

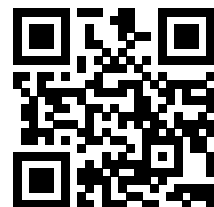


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Contact address of the editor:
Faculty of Economics and Statistics
University of Innsbruck
Universitaetsstrasse 15
A-6020 Innsbruck
Austria
Tel: + 43 512 507 96136
E-mail: Dean-EconStat@uibk.ac.at

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The Consequences of Narrow Framing for Risk-Taking: A Stress Test of Myopic Loss Aversion

Rene Schwaiger,¹ Markus Strucks,² Stefan Zeisberger^{2,3}

April 9, 2024

Abstract

Narrow bracketing in combination with loss aversion has been shown to reduce individual risk-taking. This is known as myopic loss aversion (MLA) and has been corroborated by many studies. Recent evidence has contested this notion indicating that MLA's applicability is confined to highly artificial settings. Given the impact of these findings, we reevaluated the evidence on MLA involving a total of 2,245 university students, thereby achieving substantially higher statistical power than in almost all previous studies. To clarify inconsistencies in the literature, specifically under more realistic investment environments, we systematically modified the seminal study design by Gneezy and Potters (1997) to include five key adjustments. These involved realistic, down-scaled returns, return compounding, and extended investment horizons. Contrary to some prior studies that have raised doubts about the robustness of MLA, our results—which are highly robust to analytical heterogeneity—consistently document the presence of MLA across all experimental conditions. Our findings substantiate the widespread applicability of MLA and underscore the benefits of disclosing aggregated returns in practical financial decision-making contexts.

Keywords: myopic loss aversion, narrow framing, risk-taking, meta science, replication

JEL: D14, D81, G02, G11

¹ Department of Banking and Finance, University of Innsbruck, Universitätsstraße. 15, A-6020 Innsbruck, Austria.

² Institute for Management Research, Radboud University, Heyendaalseweg 141, 6525 AJ Nijmegen, The Netherlands.

³ Department of Finance, University of Zurich, Plattenstraße. 32, 8032 Zurich, Switzerland.

*Corresponding author: stefan.zeisberger@ru.nl; Heyendaalseweg 141, 6525 AJ Nijmegen, The Netherlands.

1 Introduction

Individuals often frame decisions narrowly, segregating outcomes or frequently evaluating them (Kahneman & Lovallo, 1993; Kahneman & Tversky, 1984; Read et al., 2000; Thaler, 1985; Thaler et al., 1997). In an investment context, this particularly applies when investors evaluate their portfolios on a short-term basis. This temporal myopia demonstrates individuals' difficulty in foreseeing long-term outcomes and their implications for decisions. Coupled with prevalent loss aversion (Kahneman & Tversky, 1979), this myopia diminishes individuals' propensity to allocate investments in riskier assets. This combination of temporal myopia and loss aversion is referred to as myopic loss aversion (MLA). Given its intuitive appeal and its explanatory power regarding significant stock market anomalies, such as the equity premium puzzle (Benartzi & Thaler, 1995), MLA has garnered considerable interest in the economics and finance literature. For example, Benartzi and Thaler (1995)'s seminal work has received more than 4,500 citations, and Gneezy and Potters (1997)'s groundbreaking experimental verification of MLA has exceeded 1,600 citations, according to Google Scholar.

Research has extensively documented behavior consistent with MLA across a wide range of demographics and settings. A majority of studies have identified the manifestation of MLA among university students (Bellemare et al., 2005; Fellner & Sutter, 2009; Gneezy & Potters, 1997; Keren & Wagenaar, 1987; Langer & Weber, 2008; Thaler et al., 1997; Wendy & Asri, 2012). Furthermore, observations of MLA extend beyond students to the general population (Van der Heijden et al., 2012), financial experts and traders (Eriksen & Kvaløy, 2010; Haigh & List, 2005; Iqbal et al., 2021; Larson et al., 2016), decision-making teams (Sutter, 2007), and private investors (Wendy & Asri, 2012). Notably, natural field experiments have revealed that financial professionals exhibit MLA behaviors within their daily work environments (Larson et al., 2016). Evidence of MLA-compliant behavior extends to retirement planning and insurance (Benartzi & Thaler, 1999; Papon, 2008) as well as to experimental markets (Gneezy et al., 2003). Collectively, these studies underscore MLA's contribution to conservative decision-making and its association with generally suboptimal financial outcomes (Larson et al., 2016; Looney & Hardin, 2009; Thaler et al., 1997).

Nevertheless, recent empirical evidence has increasingly called the concept of MLA into question. Several of the aforementioned studies have implemented the design by Gneezy and Potters (1997) as a benchmark. Their investment task extended across nine periods, featuring linear return calculations. Their risky asset yielded rates of return of either +250% or -100%, which resembles an "all-or-nothing" gamble. These experimental settings and parameters markedly deviate from the more realistic scenarios of annual investment returns, compound returns, and the extended investment horizons typically observed in financial markets. Although some field studies, including that of Larson et al. (2016), have featured compound return calculations and more realistic rates of return, these studies primarily focused on financial professional traders and involved alterations beyond the scaling of returns and compounding. This complexity makes it challenging to isolate and evaluate the singular effect of these characteristics on MLA, especially within the traditional framework established by Gneezy

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and Potters (1997). In a substantial and resource intensive study, Beshears et al. (2017) have taken this as an impetus to examine whether MLA is robust to more realistic, scaled-down rates of return, return compounding, and extended investment horizons.¹ Their findings suggest that behaviors consistent with MLA may not be prevalent in more realistic investment contexts. In a series of tests they came to the conclusion that the artificial “all-or-nothing” gamble is responsible for the non-replication and that the results do not extend to settings with less extreme and more realistic risk profiles. This necessitated a thorough reevaluation of the multitude of studies utilizing Gneezy and Potters (1997)’s experimental design, thereby challenging the overarching validity of the MLA literature. By contrast, Langer and Weber (2008) found MLA-compliant behavior in a small sample of university students when applying similar modifications to the scaling of the risky asset’s return, return compounding, and investment horizon. Recently, Schwaiger and Hueber (2021) found that the original protocol by Gneezy and Potters (1997) replicates only among the more attentive crowdworkers on Amazon MTurk. Additionally, a variation of the original lottery, which only differed in terms of the probabilities of winning and losing (50% each instead of 33% and 66%, respectively) did not lead to behavior consistent with MLA. Nevertheless, the vast majority of studies primarily maintained or minimally altered the original framework set by Gneezy and Potters (1997). Apart from the study by Beshears et al. (2017), no other research has undertaken a comprehensive and systematic revision of the experimental parameters.² The path-dependent nature of research, with the vast majority of studies applying the original parameters by Gneezy and Potters (1997), thus seriously questions the external validity of the whole research field. Furthermore, different analytical choices for testing MLA behavior in published studies, such as the choice of regression models or covariates, could (partly) explain the heterogeneity of MLA results in the literature (Holzmeister et al., 2023; Menkveld et al., forthcoming; Simonsohn et al., 2020).³ Considering the divergent findings from studies deviating from Gneezy and Potters (1997)’s original protocol, a clear consensus remains elusive about whether MLA is a universal feature of investment decisions or a fragile artifact that crucially depends on stylized experimental designs and analytical choices. Furthermore, it is crucial to acknowledge the potential impact of publication bias when evaluating the scientific arguments for and against the relevance of MLA.

Previous studies questioning its robustness to real-world financial contexts as well as studies confirming the original findings by Gneezy and Potters (1997) suffered from at least one—and most often two—of the following two issues ex ante: (i) insufficient statistical power to reliably detect small- to medium-sized standardized effects and (ii) non-isolated alterations of characteristics of the original Gneezy and Potters (1997) setting. The first issue raises the question of whether MLA’s absence in more realistic contexts is genuine, or if its effects are simply diminished—rendering it unlikely to detect in studies lacking sufficient statistical power. The power curves presented in Figure 2 illustrate that even slight reductions in the true standardized effect, potentially resulting from alterations in the experimental design, lead to a notable decrease in statistical power. This would markedly hamper the ability to reliably identify diminished yet economically significant effects.⁴ The second

¹ Moreover, Beshears et al. (2017) have introduced longer delays between periods in their post-lab conditions in order to move away from short laboratory settings toward more realistic real-world investment horizons. The study cost more than \$200,000 in participant payoffs, by magnitudes more than comparable studies.

² Table B2 offers a detailed overview of the applied modifications in studies based on the experiment by Gneezy and Potters (1997). We will elaborate below on our important extensions to Beshears et al. (2017).

³ Table B7 depicts the implemented analytical pathways in published studies that adopted the Gneezy and Potters (1997) design.

⁴ For the detailed power calculations see the *R* script in the project’s OSF repository.

issue, that of concurrent modifications, complicates the attribution of specific design changes to MLA’s observed fragility. In their study, Beshears et al. (2017) not only reduced the rates of return on the risky asset but also simultaneously transitioned from the original model with periodic endowments and linear returns to a singular initial endowment and compound returns. In this modified version, each decision impacts not only the immediate outcomes but also the available funds for investment in subsequent periods, potentially prompting participants to frame the investment decision more broadly overall. Adopting a broader perspective might inherently mitigate myopia in decision-making by underscoring the long-term ramifications of present choices (Langer & Weber, 2008). However, the compound nature of returns heightens the significance of each choice as it affects the capital that is available for investments for the next periods, potentially leading to more conservative investments due to loss aversion. Increased caution may offset the mitigating effects of a broader decision-making frame on MLA. The cumulative impact on MLA from transitioning from periodic endowments without compounding to a singular initial endowment with compounding has yet to be isolated, leaving its overall effect ambiguous. Specifically, compound returns, down-scaling of returns, or the combination of both including potential interaction effects, might diminish MLA-compliant behavior compared to the original setting. The literature also only incorporated adjustments to the investment horizon alongside simultaneous reductions in rates of return. For example, Langer and Weber (2008) increased the number of investment periods to 30 and combined this with lowered return rates. The discrete effects of each modification have not been distinctly isolated in the analysis. It is plausible that some of the described alterations could counteract each other. Therefore, the degree to which MLA findings can be generalized to scenarios that differ from the common paradigm established by Gneezy and Potters (1997), as well as the specific factors influencing this generalizability, continue to be unclear.

To illuminate these critical gaps and assess the comprehensive MLA literature’s relevance and impact, we enrich the field through extensive, pre-registered online experiments with students from two large universities, in the Netherlands and in Austria. In light of conflicting findings, our objective was to ascertain the robustness of MLA and identify specific modifications to the Gneezy and Potters (1997) design that potentially mitigate individuals’ inclination toward MLA-consistent behavior. Our methodology is distinguished by its capacity for the meticulous isolation of disparate elements of experimental design choices, such as realistic rates of return, return compounding, and investment horizons. Employing a (partial) factorial design, we were able to precisely discern the impact of each of the more realistic investment attributes on MLA tendencies. Furthermore, we conducted our study with a substantially larger number of participants compared to almost all prior studies that applied the Gneezy and Potters (1997) design (detailed in Table B2). This ensured that we were sufficiently powered to reliably identify even minor to moderate standardized effects, as illustrated in Figure 2. Lastly, acknowledging the diverse statistical analyses of MLA in existing research, we introduce innovation through the adoption of a multiverse approach complemented by specification curve analysis (Simonsohn et al., 2020). This method addressed potential variations in our results arising from analytical heterogeneity, thereby enhancing the reliability of our conclusions. We based the choice of the analytical pathways on an extensive examination of the applied analyses in the related MLA literature.

Our analysis uncovered compelling evidence for the persistence of MLA across all examined setting, including more realistic, down-scaled rates of return, a compound return scheme following a single initial endowment, and longer investment horizons. The outcomes derived from the multiverse approach underscored

the consistency and reliability of our findings across more than 10,000 distinct analytical specifications, including varied sample exclusion criteria, sets of covariates, and regression methodologies. Collectively, our results present a stark contrast to prior research challenging MLA’s robustness, as we found significant evidence for the relevance of MLA in all of our conditions and, thus, for more realistic investment settings. A potential explanation for this divergence lies in the inadequate statistical power of preceding studies to reliably detect the smaller standardized effects we report for some of the more realistic investment contexts.

Our results highlight MLA’s capacity to undermine long-term wealth accumulation, particularly in an era where individuals shoulder greater responsibility for their retirement savings due to the transition from “Defined-Benefit” to “Defined-Contribution” pension schemes. Technological advancements facilitating quick and intuitive information processing may foster short-term thinking and impulsive decisions, detracting from a strategic, long-term investment approach (see, e.g., Kalda et al., 2021). Adopting policies that promote a holistic investment perspective—via tax incentives, loyalty programs for long-term financial products, or educational initiatives—could significantly improve long-term financial well-being for individuals. The success and configuration of such strategies critically depend on the presence or absence of MLA in particular investment contexts. We undertook this research to elucidate this crucial distinction by addressing and resolving prevailing inconsistencies within more authentic investment environments.

2 Experimental Design

The experimental design of this study is based on the protocol by Gneezy and Potters (1997). In the original study across nine periods, participants allocated a financial windfall between a risky asset, which had a positive expected value, and a risk-free cash option. In one of the two treatment groups, designated as HIGH, the authors introduced a higher frequency in which participants made decisions and received feedback on investment outcomes. Participants randomly assigned to treatment HIGH received outcome feedback and made decisions in each period, while the feedback and decisions in LOW always applied to three consecutive periods. Behavior aligning with MLA theory manifests when individuals in the LOW treatment group average higher investments in the risky asset compared to those in the HIGH group. Investments with a positive expected return are characterized by an increasing (non-monotonic) likelihood of aggregate positive outcomes over time, irrespective of whether returns are compound or linear. On average, this makes the investment more attractive under infrequent evaluation for a loss-averse investor. Furthermore, the commitment to decisions across multiple periods encourages more prospective thinking in the LOW group (Redelmeier & Tversky, 1992). The risky asset in Gneezy and Potters (1997) is characterized by a binary distribution, yielding periodic outcomes where there is a one-third probability of achieving a +250% gain and a two-thirds probability of incurring a total loss (-100%). As a theoretical underpinning, we consider cumulative prospect theory (CPT) to explain behavior consistent with MLA (Langer & Weber, 2005). In an extension of MLA to myopic prospect theory, Langer and Weber (2005) highlighted the relevance of other characteristics, such as probability weighting and value function curvature, as crucial factors. To assess the lotteries’ attractiveness, we assumed a CPT agent with parameters

$\alpha = \beta = 0.88$, $\gamma = 0.61$, $\delta = 0.69$, and $\lambda = 1.6$.⁵ Based on the above parameters, a myopic decision maker rejects a gamble following such a distribution since its periodic CPT value is negative (-2.2 for an investment of 100). In contrast, an aggregate evaluation of the three-period lottery results in a positive CPT value (4.3 for an investment of 100), predicting investment in the risky asset.⁶

2.1 Conditions

For this study, we replicated the original design and additionally modified it in relation to the following three critical dimensions. These changes allowed us to examine the robustness of MLA to more realistic conditions and to distinguish effects between relevant dimensions of the design.

