

deliberation characterize his decisions. He also takes into account probabilities, analyses the situation, and thus behaves more rationally according to the normative model.

Is participants' underlying motivation the need for achievement or the need for stimulation? For those who failed to resist the temptation to invest more after three or four price decreases, was their real motivation not a future economic goal, but immediate excitement? The negative recency group was more prone to the prompt gains and losses than the rest of the participants. Was their real motivation rather excitement than a future goal (manifested by the standard of living in the simulation)? Resisting the temptation requires self-regulation and a tendency to learn from mistakes. Those who deem their activity as investing and not as gambling may avoid the negative recency. Instrumental risk takers might be less exposed to this heuristic than stimulated risk takers (Zaleskiewicz, 2001).

These hypotheses should be verified through further investigation.

6.1 Limitations

Although prior studies with symmetric odds (Ball, 2012; Leopard, 1978) serve as important benchmarks for evaluating the prevalence of negative recency, our study did not include a control group operating under equal odds (1:1). This constitutes a notable limitation. Without a randomized control group experiencing symmetric probability conditions, we cannot definitively rule out the possibility that the observed effects – particularly the higher prevalence of negative recency – stem from sample-specific characteristics or contextual features rather than the asymmetry in odds *per se*. Future studies should incorporate a direct symmetric-odds control condition to confirm this effect.

Due to its simplicity and short-term feature, this simulation differs significantly from real-world investment processes. Attributable to the prompt repeated feedback, it better models high-frequency trading. Its mental and affective processes are closer to day trading, in which emotions play a greater role.

In these simulations, only the series of price changes was identical for all investors. However, it was not possible to ensure that all participants were in the same financial situation as well, as it was contingent on their previous investment results, which differed for everyone. Nevertheless, there is evidence that people can respond to winning or losing series in very different ways, depending on their resources. Ball (2012) tried to control participants' financial situation and managed to keep it within a given range, but he was still not able to ensure that participants had at least similar levels of wealth at the same point in time.

Our analysis took the share price changes into account as outcome variables and not the profits made. The impact of the gains and losses was considered through the controlling effect of wealth in the partial correlation. There was little difference between the two: 51 or 57 participants in the first simulation, and 17 or 20 in the second simulation were identified with negative recency throughout the two measures, separately.

Another possible explanation for the negative recency effect observed could be tied to the break-even effect (Thaler & Johnson, 1990), where investors take more risks to return to their initial financial status after losses. When we fail to realize a loss on our mental account, that is, we do not want to accept that we have lost, we can increase our risk-taking to recoup our wealth. Then the break-even effect becomes operative. If a series of price declines results in the investor losing some, or even a significant part of his wealth, he may have to increase the invested amount in order to return to the status quo.

Since there was no "short position," one could not sell, just buy the share. Thus, the minimum investment amount was limited to zero. This limited the ability of participants to express their belief in reversing after price decrease runs, as one could not decrease one's investment below zero. To overcome this asymmetry, the simulation could be modified to allow for selling the share. Short selling would give participants the chance to regain lost wealth by betting on price decreases, rather than solely relying on increased investment in loser shares.

Introducing shorting would enable a clearer distinction between loss recovery strategies and simple heuristic errors like negative recency. It could also provide more clarity on whether the negative recency observed is genuinely a bias or a rational, though risky, attempt to recover from a loss. If you could bet on the price decrease, you would have the opportunity to regain your lost money from the previous rounds by betting

on it. Thus, investing after a series of price declines would no longer be the only option for returning to the status quo. Shorting would clearly separate the two effects.

Positive recency was not examined in this article because it is not a maladaptive heuristic in this simulation design. It coincides substantially with normative rational behaviour, and thus, this simulation is not the proper tool for detecting this bias.

6.2 Future Directions

Previous outcomes of random events have a substantial impact on consecutive risk-taking in economic decision-making. There are always some people who believe so strongly that the price decrease runs must reverse that they invest more, even while knowing that a loser type share is being traded and that there is a higher probability of losing the investment. It would be worth investigating whether the belief in the law of small numbers is so resilient that it would overrule dominant winning strategies even in the case of 1:3 or 1:5 odds. How fixed is this heuristic? Would it overcome the rational strategy even if it was still more pronounced and harmful? Does negative recency depend at all on the different odds ratios, or is it insensitive to them?