(1) **Rates of Return:** The properties of the risky asset in Gneezy and Potters (1997) do not resemble those of typical retail investment products. To enhance realism, we adjusted the rates of return, scaling them down to +25% and -10%, mirroring the approach by Beshears et al. (2017). The authors came to the conclusion that MLA in the Gneezy and Potters (1997) experiment only holds true under unrealistic return scenarios as they did not find evidence for MLA with such down-scaled rates of return. In our setting, scaling down rates of return reduces the CPT values of one- vs. three-period prospects to around -0.3 and 0.6 , respectively. Theoretically, a decision-maker guided by CPT still only accepts the three-period prospect. However, the practical impact of such a slight absolute value difference between the one- and three-period prospects on empirical outcomes might be reflected in smaller true effect sizes. Such a consideration could potentially explain why previous studies without sufficient statistical power have detected no effect. Should the effect disappear or lose economic significance, determining whether the cause is the reduced overall appeal of the prospect or the manner in which returns are scaled becomes challenging. Therefore, we introduced an additional condition featuring asset rates of return of +230% and -90% . By reducing the potential periodic loss to -90% of the invested amount, we were able to examine whether MLA behavior persists when the asset profile does not follow an “all-or-nothing” return framing. Again, a narrow one-period evaluation predicts rejection by a CPT decision maker, whereas a broader and aggregate evaluation of the three-period return distribution predicts acceptance of the gamble ($CPT_1 = -1.2$; $CPT_3 = 6.1$).⁷

(2) **Compound Returns:** In the original Gneezy and Potters (1997) study, participants received a new endowment in each of the nine periods for making investment decisions specific to each period. Periodic earnings were calculated for each of these separate decisions, and total earnings equaled the sum of all

⁵ Value function curvature and probability weighting parameters are based on Tversky and Kahneman (1992). In line with empirical estimates, however, we assumed a lower magnitude of loss aversion (Walasek et al., 2018). Applying the loss aversion parameter of Tversky and Kahneman (1992), $\lambda = 2.25$, the three-period lottery would still be preferred, but CPT would predict rejection of both gambles.

⁶ For the detailed calculations see the R script in the project’s [OSF repository](#).

⁷ We adjusted the up-scaling from 250% to 230% to align the CPT values more closely with those in Gneezy and Potters (1997). We strongly believe that variances in MLA behaviors, compared to the original study, would mainly be due to the reduced risk of total loss rather than the slight change in up-scaling. Keeping the up-scaling at 250% would have led to two simultaneous changes: a move away from the risk of total loss *and* a significant deviation in CPT values. In particular, CPT would have predicted acceptance of both the one-period and the aggregated three-period lottery ($CPT_1 = 2$; $CPT_3 = 15.1$).

independent periodic earnings. However, subsequent studies by Langer and Weber (2008) and Beshears et al. (2017) highlighted that this approach, resulting in linear returns, diverges from typical investment practices. In real investment contexts, investors benefit from the compounding of capital gains and the reinvestment of dividends. Moreover, investors usually do not invest for predetermined periodic intervals and are not forced to liquidate their position after each period. Therefore, building upon the framework of Beshears et al. (2017), to simulate compound returns, we provided participants with an initial endowment (I), set as the product of the number of periods (K) and the periodic endowment (P), that is, $I = K \times P$. This endowment was allocated at the start, and the balance was adjusted at each period's end to reflect any gains or losses, effectively carrying the balance forward through the experiment. For instance, if participants invested a fraction x of their initial endowment I in the first period with a return of r_1 , the endowment for the second period I_2 would be recalculated to include the gains or losses from that investment, that is, $I_2 = I \cdot (1 - x) + I \cdot x \cdot (1 + r_1)$. Figure 1 illustrates the comparison between linear and compound return calculations across the experiment's duration.

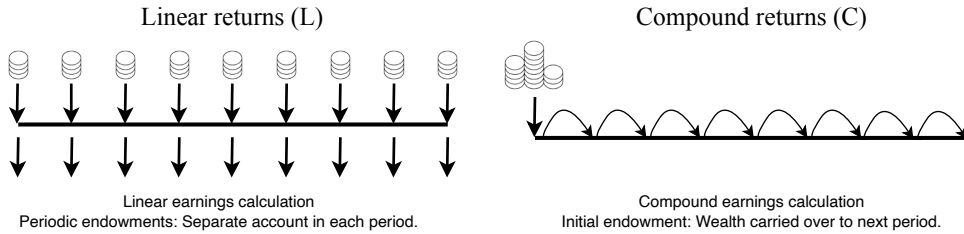


Figure 1: Linear versus compound return calculation.

We argue that the decision of which return calculation method to adopt is potentially consequential in an experiment testing MLA. Compared to Gneezy and Potters (1997), allocating a one-time initial endowment may shape participants' investment strategies by highlighting the enduring consequences of their initial choices on future investment balances. Consequently, this upfront endowment has the potential to counteract narrow bracketing, particularly in condition HIGH, and to promote a more far-sighted approach to investment evaluations. Conversely, this approach might predispose participants to adopt more conservative strategies upfront, mindful of their decisions' prolonged repercussions. The net effect of these potentially opposing influences is complex and remains an open question. Klos et al. (2013) found that highlighting the final outcome distribution might mitigate MLA. Notably, Beshears et al. (2017) altered both the return scaling *and* return compounding and concluded that it is likely the former that drives their insignificant results, but that the latter is a possible reason as well.

(3) **Investment Horizon:** When participating in the investment task over nine periods, participants in condition LOW only make three decisions. Shorter investment horizons may skew myopic evaluations of risky assets, particularly if their effects differ between the LOW and HIGH treatment groups. Generally, the tendency to overestimate loss risks increases with longer investment horizons, subsequently dampening risk-taking propensities (Ponti & Tomás, 2021). By elevating decision-making and feedback instances—from 3 to 10 in the LOW condition, and from 9 to 30 in the HIGH condition—might lead

to more uniform investment behaviors across treatments due to sufficiently prolonged decision and investment horizons in both groups, especially in group `LOW`. This is also consistent with the first experiment in Beshears et al. (2017). Here, the authors implemented the return histogram design by Benartzi and Thaler (1999) and extended the investment horizon to 52 periods with real-time delays of one week. They did not find behavior consistent with MLA. To systematically examine the investment horizon’s effect on MLA, we introduced extended periods of 30 to guarantee a multiple of three based on the original design in Gneezy and Potters (1997). This is consistent with Langer and Weber (2008) and adapts our experiment to reflect more conventional long-term investment scenarios. This modification allows us to delve into how extended decision-making frames might mitigate or accentuate MLA tendencies.

Table 1 depicts the characteristics of the six different conditions under which we tested the robustness of MLA. Alongside a baseline condition (250-100L9) identical to Gneezy and Potters (1997)’s design, our study was structured to isolate the effects of scaled-down rates of return and a departure from “all-or-nothing” gamble framing on MLA (top left box with conditions 250-100L9, 230-90L9, and 25-10L9). The CPT value differences between the `LOW` and `HIGH` treatments under the 230-90L9 setup closely mirrored those in the original lottery, maintaining the value relationship between the `LOW` versus `HIGH` scenarios. Thus, condition 230-90L9 primarily deviates from the original by not featuring the potential for a total loss. Additionally, our experiment featured a 2 (linear vs. compound returns) \times 2 (short vs. long horizon) design contrasting linear versus compound returns and short versus long investment horizons, all under more realistic, scaled-down rates of return (all four boxes with conditions 25-10L9, 25-10L30, 25-10C9, and 25-10C30). In contrast to prior research on the robustness of MLA, we were thus able to disentangle the influence of the return scaling and the influence of the return calculation.

Table 1: Experimental Conditions Overview: This figure delineates the between-subjects experimental setup. First, our design enables us to examine the isolated impact of scaled-down rates of return and the shift from an “all-or-nothing” gamble framing on MLA (top left box with conditions 250-100L9, 230-90L9, and 25-10L9). Furthermore, it illustrates how the investment horizon and return calculation variables are systematically varied within a 2×2 factorial design, incorporating realistic return rates (all four boxes with conditions 25-10L9, 25-10L30, 25-10C9, and 25-10C30).

		Investment Horizon	
		9 Periods	30 Periods
Return Calculation	Linear	250-100L9 230-90L9 25-10L9	25-10L30
	Compound	25-10C9	25-10C30

2.2 Procedure

After providing informed consent to the study’s terms and conditions,⁸ participants viewed an elaborate description and illustration of the asset’s return distribution. To maintain comparability, our instructions were identical to those of Beshears et al. (2017) except for necessary minor edits due to the online experimental setting (see Appendix C for the full set of the experimental instructions). In conditions with linear returns (250-100L9, 25-10L9, 25-10L30, and 230-90L9), participants received 100 experimental currency units (ECU) in each period, whereas in conditions with compound returns (25-10C9 or 25-10C30) participants received either 900 ECU or 3,000 ECU in Period 1 to be invested over either 9 or 30 periods. Participants in the LOW treatment were informed that each of their decisions would apply to the subsequent three periods and that their investment results would be presented in three-period blocks. In contrast, participants in the HIGH treatment were informed that they would make decisions and receive feedback on a period-by-period basis.

In each of the six conditions and each of the two treatments, HIGH and LOW, participants indicated their investment as a percentage of the endowment in ECU. This standardized approach ensured that the set of investment allocations was consistently scaled across all conditions. Requesting investments as percentages facilitates consistent scaling across conditions, irrespective of the fluctuating absolute amounts in compound return scenarios. Furthermore, these percentages could be readily converted to their corresponding absolute amounts, ensuring comparability across different conditions. On each feedback screen, we presented the return outcome(s) of the risky asset, the amount gained or lost, and the total earnings from the previous period (HIGH) or the previous three periods (LOW). Importantly, as in earlier studies (with the exception of Hardin & Looney, 2012), single-period outcomes and earnings were also displayed for participants in LOW. After the final period, participants received information about their final payoff. Due to the different structures and lengths of conditions, incentives varied slightly in magnitude.⁹

The experiment concluded with pre-registered survey questions on perceptions of ambiguity and risk associated with the lottery, which were aimed at uncovering potential explanations for variations in risk-taking across conditions (Venkatraman et al., 2006).¹⁰ In addition, as pre-registered, we included three questions on the understanding of the risky asset return distribution to identify and exclude participants who were inattentive or did not understand relevant information from the sample that we used for a robustness check. Finally, we collected basic demographic data to be used in sample balancing checks and to be added as control variables in our regression analyses.

⁸ The study has been approved by the ethics board of the University of Zurich.

⁹ In the conditions with nine periods, the payment in Euro equalled the total ECU earnings in the experiment divided by 1,200. In the conditions with thirty periods, we divided the total ECU earnings by 400 to achieve similar payments and also to compensate participants for the slightly longer time spent on the additional investment periods.

¹⁰ Since these questions were exclusively pre-registered and asked during Wave 3, we have detailed their corresponding results in Appendix A. This approach allowed us to focus on the most relevant findings based on the combination of all waves in the paper’s analysis section.

3 Results

3.1 Statistical Power and Sample

All analyses presented herein, unless noted otherwise, were pre-registered on “AsPredicted”.¹¹ We adhered to significance levels (α) of 5%, 1%, and 0.1%, respectively, for all analyses. Our final sample consists of data we collected via online experiments in three waves with students at Radboud University in the Netherlands (Wave 1 & 2) and the University of Innsbruck in Austria (Wave 3). We invited students from different universities to ensure a sufficient number of participants. This enabled us to achieve a high statistical power to reliably detect small to medium-sized standardized effects.

We conducted ex-ante statistical power analyses for which we used Cohen’s d as a standardized effect size. With our 2,245 participants (pre-registered: 2,200) in total, we generated on average 187 independent observations per treatment—HIGH and LOW—across all six conditions. Thus, we had a statistical power of at least 80% (90%) to reliably detect a standardized effect size equal to or larger than Cohen’s $d = 0.29$ ($d = 0.34$), given a Type I error rate of $\alpha = 0.05$ in pairwise comparisons via two-sided unpaired-sample t -tests (see Figure 2—also for a comparison to related studies in the literature).

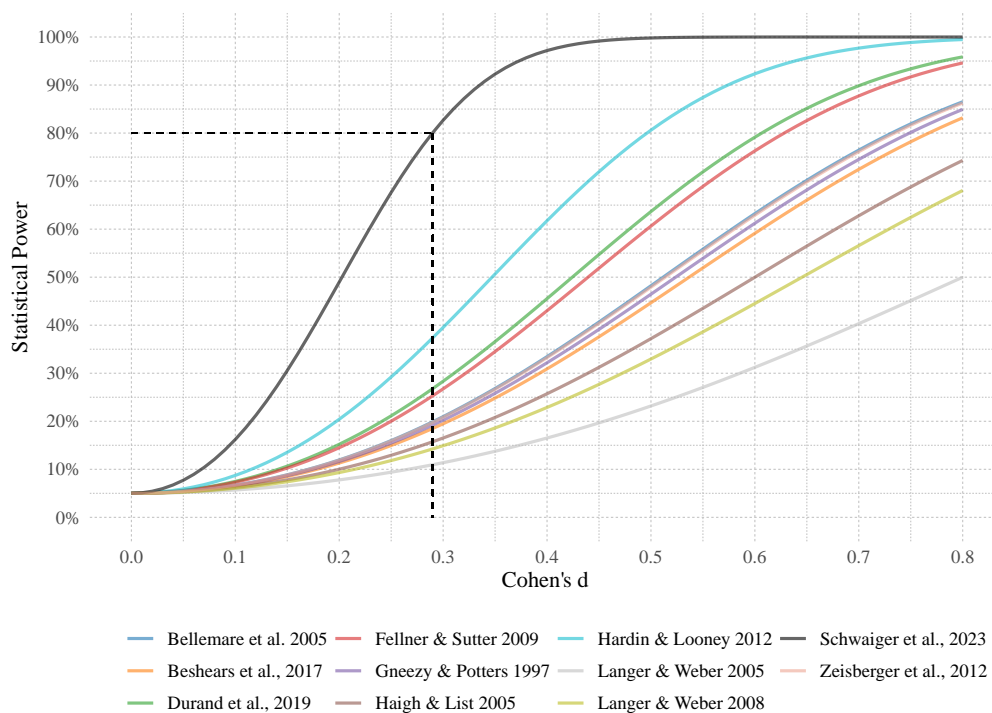


Figure 2: Statistical power calculations for the treatment comparison HIGH versus LOW based on the sample size of our study and of major experimental studies in the field of MLA, applying a variant of the Gneezy and Potters (1997) design. $\alpha = 0.05$.