If shorting is allowed, and one can bet on price decreases, will the belief in a reversal occur more noticeably after a series of price increases? And would belief be diminished after a series of price depreciations, if it were possible to break even in a more adaptive way of risk-taking?

It would also be worthwhile to examine whether those who invested based on negative recency would make the same mistake by repeating the simulation. Is a one-time negative feedback enough for the decision maker to correct his strategy? Or is there any other way to fix this heuristic?

Understanding such biases could help to eliminate this maladaptive behaviour, which can result in severe high-risk losses and prevent low-risk gains.

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Data availability statement: All data required to support the results and conclusions of this study are provided, and the corresponding scripts are available on GitHub: <https://github.com/AjnaUa/InvestmentSimulation/blob/main/Failing%20despite%20knowing.R>.

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Appendix 1

Suppose you invest $0 \leq V \leq 1$ proportion of your W wealth (HUF) and win $W \times V$ with probability p or lose the same with probability $1 - p$, depending on the change of share price S . The expected utility of your wealth is:

$$E_p[U(W \times (1 + V \times S))] \rightarrow \max_{0 \leq V \leq 1}, \quad (A1)$$

where E is the expected value, U is the utility, and S is +1 if the share price increases and -1 if it decreases. For the mathematical specification of risk preferences, we assumed a constant function of the relative risk avoidance property:

$$U(x) = \frac{x^{1-\sigma}}{1-\sigma}, \quad (A2)$$

where σ is risk-taking propensity. Higher σ corresponds to more risk-averse individuals. In the case of risk-neutral, it takes on 0.

According to EUT participants will invest so that it will result in the highest expected utility (equation (A1)). We defined the normative risk-taking strategy according to this rational economic behaviour. The optimal proportion V^* to be invested in line with the rational investment strategy is the solution of equation (A1). It takes on:

$$V^* = \frac{1 - \left(\frac{3}{p+1} - 1\right)^{1/\sigma}}{1 + \left(\frac{3}{p+1} - 1\right)^{1/\sigma}}, \quad (A3)$$

if $p > 0.5$, else $V^* = 0$, where p is the posterior probability of trading with the winner share. In case of commonly assumed risk-averse propensity ($\sigma = 1$), the solution for the utility maximization of the investment decision is the function of the posterior probability of trading with the winner type share.

$$V^* = \frac{1 - \left(\frac{3}{p+1} - 1\right)}{1 + \left(\frac{3}{p+1} - 1\right)} = \frac{2p - 1}{3}. \quad (A4)$$

Appendix 2 Information for Participants

When making your investment decisions, focus solely on the development of your final wealth and the monthly income it generates (this income is shown continuously during the simulation). To help you plan for a good standard of living, we provide a typical budget for a family of four for each wealth band. These figures are only guidelines, as your actual expenses may differ depending on individual preferences.

The rules of stock market trading will be explained later, so do not worry about them for now. On the next screen, you can scroll horizontally through a table that shows different wealth bands, their associated income levels, and typical household expenses. Throughout the simulation, your current wealth – as well as the wealth bands directly below and above your current level – will be displayed to help you assess your risk.

During the simulation, you will trade a total of 10 shares, with 10 rounds of trading per share. Shares fall into two categories based on their profitability:

- **Winning shares:** Each trading round has a two-third probability of a price increase and a one-third probability of a price decrease.
- **Losing shares:** The odds are reversed; the chance of a price increase is one-third, and the chance of a price decrease is two-third.

Shares are traded sequentially: first, you trade share 1 for 10 rounds, then share 2 for 10 rounds, and so on. The computer randomly determines (with equal 50–50 odds) whether each share is a winning or losing one;

however, you will not be directly informed about this outcome. Instead, you must infer it from the price movements.

In each trading round, you decide how much of your assets to invest in the share. After each round, the market moves: if the share price rises, your invested amount doubles; if it falls, you lose the invested amount. You may invest up to your total assets, but investing everything is not recommended because a loss will end the game by depleting your assets.

For each share, after the 5th and 10th trading rounds, you will be asked to estimate, in 10% steps (from 0 to 100%), the probability that you are trading a winning share.

Before starting, you will have the opportunity to practice the simulation in two test rounds, one with each share type. There are no stakes involved during these practice rounds.

We wish you good luck and hope you enjoy the simulation!