The median duration of the experiment in the full sample was 10 minutes, with a median compensation of €2.49, corresponding to an hourly rate of €14.94. As pre-registered, we excluded the fastest and slowest 2.5% of

¹¹ See the pre-registration under the following links: [Wave 1](#), [Wave 2](#), [Wave 3](#).

participants in terms of total processing time from the analyses to increase the signal-to-noise ratio in our data. Clicking through quickly may be an indicator of a lack of focus and understanding of the procedure and the lottery (Chmielewski & Kucker, 2020; Downs et al., 2010). As a result, behavior consistent with MLA may not unfold as it would in real-world investment decisions. Conducting the experiment too slowly could also be a problem as participants may take longer breaks and forget parts of the instructions (Abbey & Meloy, 2017; Downs et al., 2010). This trimming procedure led to 2,131 observations in the final sample, which we used for the main analyses. As a robustness check, we also ran our main analysis with the full sample, for which we found consistent results, which we report in [Table B5](#) in the Appendix. Furthermore, as pre-registered, we applied another robustness check, excluding participants who gave too many incorrect answers and those who indicated that they “did not understand at all” in a set of comprehension check questions (see [Appendix C](#)). Compared to our final sample, this robustness sample also provided qualitatively identical results.

Prior to conducting our main analyses, we assessed the balance of observable characteristics within our final sample following the trimming procedure. To accomplish this, we conducted tests to identify any discrepancies in self-reported participant demographics and traits, such as gender, risk preferences, statistical knowledge, and university affiliations, across the different conditions and two treatments. This step was undertaken to address endogeneity concerns by pinpointing potential confounders due to imbalances that need to be included as control variables in our analysis. The results of the sample balancing checks are presented in [Table B1](#) in the Appendix. We found that the measured covariates did not statistically significantly differ from each other in all but one condition (250-100L9), which was characterized by higher self-assessed statistical knowledge in group HIGH compared to group LOW. For our analyses, we exercised caution and estimated econometric specifications that controlled for self-reported participant characteristics. We also tested for multicollinearity among the covariates by calculating the variance inflation factors (VIFs), all of which were below 2. Thus, multicollinearity did not pose an issue.

3.2 Main Analyses

Participants’ average invested amount in the lottery in percent of the periodic endowment or the current balance served as our main outcome variable. [Figure 3](#) shows the average investment in percent in treatment HIGH and LOW across all six conditions, 250-100L9, 230-90L9, 25-10L9, 25-10L30, 25-10C9, and 25-10C30.¹² The whiskers indicate 95% confidence intervals, and the stars indicate ranges of p -values obtained by running unpaired-sample t -tests and—as robustness check—permutation tests comparing average investment amounts between treatments LOW and HIGH in each condition. As indicated by [Figure 3](#), we found statistically significant evidence for behavior consistent with MLA in each of the six conditions (see [Table B3](#) in the Appendix for the statistical details of the applied unpaired-sample t -tests for each condition). Consistent with MLA, we report universally higher risk-taking among participants in treatment LOW compared to participants in treatment HIGH. MLA behavior was most prevalent in condition 250-100L9—our Gneezy and Potters (1997) replication—with the standardized average investment difference (LOW – HIGH) amounting to $d = 0.45$, followed closely by condition 25-10C30 with $d = 0.42$ and condition 230-90L9 with $d = 0.36$. In conditions 25-10L30 with $d = 0.29$, 25-10C9 with $d = 0.28$, and 25-10L9 with $d = 0.27$, we observed small-to-medium standardized differences. Our findings present

¹² Average round-level investments are visualized in [Figure B2](#) in the Appendix.

a coherent and consistent view: MLA emerges as a behavioral phenomenon even when we scaled down returns to more realistic levels. This pattern held true not only under the traditional linear framework of Gneezy and Potters (1997) but also in settings involving more realistic compound returns. Importantly, behavior consistent with MLA under realistic returns persisted across both shorter and longer investment horizons, regardless of whether the returns were calculated on a linear or compound basis. In particular, the significant difference in condition 25-10C30—our most realistic condition featuring down-scaled and compound returns as well as a longer investment horizon—reveals important insights into the economic significance of our results. Participants who received aggregated feedback and experienced decision commitment (LOW) allocated, on average, an additional 12.03 percentage points of their balance (see Table B3 in the Appendix) compared to those with more frequent feedback and decision-making (HIGH). To accurately reflect this in monetary terms, consider that if participants in the HIGH condition invested a certain percentage of their balance in a given period, say 40% of 3,000 ECU, their starting balance, resulting in an actual investment amount of 1,200 ECU, then participants in the LOW condition would be expected to invest $40\% + 12.03pp. = 52.03\%$ of their balance. Given a balance of 3,000 ECU, this specific investment behavior would translate to an actual investment amount of 1.561 ECU, which is larger by 361 ECU compared to group HIGH. Therefore, this effect is not just statistically significant but also reflects a considerable economic impact, underscoring the importance of MLA in investment decisions.

Our results stand in contrast with those questioning MLA in broader contexts, for example, Beshears et al. (2017), who did not observe evidence of MLA in a setting with compound returns and with returns scaled down to 25% and -10% (identical to 25-10C9). Overall, our analysis revealed that MLA remains a persistent phenomenon when the risky asset return profile deviates from the original Gneezy and Potters (1997) asset, independent from altering the earnings calculation and the investment horizon. This underscores the robustness of the original results even under modified properties of the risky asset.

To further inform our analyses, we ran multivariate fractional response regression models with logit links and heteroskedasticity-robust standard errors for each of the six conditions with the average proportional lottery investments over all respective periods (9 or 30) as the dependent variable.¹³ We report the results in Table 2, which shows average marginal effects. For each model we also included the five covariates as control variables to verify the validity of our results. The coefficient LOW represents a binary dummy that equals 0 for participants in treatment HIGH or 1 for participants in treatment LOW. FEMALE is a binary dummy variable that equals 0 for male participants or 1 for female participants. INVESTOR is a dummy variable that equals 1 if participants stated to have already invested in financial products. RISK TOLERANCE indicates the self-reported risk preferences of participants, which were measured using the German SOEP questionnaire (Dohmen et al., 2011) on Likert scales from 0 to 10. STAT.KNOWLEDGE represents participants' self-reported statistical knowledge compared to their fellow students on a seven-point scale. INNSBRUCK is a binary dummy that equals 0 for participants from the Radboud University in Nijmegen or 1 for participants from the University of Innsbruck.

As can be seen from the coefficient LOW in each specification of Table 2, the results on MLA-compliant behavior are consistent with those presented in Figure 3 and Table B3 in the Appendix when we control for all elicited covariates. Specifically, for condition 250-100L9, which corresponds to the original setting by Gneezy and

¹³ As the investments represent the only variable exhibiting variation across different periods, we averaged the investments for our models. Our results remained qualitatively consistent when we repeated the analyses using periodic data and applied clustered standard errors at the individual level (see Table B4).

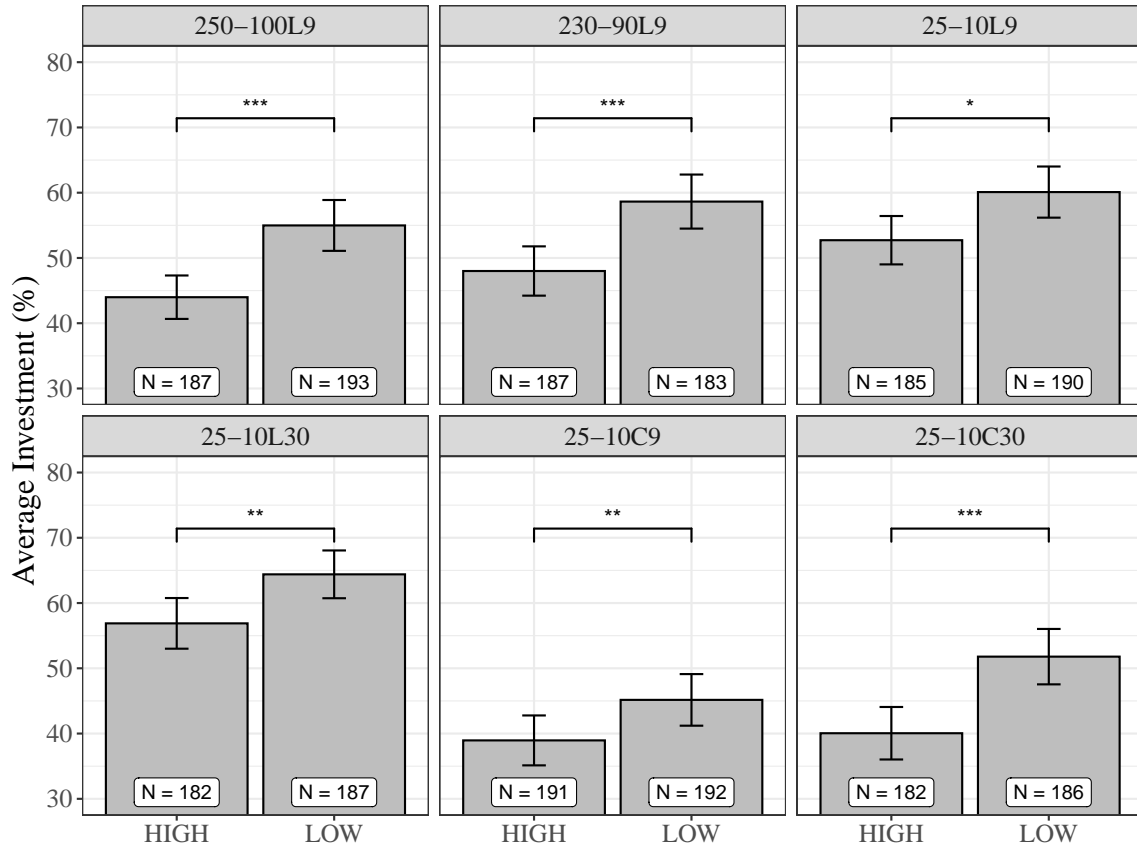


Figure 3: Average investment percentages between treatments HIGH and LOW across different conditions. HIGH features periodic feedback and decisions, whereas these are binding for three periods in LOW. 250-100L9 implements the Gneezy and Potters (1997) design, whereas the other conditions represent the different modifications (see Table 1). Error bars indicate 95% confidence intervals around mean investments in each treatment and condition. The stars indicate ranges of p -values obtained by running unpaired-sample t -tests and—as robustness check—permutation tests comparing average investment amounts between treatments LOW and HIGH in each condition ($*p < 0.05$, $**p < 0.01$, $***p < 0.001$). Details on differences in risk-taking and the results of pairwise unpaired-sample t -tests are provided in Table B3.

Potters (1997), Model (1) predicts that participants in treatment LOW invest on average 11.60 percentage points more in the lottery compared to their counterparts in treatment HIGH. Simply scaling the rates of return in the 25-10L9 condition, our regression predicts a difference in risk-taking between LOW and HIGH of only 7.00 percentage points and, additionally, switching to 30 instead of 9 periods corresponds to a predicted investment difference between both treatments of 5.90 percentage points. 25-10C30, the condition most closely mimicking realistic settings, produced the largest average gap in risk taking between treatments LOW and HIGH. Despite the fact that behavior consistent with MLA is a robust finding in our data, it appears that MLA is not equally pronounced in all conditions. Similarly, other studies modifying the design properties of Gneezy and Potters (1997) find attenuated evidence of MLA (see, e.g., Charness & Gneezy, 2010; Schwaiger & Hueber, 2021). Because of the low statistical power of most studies (see Figure 2), smaller true MLA effect sizes that might result from deviations from the original design of Gneezy and Potters (1997) would only be detected with a low likelihood.

Table 2: Average marginal effects fractional response models with logit links and the amount invested in percent of the endowment as dependent variables. The binary dummy variable `LOW` is coded 0 for participants in the `HIGH` treatment and 1 for those in the `LOW` treatment. `FEMALE` is a binary dummy variable that equals 0 for male participants or 1 for female participants. `INVESTOR` is a dummy variable that equals 1 if participants stated to have already invested in financial products. `RISKTOLERANCE` indicates the self-reported risk preferences of participants, which were measured using the German SOEP questionnaire (Dohmen et al., 2011) on Likert scales from 0 to 10. `STAT.KNOWLEDGE` represents participants’ self-reported statistical knowledge compared to their fellow students on a seven-point scale. `INNSBRUCK` is a binary dummy that equals 0 for participants from the Radboud University in Nijmegen or 1 for participants from the University of Innsbruck.

	<i>Dependent variable: Investment (%)</i>					
	<i>Conditions:</i>					
	250-100L9	230-90L9	25-10L9	25-10C9	25-10L30	25-10C30
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
<code>LOW</code>	0.116*** (0.025)	0.102*** (0.028)	0.070* (0.028)	0.078** (0.028)	0.059* (0.027)	0.118*** (0.028)
<code>FEMALE</code>	-0.088** (0.028)	-0.052 (0.035)	-0.039 (0.031)	-0.104** (0.034)	-0.061 (0.032)	-0.148*** (0.036)
<code>INVESTOR</code>	-0.017 (0.027)	-0.011 (0.033)	0.023 (0.033)	-0.015 (0.033)	0.071* (0.031)	-0.027 (0.034)
<code>RISKTOLERANCE</code>	0.040*** (0.007)	0.031*** (0.008)	0.019* (0.008)	0.034*** (0.008)	0.026*** (0.007)	0.030*** (0.008)
<code>STAT.KNOWLEDGE</code>	0.014 (0.011)	0.011 (0.013)	0.030* (0.013)	-0.001 (0.013)	0.004 (0.012)	0.007 (0.012)
<code>INNSBRUCK</code>	0.090** (0.028)	0.074* (0.031)	0.087** (0.030)	0.049 (0.030)	0.079** (0.031)	0.074* (0.031)
Permutation p -value <code>LOW</code>	0.0000	0.0002	0.0096	0.0045	0.0333	0.0002
Observations	350	359	348	359	360	355

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Heteroskedasticity-robust standard errors in parentheses.

Furthermore, in most conditions, we observed a large and statistically significant association between gender and risk-taking behavior. Averaging coefficients of `FEMALE` across the six different models, we found that male participants invested 8.2 percentage points more in the lottery than female participants. This finding aligns with prior research indicating that men tend to take greater risks than women, particularly in financial contexts (Charness & Gneezy, 2012). Additionally, the results demonstrate that participants who identify themselves as more risk-seeking in financial matters invested higher amounts in the lottery, which can be seen from the statistically significant coefficient `RISKTOLERANCE` in all models of Table 2. With respect to general risk-taking behavior, we found cohort effects. In particular, participants from Innsbruck were predicted to invest more in the risky lottery compared to students from Nijmegen.

As a robustness check, we repeated the main analyses presented in Table 2 with the full sample. We show the results in Table B5 in the Appendix. The results remained robust and we observed the same qualitative patterns with respect to MLA in all conditions. In addition, we performed another pre-registered robustness check based on three questions we implemented in the experiment to test participants’ comprehension of the investment task. Specifically, for the robustness check we excluded participants from the analysis who answered at least two of the three questions incorrectly and those who answered “did not understand at all” (after the decision task; see Appendix C). We present the results of this robustness check in Table B6 in the Appendix.

Again, identical qualitative patterns emerged with respect to MLA-compliant behavior. In comparison to our final sample, MLA appears to be a marginally more pronounced characteristic among participants who demonstrated a better understanding of the task.

3.3 Multiverse Analysis of Main Results

Typically, researchers enjoy a degree of freedom in choosing study populations, experimental designs, and analytical pathways for a given research question. Existing evidence has demonstrated marked variability in outcomes based on differences in these choices (Holzmeister et al., 2023; Landy et al., 2020; Menkveld et al., forthcoming; Simonsohn et al., 2020; Wicherts et al., 2016). Thus, the integrity of research findings, including those from pre-registered analyses, may still be influenced by the researcher’s specific field of expertise or prior experience (Simmons et al., 2011). Such researcher degrees of freedom, particularly in the context of analytical heterogeneity, hold high relevance in empirical studies (Menkveld et al., forthcoming). This concept pertains to the discretion afforded to researchers in deciding upon data analysis methods, such as choosing specific statistical models, variables, or methods of interpretation. Such freedom can inadvertently introduce biases or lead to varying conclusions from the same dataset and given the same hypothesis.

To counter the challenges posed by analytical heterogeneity, multiverse analysis has emerged as a vital tool. Applying such analysis, researchers systematically explore all reasonable and non-redundant analytical choices for studying the same dataset and the same hypothesis, encompassing different combinations of statistical techniques, variables, and model specifications. By examining the results across these numerous scenarios, researchers can identify how sensitive their findings are to different analytical decisions. This is referred to as “specification curve analysis” (Simonsohn et al., 2020). It effectively limits the flexibility in model selection that might otherwise align closely with a researcher’s preconceived hypotheses. The multiverse analysis approach not only bolsters the robustness and credibility of findings but also yields a more comprehensive understanding of the data.

This type of analysis necessitates a definition of multiple branches for both sample selection and model specification. Based on a thorough examination of the literature on MLA, we identified several key dimensions along which we varied our main analysis to ensure a comprehensive and unbiased analytical approach.¹⁴ Next, we outline the various choices adopted in the literature linked to multiple dimensions, which we categorize as distinct branches within our multiverse analysis:

Cleaning: We considered (i) the full sample and (ii) applied exclusion criteria. To enhance data quality, we excluded participants demonstrating a lack of understanding of the task or poor response to straightforward questions about the lottery. In particular, we excluded participants with low self-stated understanding of the experiment (“Did not understand at all” or “I had quite some difficulties”) and those who answered two out of three simple test questions incorrectly.¹⁵

Condition: We analyzed (i) pooled data from all conditions or (ii) tested MLA in each condition separately. In the pooled dataset, we also introduced a branch with dummy control variables for each condition (with 250-100L9 as the reference category).

¹⁴ Table B7 provides an overview of the different analytical paths in the related MLA studies adopting the Gneezy and Potters (1997) paradigm.

¹⁵ The associated understanding and test questions are displayed in Appendix C.

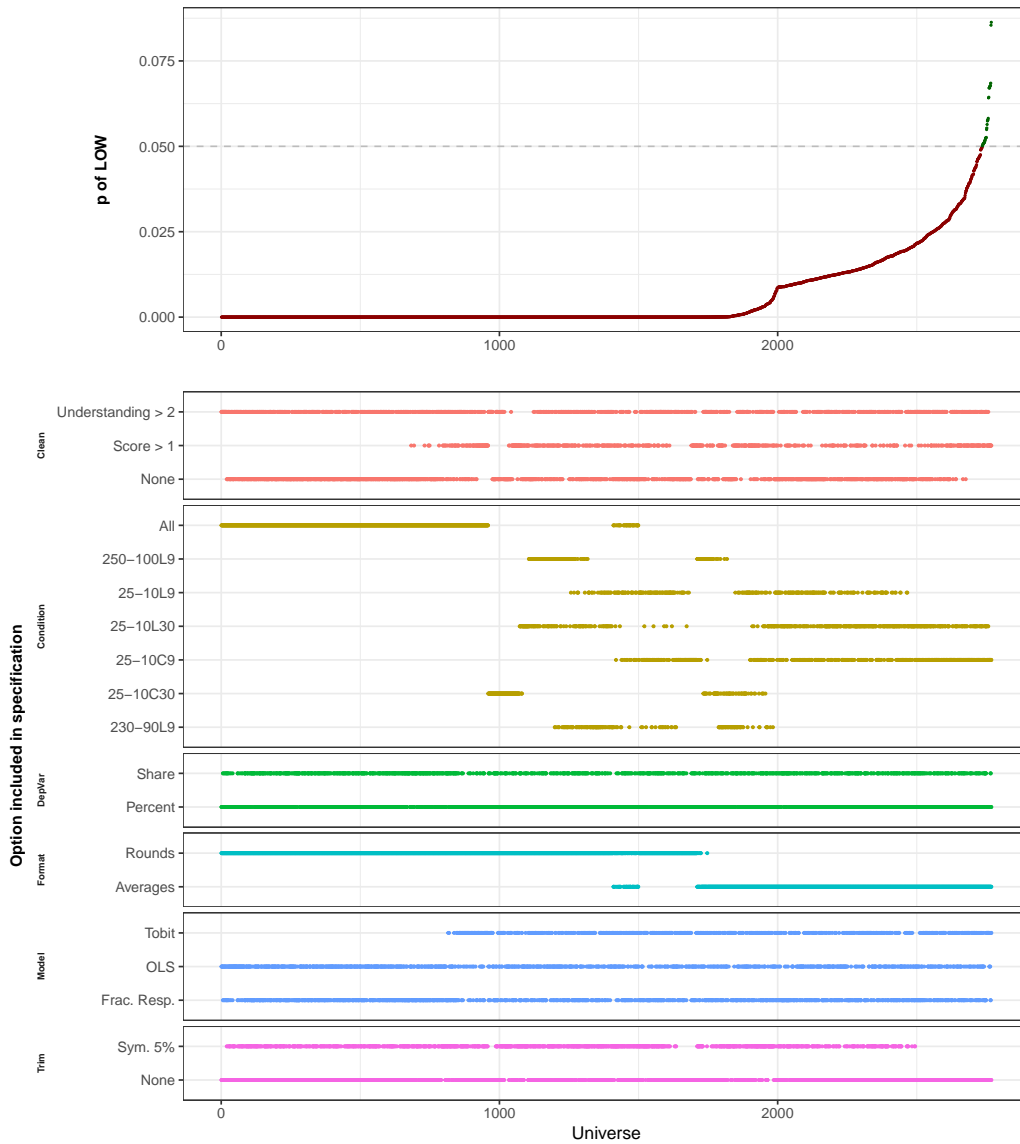


Figure 4: Multiverse analysis of main results. The upper panel illustrates the highest and lowest 5% of p -values of the coefficient LOW and a randomly drawn subset of 10% of p -values in between, out of the 13,824 analysis paths. The lower panel features the tested specification. For the purpose of illustration, in- or exclusion of each control variable has been left out in the lower panel.

Dependent Variable: The dependent variable *Investment in the risky asset* was (i) expressed as a portion (between 0 and 1) and (ii) as a percentage (between 0% and 100%) of the endowment. Absolute investment levels were not considered since these differed across conditions for linear versus compound return calculation as well as short versus long investment horizons.

Model: We utilized (i) the fractional response regression model when the investment was expressed in shares. Both (ii) Tobit and (iii) OLS regressions were applied for the percentage dependent variable format.

Data Format: We examined (i) individual investments averaged across all periods as well as (ii) panel (period-level) data with nine or thirty observations per participant. In panel data analyses, we additionally control for the period number.

Trimming: We considered (i) no trimming procedure and (ii) a symmetric cutoff below the 5th and above the 95th percentile of the individual time taken to complete the experiment.

Control Variables: All possible combinations of our control variables `FEMALE`, `INVESTOR`, `RISKTOLERANCE`, `STAT.KNOWLEDGE`, and `INNSBRUCK`, as well as a version without any control variables, were included in the analysis.

All combinations of these choices yielded a total of 13,824 specifications. To validate the robustness of our results to variations in analytical approaches, we expected at least 95% of all “LOW” coefficients to be statistically significant at the 5% level. [Figure 4](#) displays the highest and lowest 5% of p -values among all applied analysis paths as well as an additional 10% of p -values randomly sampled from the remaining set. The upper panel demonstrates that all p -values fall beneath 0.08, encompassing a variety of different branch combinations, as portrayed in the lower panel. Specifically, our multiverse results indicated that in total, 13,793 specifications (99.78%) led to a statistically significant coefficient of `LOW`.¹⁶ When we based our formal multiverse analysis of MLA on the median of all 13,824 p -values (Simonsohn et al., 2020), we found that increased risk-taking under low decision and feedback frequency (`LOW`) was highly statistically significant ($p < 0.001$). We thus conclude that behavior consistent with MLA withstands alterations to the sample composition and model specification within the realm of reasonable and non-redundant configurations informed by the existing MLA literature.

3.4 Determinants of Myopic Loss Aversion

Finally, we addressed the question of which factors determine the magnitude of behavior consistent with MLA, which appeared to be attenuated in most conditions compared to condition 250-100L9. Differences in MLA across conditions can be a result of either higher risk-taking in the `HIGH` group, lower risk-taking in the `LOW` group, or both. In non-pre-registered analyses, we explored this further by comparing investment allocations in groups `HIGH` and `LOW` in each condition to the behavior of their counterparts in condition 250-100L9—analagous to the original design by Gneezy and Potters (1997). The left panel of [Figure 5](#) depicts coefficient plots based on the applied fractional response regressions (see [Table 2](#)) with treatments `HIGH` or `LOW` in condition 250-100L9 as reference groups. Participants in `HIGH` invested significantly higher amounts in conditions 25-10L9, 25-10C9, and 230-90L9 compared to their counterparts in 250-100L9. Although not statistically significant, in the other two conditions, we observed the opposite pattern (see 25-10L30 and 25-10C30). Investment amounts by participants in group `LOW` were lower only in condition 25-10L30 but higher in conditions 25-10L9 and 25-10C9 compared to group `LOW` in condition 250-100L9. Visible in the right panel of [Figure 5](#), when benchmarked against the baseline setting by Gneezy and Potters (1997), the difference-in-difference MLA effect between conditions tends to be negative across all but two cases. However, these attenuations of MLA did not reach statistical significance, indicated by the 95% confidence intervals. Thus, our findings suggest that MLA was not statistically significantly less pronounced in settings different from the traditional Gneezy and Potters (1997) experiment. Given

¹⁶ At a significance level of 1%, the coefficient of `LOW` was significant in 95.47% of all cases. [Figure B3](#) illustrates the cumulative distribution of p -values for the coefficient `LOW`.

the inherent complexity in reliably detecting interaction effects, which typically necessitates a considerably larger sample size compared to detecting equivalent non-interaction effects, it is important to acknowledge that our study may lack sufficient power for small-to-medium difference-in-difference effects, despite our comparatively large sample sizes. Thus, in [Figure 5](#) we also depict the results of equivalence tests based on the two one-sided tests (TOST) approach. This procedure provides a nuanced statistical method for establishing similarity of conditions by testing for equivalence with the null hypothesis. For our paper, we adopted a methodological approach that leverages coefficient plots of the difference-in-difference effects with 90% confidence intervals. Specifically, we used these plots to graphically indicate the effects we can rule out with high confidence—that is, any difference-in-difference effect sizes that fall outside the 90% confidence bounds of the effects can be considered statistically implausible based on our data. Across all conditions, we could confidently rule out differences in behavior consistent with MLA to our Gneezy and Potters (1997) replication exceeding a standardized magnitude of approximately $d = 0.25$. However, we cannot confidently reject even smaller, possibly still economically significant, variations in MLA across conditions.

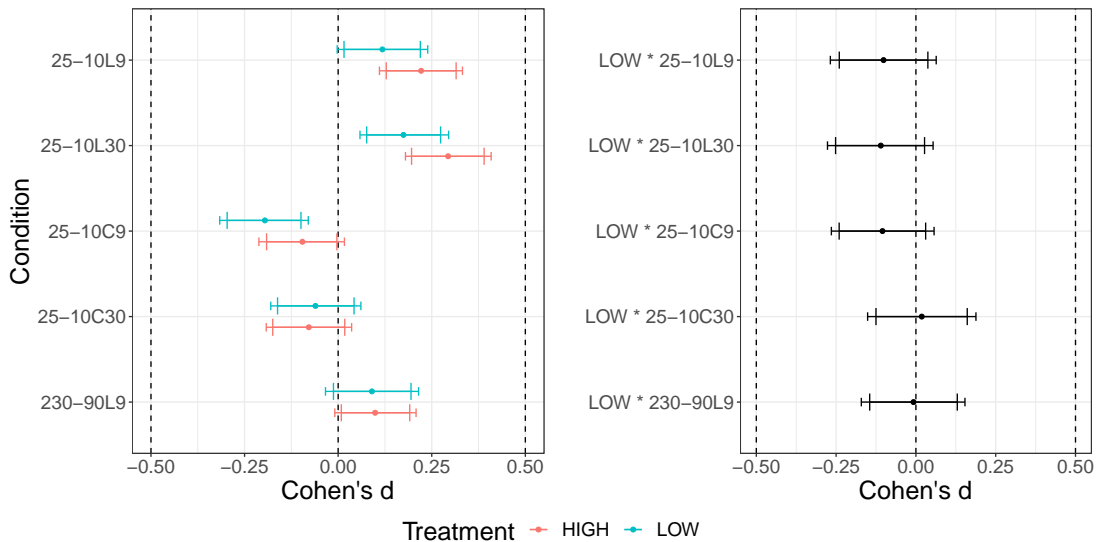


Figure 5: Forest plots of fractional response regression coefficients. Left panel: Condition effects separately in the HIGH and LOW treatments with the 250-100L9 condition as the reference category for both. Right panel: Difference-in-difference MLA effect in the full sample with 250-100L9 as the reference category. Bandwidths indicate 90% and 95% confidence intervals of estimated coefficients. The corresponding regression results are displayed in [Table B8](#) in the Appendix.

4 Discussion

While previous studies have questioned the robustness of myopic loss aversion (MLA) in investment settings closer to reality, they often fell short in statistical power and in systematically exploring the underlying mechanisms that could mitigate behavior consistent with MLA. To bridge this gap, our highly statistically powered study enabled a detailed examination of factors potentially influencing MLA. Contrary to some earlier

studies, our research revealed that MLA remains prevalent under more realistic rates of return, compounding, and longer investment horizons.

Introducing rates of return resembling those of annual investment return distributions more closely did not mitigate MLA behavior with or without return compounding. This finding diverges from Beshears et al. (2017) who adopted identical rates of return and return compounding simultaneously. One plausible explanation may be the difference in sample sizes, suggesting that with our sample we were able to capture smaller-sized MLA effects with higher likelihood. In their main study, conducted over the course of a year and involving high stakes, counteracting effects among the four different intervention mechanisms may have further contributed to the absence of support for MLA-consistent behavior. Our findings regarding the robustness of MLA within the framework of Gneezy and Potters (1997), resonate with other MLA research that incorporated realistic rates of return. Thaler et al. (1997) based experimental risky asset returns on value-weighted stock index returns. They found marked increases in risk-taking when participants made decisions over longer horizons. Benartzi and Thaler (1999) demonstrated increased risk-taking of pension plan participants when historical distributions of 30-year stock fund returns were displayed compared to when annual returns were displayed.

Theoretically, return compounding in our setting may shift individuals' focus to final investment outcomes after nine or thirty periods, potentially mitigating the effects of high evaluation and decision frequency. Klos et al. (2013)'s findings, in which MLA tendencies were significantly reduced after eliciting participants' total lottery return expectations, seem to support this hypothesis. Similarly, in Zeisberger et al. (2012), MLA behavior was slightly attenuated when returns were compound. However, under return compounding, MLA persisted in our study, consistent with Langer and Weber (2008). Cognitive limitations in individuals' ability to envision long-term aggregates of a geometric series may limit any effect of a focus on final investment outcomes (Enke et al., 2023; Stango & Zinman, 2009). In 25-10C30, expected return aggregation is particularly challenging in LOW compared to HIGH due to the increased investment horizon.

Our analysis also suggested overall lower levels of risk-taking in both HIGH and LOW (see Figure 3) under compounding compared to linear return scenarios. The relatively more cautious investment approach in compound return settings might be attributed to the singular initial endowment. Since relative risk—risky asset investment relative to overall wealth—decreases in linear return conditions for later periods but remains the same in compound return conditions (100%), participants in the former might increase their risky asset allocations throughout the experiment more than participants in the latter (Looney & Hardin, 2020).

Finally, our results revealed that MLA is resilient to variations in the investment horizon. Longer planning horizons are typically associated with increased investment risk-taking (see, e.g., Anderson & Settle, 1996; Dierkes et al., 2010). In our experiment, additional periods allowed participants to experience the long-term dynamics of the risky asset, enabling better understanding of the underlying return distribution. It was unclear, however, whether this affects participants in HIGH or LOW differently. We did not observe significant differences in MLA behavior for longer investment horizons. Instead, risk-taking seemed to have increased almost proportionally in HIGH and LOW compared to the corresponding conditions with 9 periods (see Figure 3). Following the relative risk argument by Looney and Hardin (2020), it seems conceivable that risk-taking over longer horizons increases further in linear return conditions, but it does not explain the similar increases in

risk-taking in HIGH and LOW over time in the compound return conditions (see [Figure B2](#)). Instead, such development could potentially be explained by wealth effects.

Our findings imply considerable challenges in designing and communicating the risks of financial assets. Today, individual tendencies to make short-sighted decisions are being reinforced by technological developments around the rapid transmission of information and an overload of stimuli due to the use of technology (see, e.g., [Kalda et al., 2021](#)). This is particularly pertinent in decisions regarding the accumulation of retirement or other forms of long-term savings. Management policies fostering broad bracketing of investment outcomes, such as extending minimum return horizon disclosure, as demonstrated by [Shaton \(2017\)](#), or aggregating returns, could help mitigate the negative consequences of myopic financial decision-making. By reducing the focus on short-term fluctuations, investors can be better positioned to make decisions aligned with their long-term financial goals. For mitigating MLA, advanced technological solutions, including software programs, can play a crucial role ([Looney & Hardin, 2009](#)). Such programs can be designed to dynamically inform investors about risky assets and the long-term outcomes of their investments. By highlighting the consequences of short-term market reactions on long term financial outcomes, these tools can encourage a focus on long-term financial strategies, effectively guiding investors away from reactive decision-making (see, e.g., [Hueber & Schwaiger, 2022](#); [Kaufmann et al., 2013](#)). Additionally, educational initiatives aimed at increasing financial literacy can play a pivotal role. They can emphasize the importance of long-term planning and the potential pitfalls of reactive decision-making based on short-term market movements. Furthermore, organizational and regulatory frameworks may be structured to incentivize long-term investments for clients. This can be achieved through measures such as an offering of tax benefits for longer holding periods, creating tiered investment products to encourage clients to maintain investments over longer durations for greater benefits, or implementing loyalty bonuses for long-term investments (in a similar fashion as proposed by [Bolton & Samama, 2013](#)), which might further reward and motivate sustained investment behavior. Such measures would not only mitigate the impact of myopia on individual investors but also contribute to greater stability in financial markets ([Davies et al., 2014](#)).

5 Conclusion

Following the influential work by [Benartzi and Thaler \(1995\)](#) and [Gneezy and Potters \(1997\)](#), the academic community has investigated the applicability of the theory of myopic loss aversion (MLA) across diverse settings. Previous research has extensively discussed the real-world implications of MLA and its importance has been mentioned in many popular media outlets and investing websites. For example, a search within the News on the Web corpus yields 47 entries related to the concept of myopic loss aversion. In contrast, other widely recognized behavioral concepts such as regret aversion yield a comparatively smaller number of results ([NOW Corpus, 2024](#)). Recently, however, as the focus on replicability ([Camerer et al., 2018](#); [Huber et al., 2023](#)) and reproducibility ([Menkveld et al., forthcoming](#)) of economic experiments has intensified, there has been a growing discourse on the robustness and generalizability of MLA, notably propelled by the contribution of [Beshears et al. \(2017\)](#)'s work, which suggested that evidence for MLA could be confined to a narrow range of experimental designs. Prior studies attempting to modify experimental design features in this context often encountered challenges related to

statistical power or lacked a refined design to clearly dissect the factors influencing MLA-compliant behavior. This left a void in our understanding of MLA’s robustness and drivers.

Given both the number of studies and the mentioned practical consequences of MLA, our research endeavored to fill this gap by rigorously examining the resilience of MLA to more conventional investment scenarios. We tackled this by isolating the effects of more realistic rates of return, commonly used investment procedures featuring return compounding, and a longer, more representative investment duration in the established Gneezy and Potters (1997) experimental design across six between-subject conditions. Our results consistently demonstrated the resilience of MLA behavior, even amidst these significant modifications to the original experiment by Gneezy and Potters (1997).

Specifically, MLA persisted in various modified conditions: when the possibility of a total loss was reduced while maintaining similar CPT valuations compared to the original (condition 230-90L9), and when return rates were scaled down to a fraction of the original rates under both compound returns with a dynamic endowment balance (condition 25-10C9) and under linear returns with a period-by-period endowment (condition 25-10L9). The down-scaling of returns did not mitigate MLA under extended investment horizons either, for both compound and linear returns (25-10L30 and 25-10C30). Remarkably, behavior consistent with MLA was most pronounced in condition 25-10C30, the scenario that most closely mirrored real-world investment settings. Here, the effect was close to the one reported in our Gneezy and Potters (1997) replication (condition 250-100L9). Our results were further validated by a multiverse analysis, which confirmed MLA’s stability by effectively addressing concerns about analytical researcher degrees of freedom. While MLA appeared somewhat reduced in some conditions that deviated from the original Gneezy and Potters (1997) design, we found no evidence of interaction between these alterations and the magnitude of MLA and could confidently rule out standardized differences in MLA larger than $d = 0.25$ compared to the original design (condition 250-100L9). We conclude that the non-replication of MLA by Beshears et al. (2017) in their second aggregation experiment is likely the result of a false negative. The reason is that despite the substantial costs of the study in terms of monetary incentives, the high number of conditions limited statistical power in the pairwise comparisons.

Our study demonstrates that MLA constitutes a persistent behavioral pattern with significant implications for individual investment decisions, and extends well beyond the confines of the protocol in Gneezy and Potters (1997). This finding is consistent with studies utilizing field data (Larson et al., 2016) and those reevaluating MLA in less abstract lab-in-the-field environments (Iqbal et al., 2021). Considering the demonstrated prevalence of MLA, there is a pressing need for measures that either reduce the frequency of portfolio evaluations or mitigate individuals’ sensitivity to frequent assessments, especially in areas requiring long-term consideration, such as retirement planning, healthcare, and environmental stewardship. Techniques such as experience sampling of historical returns (Hueber & Schwaiger, 2022; Kaufmann et al., 2013) and comprehensive performance disclosure (Gerhard et al., 2017) have been suggested. Despite these promising strategies, many platforms currently continue to emphasize short-term perspectives (Borsboom et al., 2022).

While our study contributes important insights, it also opens new paths for future examination. Our analysis, focusing on modifications to return rates, investment procedures, and time horizons, did not reveal significant differences in MLA-compliant behaviors. We cannot rule out the possibility of very small-sized effects but they are likely less significant economically. Thus, any real-world impact of our alterations, either applied

individually or jointly, is likely limited. Future research could investigate whether other variables, such as outcome probabilities of risky assets (see, e.g., Schwaiger & Hueber, 2021), higher moments (see, e.g., Haisley et al., 2008), or longer times delays between investment decisions, play a systematic role in influencing MLA tendencies. Such studies are vital to allow us to fully comprehend the factors driving MLA. Equipped with high statistical power, our research establishes that MLA transcends the synthetic design choices characteristic of earlier path-dependent investigations, proving its applicability in more realistic settings. This furnishes compelling evidence of MLA's relevance, highlighting its potential for broader real-world applicability and impact across various domains.

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Appendices

for Online Publication

The Consequences of Narrow Framing for Risk-Taking:

A Stress Test of Myopic Loss Aversion

Rene Schwaiger[†], Markus Strucks[§],

Stefan Zeisberger^{§,‡}

[†] Department of Banking and Finance, University of Innsbruck

[§] Institute for Management Research, Radboud University

[‡] Department of Banking and Finance, University of Zurich

* Corresponding author: stefan.zeisberger@ru.nl

A Perceptions

Aligned with the methodology of Venkatraman et al. (2006), we conducted a post-investment game survey in Wave 3 (Innsbruck) to explore psychological factors and perceptions related to risk-taking behaviors. While such variables are typically integral to risk-taking analysis, our study specifically aims to understand the dynamics of MLA and how variations in these factors might contribute to different levels of risk-taking between the groups HIGH and LOW across various conditions. We hypothesize that frequent evaluations and decision-making lead to a heightened perception of loss magnitude and likelihood, thus promoting a decrease in risk-taking. Furthermore, this process may also affect individual emotions, potentially increasing worry and diminishing satisfaction with investment choices.

Figure A1 displays the average scores for the key variables—risk perception, worry, satisfaction, perceived loss probability, and perceived loss magnitude—under the different experimental conditions. The results of independent-sample *t*-tests regarding these key variables between HIGH and LOW in each condition are outlined in Table A1. Notably, the anticipated disparities were evident primarily in the 230-90L9 condition, where worry and perceived loss probability were significantly higher in the HIGH group compared to the LOW group. Conversely, satisfaction levels were higher in the LOW group. This latter pattern also held for the entire sample, encompassing all conditions. Interestingly, despite higher investments, participants in group LOW perceived greater losses and loss likelihoods than those in HIGH under the 25-10C30 condition. This observation is particularly striking in the context of a long-horizon multiplicative setting, suggesting that participants might feel more confident in overcoming short-term losses due to the potential for cumulative gains over time leading to higher risk-taking.

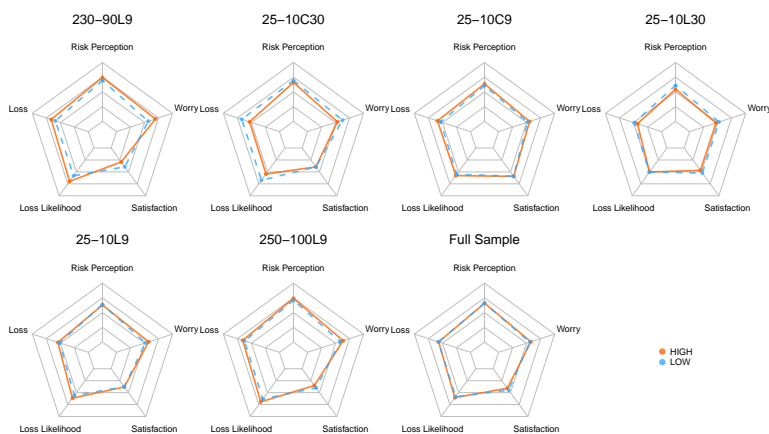


Figure A1: Radar charts of mean scores on perception variables. Each variable is measured by means of subject assessment on a seven-item Likert scale. The corresponding *t*-test results are displayed in Table A1.

Table A1: T-tests of perception differences between treatments. The table shows mean differences of selected perceptions variables in HIGH- LOW in each condition using independent-samples t-tests.

Condition	N	Risk Perception	Worry	Satisfaction	Loss Probability	Loss
250-100L9	160	0.21	0.30	-0.29	0.35	0.19
230-90L9	166	0.31	0.77**	-0.61*	0.70*	0.44
25-10L9	172	-0.04	0.33	0.01	0.35	0.18
25-10L30	157	-0.40	-0.31	-0.34	-0.01	-0.34
25-10C9	157	0.19	0.21	0.03	0.16	0.34
25-10C30	170	-0.20	-0.54	-0.003	-0.78**	-0.83**
Full Sample	982	0.01	0.12	-0.24**	0.12	-0.02

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

B Additional Tables & Figures

Table B1: Final sample randomization checks. `FEMALE` is a binary dummy variable that takes the value of 0 for male participants and the value of 1 for female participants. `INVESTOR` is a dummy variable that equals 1 if participants have already invested in financial products. `RISKTOLERANCE` indicates the self-reported risk preferences of participants on Likert scales from 0 to 10. `STAT.KNOWLEDGE` represents self-assessed statistical knowledge from 1 to 7. `INNSBRUCK` is a binary dummy that takes the value of 0 for participants from the Radboud University in Nijmegen and the value of 1 for participants from the University of Innsbruck.

Condition	Variable	Test	Chi2-Statistic	N
250-100L9	FEMALE	chi2	0.003	347
250-100L9	INVESTOR	chi2	0.566	347
250-100L9	RISKTOLERANCE	Kruskal-Wallis	0.119	347
250-100L9	STAT.KNOWLEDGE	Kruskal-Wallis	6.498*	347
250-100L9	INNSBRUCK	chi2	1.151	347
230-90L9	FEMALE	chi2	0.045	358
230-90L9	INVESTOR	chi2	0.250	358
230-90L9	RISKTOLERANCE	Kruskal-Wallis	0.371	358
230-90L9	STAT.KNOWLEDGE	Kruskal-Wallis	0.051	358
230-90L9	INNSBRUCK	chi2	0.224	358
25-10L9	FEMALE	chi2	2.260	346
25-10L9	INVESTOR	chi2	0.277	346
25-10L9	RISKTOLERANCE	Kruskal-Wallis	0.798	346
25-10L9	STAT.KNOWLEDGE	Kruskal-Wallis	0.430	346
25-10L9	INNSBRUCK	chi2	2.307	346
25-10C9	FEMALE	chi2	0.328	359
25-10C9	INVESTOR	chi2	2.009	359
25-10C9	RISKTOLERANCE	Kruskal-Wallis	0.217	359
25-10C9	STAT.KNOWLEDGE	Kruskal-Wallis	0.169	359
25-10C9	INNSBRUCK	chi2	2.121	359
25-10L30	FEMALE	chi2	0.068	359
25-10L30	INVESTOR	chi2	1.899	359
25-10L30	RISKTOLERANCE	Kruskal-Wallis	2.612	359
25-10L30	STAT.KNOWLEDGE	Kruskal-Wallis	0.879	359
25-10L30	INNSBRUCK	chi2	0.402	359
25-10C30	FEMALE	chi2	0.000	348
25-10C30	INVESTOR	chi2	1.691	348
25-10C30	RISKTOLERANCE	Kruskal-Wallis	0.038	348
25-10C30	STAT.KNOWLEDGE	Kruskal-Wallis	0.041	348
25-10C30	INNSBRUCK	chi2	0.002	348

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table B2: Overview of previous MLA studies in chronological order. Selected studies use the between-subjects Gneezy and Potters (1997) investment experiment with a binary-outcome risky asset and the same exogenous manipulation of myopia between HIGH and LOW. Columns 1–4 indicate how the original experiment is modified (blank indicates no modification compared to Gneezy and Potters (1997)). Per-Treatment Sample Size indicates the rounded average number of participants in each condition HIGH/LOW. Total Sample Size refers to the total number of recruited participants in exogenous MLA conditions.

Study	Rates of Return	Probabilities	Earnings	Horizon	Per-Treatment Sample Size	Total Sample Size
Gneezy and Potters (1997)	+250% / -100%	0.33 / 0.67	Linear	9 Periods	42	84
Langer and Weber (2005)	+30(15)% / -100%	0.1 / 0.9			17	35
Bellemare et al. (2005)					29	88
Haigh and List (2005)					30	118
Langer and Weber (2008)	+7% / -3%	0.4 / 0.6	Compound	30 Periods	27	54
Fellner and Sutter (2009)				18 Periods	30	118 ^a
Hardin and Looney (2012)				30 Periods	31	622
Zeisberger et al. (2012)	+230(190)% / -100%	0.4 / 0.6	Compound	36 Periods	48	190
Beshears et al. (2017)	+25% / -10%		Compound		40	320
Durand et al. (2019)					64	128
Schwaiger and Hueber (2021)		0.5 / 0.5			234	937
Hueber and Schwaiger (2022)					224	894
This study	+25% / -10%		Compound	30 Periods	187	2,245

^a Including endogenous-choice treatments, their study comprises a total sample of 444 participants.

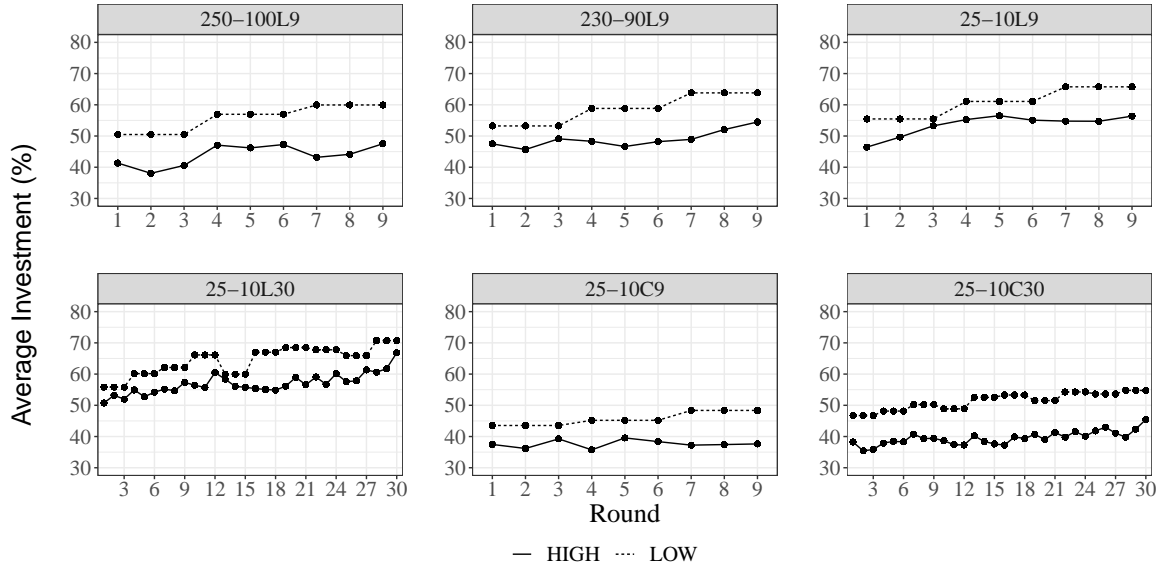


Figure B2: Round-level average investment percentages between treatments HIGH and LOW across different conditions. Conditions 250-100L9, 230-90L9, 25-10L9, and 25-10C9 display the development of average investments over nine periods. 25-10L30 and 25-10C30 display thirty-period developments of average investments.

Table B3: T-tests of differences between treatments. The table shows mean differences of investment amounts in HIGH and LOW in each condition using independent-samples t-tests. The last column indicates the p-value results of a permutation (asymptotic general independence) test.

Condition	N	Mean diff. (H - L)	lower 95% conf. int.	upper 95% conf. int.	t-stat	Std. Error	p	Perm. test p
250-100L9	350	-11.505***	-16.855	-6.156	-4.231	2.719	0.000	0.000
230-90L9	360	-9.913***	-15.615	-4.211	-3.419	2.899	0.001	0.001
25-10L9	359	-7.218*	-12.842	-1.594	-2.525	2.859	0.012	0.012
25-10C9	348	-7.753**	-13.420	-2.085	-2.690	2.882	0.007	0.008
25-10L30	359	-7.640**	-13.105	-2.174	-2.749	2.779	0.006	0.006
25-10C30	355	-12.029***	-17.960	-6.099	-3.990	3.015	0.000	0.000

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. 95%-confidence interval in parentheses.

Table B4: Average marginal effects fractional response models with logit links and the amount invested per period in percent of the endowment as dependent variables. The binary dummy variable `LOW` is coded 0 for participants in the `HIGH` treatment and 1 for those in the `LOW` treatment. `FEMALE` is a binary dummy variable that takes the value of 0 for male participants and the value of 1 for female participants. `INVESTOR` is a dummy variable that equals 1 if participants have already invested in financial products. `RISKTOLERANCE` indicates the self-reported risk preferences of participants on Likert scales from 0 to 10. `STAT.KNOWLEDGE` represents participants' self reported statistical knowledge compared to their fellow students on a 7-point scale. `INNSBRUCK` is a binary dummy that takes the value of 0 for participants from the Radboud University in Nijmegen and the value of 1 for participants from the University of Innsbruck.

	<i>Dependent variable: Investment (%)</i>					
	<i>Conditions:</i>					
	250-100L9	230-90L9	25-10L9	25-10C9	25-10L30	25-10C30
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
<code>LOW</code>	0.121*** (0.011)	0.100*** (0.011)	0.070*** (0.011)	0.081*** (0.011)	0.058*** (0.007)	0.117*** (0.006)
<code>FEMALE</code>	-0.091*** (0.012)	-0.055*** (0.014)	-0.042*** (0.012)	-0.106*** (0.013)	-0.061*** (0.008)	-0.143*** (0.008)
<code>INVESTOR</code>	-0.014 (0.012)	-0.013 (0.013)	0.016 (0.013)	-0.023 (0.012)	0.070*** (0.007)	-0.025*** (0.008)
<code>RISKTOLERANCE</code>	0.040*** (0.003)	0.033*** (0.003)	0.019*** (0.003)	0.033*** (0.003)	0.026*** (0.002)	0.031*** (0.002)
<code>STAT.KNOWLEDGE</code>	0.013** (0.005)	0.008 (0.005)	0.031*** (0.005)	-0.0004 (0.005)	0.003 (0.003)	0.007** (0.003)
<code>INNSBRUCK</code>	0.081*** (0.012)	0.082*** (0.012)	0.086*** (0.012)	0.050*** (0.011)	0.080*** (0.007)	0.076*** (0.007)
Observations	3,042	3,159	3,096	3,177	10,680	10,590

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Clustered standard errors at the subject level in parentheses.

Table B5: Full Sample average marginal effects fractional response models with logit links and the amount invested in percent of the endowment as dependent variables. The binary dummy variable `LOW` is coded 0 for participants in the `HIGH` treatment and 1 for those in the `LOW` treatment. `FEMALE` is a binary dummy variable that takes the value of 0 for male participants and the value of 1 for female participants. `INVESTOR` is a dummy variable that equals 1 if participants have already invested in financial products. `RISKTOLERANCE` indicates the self-reported risk preferences of participants on Likert scales from 0 to 10. `STAT.KNOWLEDGE` represents participants' self reported statistical knowledge compared to their fellow students on a 7-point scale. `INNSBRUCK` is a binary dummy that takes the value of 0 for participants from the Radboud University in Nijmegen and the value of 1 for participants from the University of Innsbruck.

	<i>Dependent variable: Investment (%)</i>					
	<i>Conditions:</i>					
	250-100L9	230-90L9	25-10L9	25-10C9	25-10L30	25-10C30
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
<code>LOW</code>	0.111*** (0.025)	0.108*** (0.027)	0.072** (0.027)	0.066* (0.027)	0.058* (0.026)	0.117*** (0.028)
<code>FEMALE</code>	-0.100*** (0.027)	-0.059 (0.034)	-0.023 (0.029)	-0.081* (0.033)	-0.056 (0.031)	-0.153*** (0.035)
<code>INVESTOR</code>	-0.014 (0.027)	-0.015 (0.033)	0.005 (0.031)	-0.014 (0.032)	0.068* (0.030)	-0.025 (0.033)
<code>RISKTOLERANCE</code>	0.038*** (0.007)	0.033*** (0.007)	0.020* (0.008)	0.038*** (0.007)	0.027*** (0.007)	0.032*** (0.007)
<code>STAT.KNOWLEDGE</code>	0.012 (0.011)	0.009 (0.013)	0.031* (0.013)	-0.002 (0.013)	0.005 (0.012)	0.008 (0.012)
<code>INNSBRUCK</code>	0.101*** (0.027)	0.080** (0.030)	0.093** (0.030)	0.040 (0.029)	0.077* (0.030)	0.070* (0.030)
Observations	380	370	375	383	369	368

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Robust standard errors in parentheses.

Table B6: Robustness sample average marginal effects fractional response models with logit links and the amount invested in percent of the endowment as dependent variables. The binary dummy variable `LOW` is coded 0 for participants in the `HIGH` treatment and 1 for those in the `LOW` treatment. `FEMALE` is a binary dummy variable that takes the value of 0 for male participants and the value of 1 for female participants. `INVESTOR` is a dummy variable that equals 1 if participants have already invested in financial products. `RISKTOLERANCE` indicates the self-reported risk preferences of participants on Likert scales from 0 to 10. `STAT.KNOWLEDGE` represents participants' self reported statistical knowledge compared to their fellow students on a 7-point scale. `INNSBRUCK` is a binary dummy that takes the value of 0 for participants from the Radboud University in Nijmegen and the value of 1 for participants from the University of Innsbruck.

	<i>Dependent variable: Investment (%)</i>					
	<i>Conditions:</i>					
	250-100L9	230-90L9	25-10L9	25-10C9	25-10L30	25-10C30
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
<code>LOW</code>	0.128*** (0.029)	0.117*** (0.031)	0.102** (0.032)	0.097** (0.035)	0.064* (0.032)	0.117*** (0.034)
<code>FEMALE</code>	-0.102** (0.034)	-0.014 (0.039)	-0.069* (0.034)	-0.122** (0.044)	-0.055 (0.038)	-0.152*** (0.042)
<code>INVESTOR</code>	-0.011 (0.030)	-0.012 (0.036)	0.050 (0.037)	-0.041 (0.040)	0.062 (0.035)	-0.058 (0.039)
<code>RISKTOLERANCE</code>	0.040*** (0.009)	0.039*** (0.008)	0.019* (0.009)	0.032** (0.010)	0.029*** (0.009)	0.035*** (0.009)
<code>STAT.KNOWLEDGE</code>	0.008 (0.014)	0.018 (0.015)	0.029 (0.015)	0.009 (0.017)	0.0003 (0.014)	0.014 (0.015)
<code>INNSBRUCK</code>	0.095** (0.032)	0.078* (0.035)	0.098** (0.034)	0.020 (0.040)	0.058 (0.037)	0.089* (0.038)
Observations	288	286	258	239	281	262

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Robust standard errors in parentheses.

Table B7: Overview of analytical heterogeneity across previous MLA studies in chronological order. Selected studies use the between-subjects Gneezy and Potters (1997) investment experiment with a binary-outcome risky asset and the same exogenous manipulation of myopia between HIGH and LOW. For an overview of the different conditions in the experimental design, see Table B2. Blank cells indicate no (additional) deviation from the analytical framework of Gneezy and Potters (1997).

Study	Dependent Variable	Model	Data Format	Cleaning/Trimming	Controls
Gneezy and Potters (1997)	Absolute & relative	Mann-Whitney test	Periods & averages	No	No
Langer and Weber (2005)	Relative	Mann-Whitney test	Averages	No	No
Bellemare et al. (2005)	Absolute & relative	Mann-Whitney test	Periods & averages	No	No
Haigh and List (2005)	Absolute	Tobit regression	Periods	No	No
Langer and Weber (2008)	Relative	Mann-Whitney test	Averages	No	No
Fellner and Sutter (2009)	Absolute	Tobit Regression	Periods	No	Yes
Hardin and Looney (2012)	Relative	Linear mixed modelling	Averages	No	Yes
Zeisberger et al. (2012)	Absolute	Mann-Whitney test	Periods & averages	No	No
Beshears et al. (2017)	Relative	OLS regression	Averages	No	No
Durand et al. (2019)	Absolute	Tobit regression	Periods	No	Yes
Schwaiger and Hueber (2021)	Relative	Tobit regression	Averages	Yes	Yes
Hueber and Schwaiger (2022)	Relative	Tobit regression	Averages	Yes	Yes

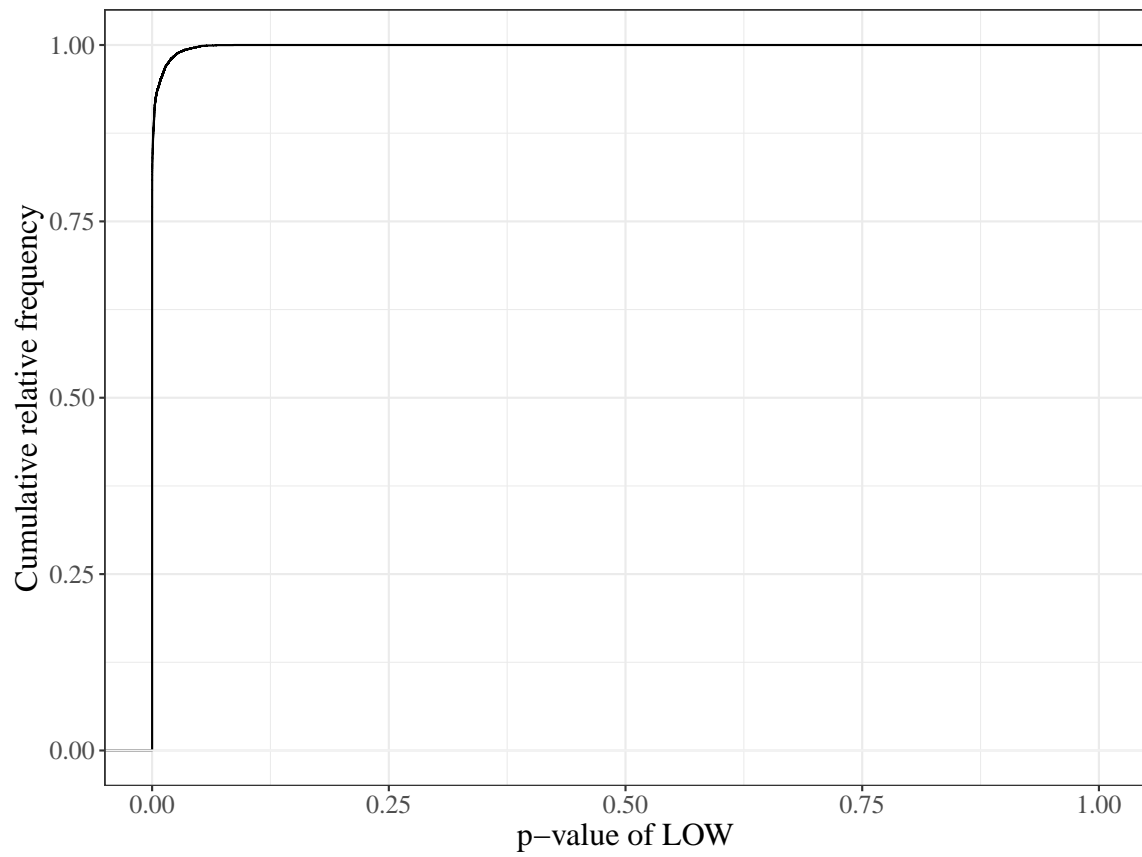


Figure B3: Cumulative distribution of p -values in multiverse analysis. The figure displays the cumulative relative frequency of p -values of LOW from all regressions in our multiverse analysis. The multiverse analysis is based on 13,824 regressions featuring different analytical choices as outlined in [section 3](#).

Table B8: Condition effects fractional response models with logit links and the amount invested in percent of the endowment as dependent variables. The binary dummy variable `LOW` is coded 0 for participants in the `HIGH` treatment and 1 for those in the `LOW` treatment. `FEMALE` is a binary dummy variable that takes the value of 0 for male participants and the value of 1 for female participants. `INVESTOR` is a dummy variable that equals 1 if participants have already invested in financial products. `RISKTOLERANCE` indicates the self-reported risk preferences of participants on Likert scales from 0 to 10. `STAT.KNOWLEDGE` represents participants' self reported statistical knowledge compared to their fellow students on a 7-point scale. `INNSBRUCK` is a binary dummy that takes the value of 0 for participants from the Radboud University in Nijmegen and the value of 1 for participants from the University of Innsbruck.

	<i>Dependent variable: Investment (%)</i>		
	HIGH	LOW	Full
LOW			0.484*** (0.115)
230-90L9	0.211 (0.110)	0.161 (0.119)	0.207 (0.114)
25-10L9	0.453*** (0.111)	0.247* (0.121)	0.447*** (0.115)
25-10L30	0.542*** (0.110)	0.313** (0.121)	0.536*** (0.114)
25-10C9	-0.197 (0.111)	-0.341** (0.119)	-0.195 (0.116)
25-10C30	-0.148 (0.111)	-0.115 (0.118)	-0.152 (0.116)
female	-0.277*** (0.075)	-0.410*** (0.081)	-0.344*** (0.055)
INVESTOR	-0.022 (0.071)	0.052 (0.078)	0.014 (0.053)
RISKTOLERANCE	0.113*** (0.017)	0.152*** (0.019)	0.131*** (0.013)
STAT.KNOWLEDGE	0.068* (0.027)	0.012 (0.031)	0.043* (0.020)
INNSBRUCK	0.190** (0.069)	0.461*** (0.076)	0.321*** (0.051)
LOW * 230-90L9			-0.056 (0.162)
LOW * 25-10L9			-0.208 (0.163)
LOW * 25-10L30			-0.216 (0.163)
LOW * 25-10C9			-0.152 (0.162)
LOW * 25-10C30			0.025 (0.162)
Observations	1,063	1,068	2,131

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses.

C Screenshots

Screenshots of the whole experiment for our baseline condition 250-100L9 are shown in [subsection C.1](#). Headers distinguish alternative pages for participants in HIGH or LOW (instructions, decisions and feedback). [subsection C.2](#) displays the experimental instructions in all other conditions for HIGH and LOW, respectively.

C.1 250-100L9

Thank you for participating in this study.

This is part of a research investigation conducted by the University of Innsbruck (Austria), the University of Zurich (Switzerland) and Radboud University (the Netherlands), and was reviewed and approved by the University of Zurich's institutional review board for ethical issues. For any questions contact stefan.zeisberger@ru.nl.

As part of this study, we will ask you to play an investment game and answer some questions. We expect this to take you approximately 12 minutes. **Depending on your decisions in the experiment you will be financially compensated for taking part.** We will provide further details and instructions in the relevant sections.

We ask you to complete all the sections and not to close the browser before reaching the end. Please read the instructions carefully. **Note that you will only be paid for your participation if you complete the task and survey in full.** Information about your final payoff will be provided at the end of the task.

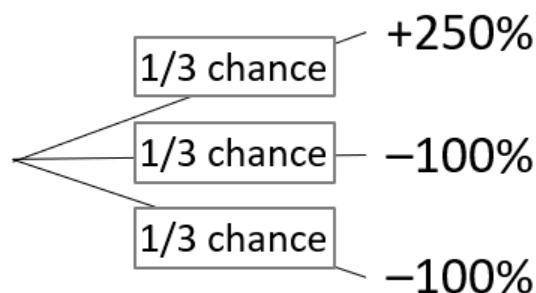
By taking part in this study, you acknowledge that your participation is voluntary and that your responses, including basic demographic information will be saved, but no identifiable personal data will be stored, except for payment purposes. This participation and payment relevant data will be deleted afterwards. All data will be anonymized and used for scientific research purposes only. Your data will not be passed on to third parties.

HIGH

This study consists of nine successive rounds. You may take as much time as you need to make your choices.

In each round, you will start with an amount of 100 Experimental Currency Units (ECU). You must decide which part of this amount (between 0% and 100%) you wish to bet in the following gamble whose outcome will be randomly determined by the computer in each round.

- You have a 2 out of 3 chance (67%) of losing 100% of the amount that you bet.
- You have a 1 out of 3 chance (33%) of getting the amount that you bet back, plus an additional 250% of the amount that you bet.



The lottery results of previous rounds have no influence on the probability of winning or losing in the current or in future rounds.

Your total earnings for the round are equal to 100 ECU (your starting amount) plus your gains or losses in the gamble.

At the end of each round, you will learn how much money you gained or lost from the gamble and your total earnings for the round.

After that, you will make your choice for the next round. Again you start with 100 ECU, a part of which (between 0% and 100%) you can bet in the gamble. You may not bet money from previous rounds in the gamble. The same procedure as described above determines

your earnings for this round. All subsequent rounds will also proceed in the same manner.

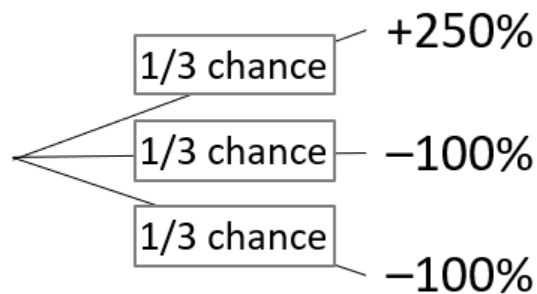
Your total earnings for this study in real euros are equal to your total ECU earnings (summed over all nine rounds) divided by 400. As an example, 1000 ECU equal 2.50€ in real money. You will be paid automatically by bank transfer very shortly after the study.

LOW

This study consists of nine successive rounds. You may take as much time as you need to make your choices.

In each round, you will start with an amount of 100 Experimental Currency Units (ECU). You must decide which part of this amount (between 0% and 100%) you wish to bet in the following gamble whose outcome will be randomly determined by the computer in each round.

- You have a 2 out of 3 chance (67%) of losing 100% of the amount that you bet.
- You have a 1 out of 3 chance (33%) of getting the amount that you bet back, plus an additional 250% of the amount that you bet.



The lottery results of previous rounds have no influence on the probability of winning or losing in the current or in future rounds.

In round 1, you will decide how much to bet in the gamble for rounds 1, 2, and 3. You must bet the same amount in all three rounds. Thus, if you decide to bet X% in the gamble for round 1, then you will also bet X% in the gamble for rounds 2 and 3. Therefore, three consecutive rounds are joined together.

After making your bet choice, you will learn how much money you gained or lost from the three gambles simultaneously, as well as your total earnings for the three rounds. Your total earnings for the

three rounds are equal to 300 ECU (three times your starting amount of 100 ECU per round) plus your gains and losses in the three gambles.

After that, you will make your choice for the next three rounds (4-6). For each of the three rounds you again start with 100 ECU, a part of which (between 0% and 100%) you can bet in the gamble. You may not bet money from previous rounds in the gamble. The same procedure as described above determines your earnings for these three rounds, and you will again learn the outcomes of the three gambles simultaneously. The subsequent three rounds (7-9) will also proceed in the same manner.

Your total earnings for this study in real euros are equal to your total ECU earnings (summed over all nine rounds) divided by 400. As an example, 1000 ECU equal 2.50€ in real money. You will be paid automatically by bank transfer very shortly after the study.

HIGH

Round 1:

What percentage of your endowment of 100 ECU do you bet in the following gamble in this round?

- You have a 2 out of 3 chance (67%) of losing 100% of the amount that you bet.
- You have a 1 out of 3 chance (33%) of getting the amount that you bet back, plus an additional 250% of the amount that you bet.

0 10 20 30 40 50 60 70 80 90 100



LOW

Round 1:

What percentage of your endowment of 100 ECU do you bet in the following gamble in the next three rounds?

- You have a 2 out of 3 chance (67%) of losing 100% of the amount that you bet.
- You have a 1 out of 3 chance (33%) of getting the amount that you bet back, plus an additional 250% of the amount that you bet.

0 10 20 30 40 50 60 70 80 90 100



HIGH

Round	Realization of Gamble	Your Gain/Loss Amount (Last Round)	Your Total Earnings (Last Round)
1	LOSS	-50 ECU	50 ECU

You **lost -50 ECU** from the gamble in the last round.

Your total earnings of the last round are 50 ECU.

LOW

Round	Realization of Gamble	Your Gain/Loss Amount (Last 3 Rounds)	Your Total Earnings (Last 3 Rounds)
1	WIN	+200 ECU	500 ECU
2	WIN		
3	LOSS		

You **gained +200 ECU** from the gamble in the last three rounds.
Your total earnings of the last three rounds are 500 ECU.

Your total earnings are 800 ECU, which amounts to 2€.

How satisfied are you with your return?

1 - Completely unsatisfied

2

3

4

5

6

7 - Completely satisfied

How well did you understand what to do and how to answer in this study?

- Did not understand at all
- I had quite some difficulties
- Understood somehow what to do
- Understood well
- Everything was clear

I have sufficient information to play this gamble.

Strongly disagree

Moderately disagree

Somewhat disagree

Neither agree nor disagree

Somewhat agree

Moderately agree

Strongly agree

How risky is this gamble?

Very safe	Moderately safe	Somewhat safe	Neither risky nor safe	Somewhat risky	Moderately risky	Very risky
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

Please indicate to what extent you agree or disagree with the following statements:

It is very likely that I will lose money if I decide to play this gamble.

Strongly disagree	Moderately disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Moderately agree	Strongly agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

If I decide to play this gamble, I would worry about the consequences.

Strongly disagree	Moderately disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Moderately agree	Strongly agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

I could incur a great loss if I decide to play this gamble.

Strongly disagree	Moderately disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Moderately agree	Strongly agree
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

What was the probability to win the gamble in each round?

- 25%
- 33%
- 10%
- 67%

What was the amount you could **win** from the gamble in each round?

- 0.33 times (=33%) of the amount that you bet
- 0.25 times (=25%) of the amount that you bet
- 2.5 times (=250%) of the amount that you bet
- 2.3 times (=230%) of the amount that you bet

What was the amount you could **lose** from the gamble in each round?

- 0.10 times (=10%) of the amount that you bet
- 0.25 times (=25%) of the amount that you bet
- 1 time (=100%) of the amount that you bet
- 0.90 times (=90%) of the amount that you bet

Imagine you had bet 100% of your ECU in each round. What final wealth would you expect to have at the end of the nine rounds?

Imagine you had bet 100% of your ECU in each round. In how many out of 100 cases would you expect a negative return at the end of the nine rounds?

What is your gender?

- Male
- Female
- Other

Do you own financial products (like stocks, mutual/exchange-traded fund shares, etc.)?

- Yes
- No

How would you describe your financial risk appetite on a scale from 1 to 10?

1 2 3 4 5 6 7 8 9 10

I am not willing to take financial risks at all. I am very willing to take financial risks.

How do you assess your statistical knowledge compared to the average of your fellow students?

1 2 3 4 5 6 7

much worse much better

We pay you by bank transfer. For this, please provide us with your IBAN of the account you would like to receive the payment on. We will delete your payment details completely one month after the payment.

Your IBAN contains a country code at the beginning, e.g. "AT", "DE" or "IT".

IBAN:

Please state your IBAN again:

Lastly: Do you have any comments for us? (optional)

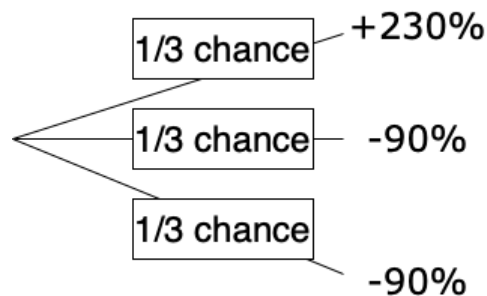
C.2 Instructions in other conditions

230-90L9 HIGH

This study consists of nine successive rounds. You may take as much time as you need to make your choices.

In each round, you will start with an amount of 100 Experimental Currency Units (ECU). You must decide which part of this amount (between 0% and 100%) you wish to bet in the following gamble whose outcome will be randomly determined by the computer in each round.

- You have a 2 out of 3 chance (67%) of losing 90% of the amount that you bet.
- You have a 1 out of 3 chance (33%) of getting the amount that you bet back, plus an additional 230% of the amount that you bet.



The lottery results of previous rounds have no influence on the probability of winning or losing in the current or in future rounds.

Your total earnings for the round are equal to 100 ECU (your starting amount) plus your gains or losses in the gamble.

At the end of each round, you will learn how much money you gained or lost from the gamble and your total earnings for the round.

After that, you will make your choice for the next round. Again you start with 100 ECU, a part of which (between 0% and 100%) you can bet in the gamble. You may not bet money from previous rounds in the gamble. The same procedure as described above determines

your earnings for this round. All subsequent rounds will also proceed in the same manner.

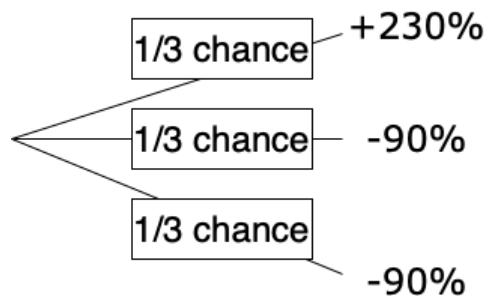
Your total earnings for this study in real euros are equal to your total ECU earnings (summed over all nine rounds) divided by 400. As an example, 1000 ECU equal 2.50€ in real money. You will be paid automatically by bank transfer very shortly after the study.

230-90L9 LOW

This study consists of nine successive rounds. You may take as much time as you need to make your choices.

In each round, you will start with an amount of 100 Experimental Currency Units (ECU). You must decide which part of this amount (between 0% and 100%) you wish to bet in the following gamble whose outcome will be randomly determined by the computer in each round.

- You have a 2 out of 3 chance (67%) of losing 90% of the amount that you bet.
- You have a 1 out of 3 chance (33%) of getting the amount that you bet back, plus an additional 230% of the amount that you bet.



The lottery results of previous rounds have no influence on the probability of winning or losing in the current or in future rounds.

In round 1, you will decide how much to bet in the gamble for rounds 1, 2, and 3. You must bet the same amount in all three rounds. Thus, if you decide to bet X% in the gamble for round 1, then you will also bet X% in the gamble for rounds 2 and 3. Therefore, three consecutive rounds are joined together.

After making your bet choice, you will learn how much money you gained or lost from the three gambles simultaneously, as well as your total earnings for the three rounds. Your total earnings for the three rounds are equal to 300 ECU (three times your starting

amount of 100 ECU per round) plus your gains and losses in the three gambles.

After that, you will make your choice for the next three rounds (4-6). For each of the three rounds you again start with 100 ECU, a part of which (between 0% and 100%) you can bet in the gamble. You may not bet money from previous rounds in the gamble. The same procedure as described above determines your earnings for these three rounds, and you will again learn the outcomes of the three gambles simultaneously. The subsequent three rounds (7-9) will also proceed in the same manner.

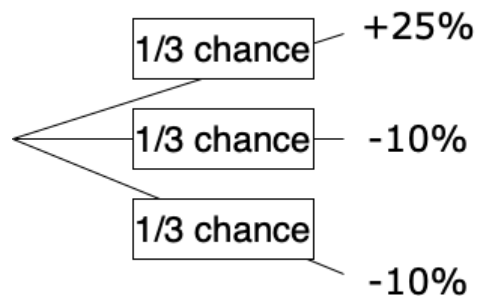
Your total earnings for this study in real euros are equal to your total ECU earnings (summed over all nine rounds) divided by 400. As an example, 1000 ECU equal 2.50€ in real money. You will be paid automatically by bank transfer very shortly after the study.

25-10L9 HIGH

This study consists of nine successive rounds. You may take as much time as you need to make your choices.

In each round, you will start with an amount of 100 Experimental Currency Units (ECU). You must decide which part of this amount (between 0% and 100%) you wish to bet in the following gamble whose outcome will be randomly determined by the computer in each round.

- You have a 2 out of 3 chance (67%) of losing 10% of the amount that you bet.
- You have a 1 out of 3 chance (33%) of winning 25% of the amount that you bet.



The lottery results of previous rounds have no influence on the probability of winning or losing in the current or in future rounds.

Your total earnings for the round are equal to 100 ECU (your starting amount) plus your gains or losses in the gamble.

At the end of each round, you will learn how much money you gained or lost from the gamble and your total earnings for the round.

After that, you will make your choice for the next round. Again you start with 100 ECU, a part of which (between 0% and 100%) you can bet in the gamble. You may not bet money from previous rounds in the gamble. The same procedure as described above determines

your earnings for this round. All subsequent rounds will also proceed in the same manner.

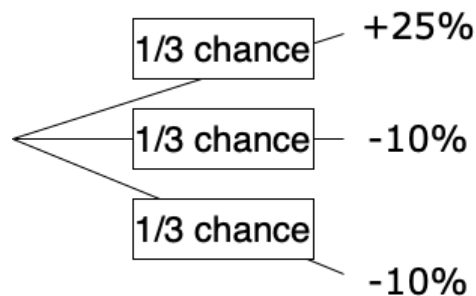
Your total earnings for this study in real euros are equal to your total ECU earnings (summed over all nine rounds) divided by 400. As an example, 1000 ECU equal 2.50€ in real money. You will be paid automatically by bank transfer very shortly after the study.

25-10L9 LOW

This study consists of nine successive rounds. You may take as much time as you need to make your choices.

In each round, you will start with an amount of 100 Experimental Currency Units (ECU). You must decide which part of this amount (between 0% and 100%) you wish to bet in the following gamble whose outcome will be randomly determined by the computer in each round.

- You have a 2 out of 3 chance (67%) of losing 10% of the amount that you bet.
- You have a 1 out of 3 chance (33%) of winning 25% of the amount that you bet.



The lottery results of previous rounds have no influence on the probability of winning or losing in the current or in future rounds.

In round 1, you will decide how much to bet in the gamble for rounds 1, 2, and 3. You must bet the same amount in all three rounds. Thus, if you decide to bet X% in the gamble for round 1, then you will also bet X% in the gamble for rounds 2 and 3. Therefore, three consecutive rounds are joined together.

After making your bet choice, you will learn how much money you gained or lost from the three gambles simultaneously, as well as your total earnings for the three rounds. Your total earnings for the three rounds are equal to 300 ECU (three times your starting

amount of 100 ECU per round) plus your gains and losses in the three gambles.

After that, you will make your choice for the next three rounds (4-6). For each of the three rounds you again start with 100 ECU, a part of which (between 0% and 100%) you can bet in the gamble. You may not bet money from previous rounds in the gamble. The same procedure as described above determines your earnings for these three rounds, and you will again learn the outcomes of the three gambles simultaneously. The subsequent rounds (7-9) will also proceed in the same manner.

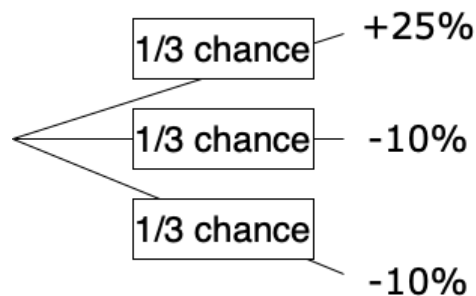
Your total earnings for this study in real euros are equal to your total ECU earnings (summed over all nine rounds) divided by 400. As an example, 1000 ECU equal 2.50€ in real money. You will be paid automatically by bank transfer very shortly after the study.

25-10C9 HIGH

This study consists of nine successive rounds. You may take as much time as you need to make your choices.

You will start with a balance of 900 Experimental Currency Units (ECU). You must decide which part of your balance (between 0% and 100%) you wish to bet in the following gamble whose outcome will be randomly determined by the computer in each round.

- You have a 2 out of 3 chance (67%) of losing 10% of the amount that you bet.
- You have a 1 out of 3 chance (33%) of winning 25% of the amount that you bet.



The lottery results of previous rounds have no influence on the probability of winning or losing in the current or in future rounds.

Your balance at the end of a round is equal to your balance at the beginning of the round plus your gains or losses in the gamble.

At the end of each round, you will learn how much money you gained or lost from the gamble and your resulting balance.

After that, you will make your choice for the next round. Again you may choose to bet between 0% and 100% of your balance in the gamble. The same procedure as described above determines your earnings for this round. All subsequent rounds will also proceed in the same manner.

Your total earnings for this study in real euros are equal to your balance divided by 400 at the end of the last round. Hence,

1000 ECU equal 2.50€ in real money. You will be paid automatically by bank transfer very shortly after the study.

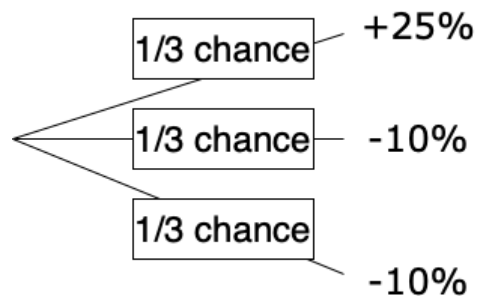
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25-10C9 LOW

This study consists of nine successive rounds. You may take as much time as you need to make your choices.

You will start with a balance of 900 Experimental Currency Units (ECU). You must decide which part of your balance (between 0% and 100%) you wish to bet in the following gamble whose outcome will be randomly determined by the computer in each round.

- You have a 2 out of 3 chance (67%) of losing 10% of the amount that you bet.
- You have a 1 out of 3 chance (33%) of winning 25% of the amount that you bet.



The lottery results of previous rounds have no influence on the probability of winning or losing in the current or in future rounds.

Your balance at the end of a round is equal to your balance at the beginning of the round plus your gains or losses in the gamble.

In round 1, you will decide what percent of your balance to bet in the gamble for rounds 1, 2, and 3. You must bet the same percent in all three rounds. Thus, if you decide to bet X% of your round 1 balance in the round 1 gamble, then you will also bet X% of your round 2 balance in the round 2 gamble and X% of your round 3 balance in the round 3 gamble. Therefore, three consecutive rounds are joined together.

After making your choice, you will learn how much money you gained or lost from the three gambles simultaneously, as well as

your resulting balance at the end of the three rounds.

After that, you will make your choice for the next three rounds (4-6). The same procedure as described above determines your gains and losses for these three rounds, and you will again learn the outcomes of the three gambles simultaneously. The subsequent rounds (7-9) will also proceed in the same manner.

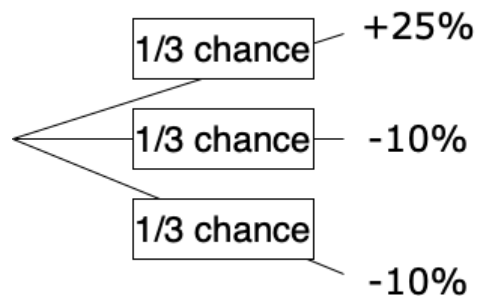
Your total earnings in real euros are equal to your balance divided by 400 at the end of the last round. Hence, 1000 ECU equal 2.50€ in real money. You will be paid automatically by bank transfer very shortly after the study.

25-10L30 HIGH

This study consists of thirty successive rounds. You may take as much time as you need to make your choices.

In each round, you will start with an amount of 100 Experimental Currency Units (ECU). You must decide which part of this amount (between 0% and 100%) you wish to bet in the following gamble whose outcome will be randomly determined by the computer in each round.

- You have a 2 out of 3 chance (67%) of losing 10% of the amount that you bet.
- You have a 1 out of 3 chance (33%) of winning 25% of the amount that you bet.



The lottery results of previous rounds have no influence on the probability of winning or losing in the current or in future rounds.

Your total earnings for the round are equal to 100 ECU (your starting amount) plus your gains or losses in the gamble.

At the end of each round, you will learn how much money you gained or lost from the gamble and your total earnings for the round.

After that, you will make your choice for the next round. Again you start with 100 ECU, a part of which (between 0% and 100%) you can bet in the gamble. You may not bet money from previous rounds in the gamble. The same procedure as described above determines

your earnings for this round. All subsequent rounds will also proceed in the same manner.

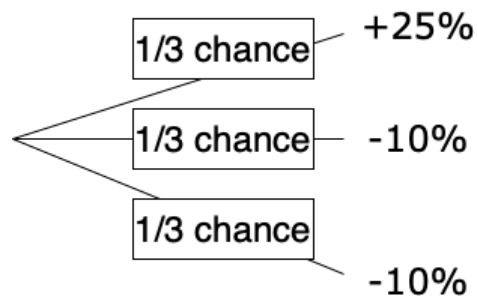
Your total earnings for this study in real euros are equal to your total ECU earnings (summed over all thirty rounds) divided by 1200. As an example, 3000 ECU equal 2.50€ in real money. You will be paid automatically by bank transfer very shortly after the study.

25-10L30 LOW

This study consists of thirty successive rounds. You may take as much time as you need to make your choices.

In each round, you will start with an amount of 100 Experimental Currency Units (ECU). You must decide which part of this amount (between 0% and 100%) you wish to bet in the following gamble whose outcome will be randomly determined by the computer in each round.

- You have a 2 out of 3 chance (67%) of losing 10% of the amount that you bet.
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The lottery results of previous rounds have no influence on the probability of winning or losing in the current or in future rounds.

In round 1, you will decide how much to bet in the gamble for rounds 1, 2, and 3. You must bet the same amount in all three rounds. Thus, if you decide to bet X% in the gamble for round 1, then you will also bet X% in the gamble for rounds 2 and 3. Therefore, three consecutive rounds are joined together.

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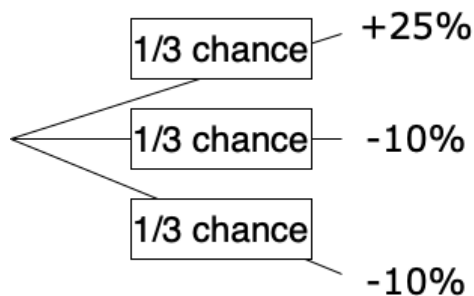
Your total earnings for this study in real euros are equal to your total ECU earnings (summed over all thirty rounds) divided by 1200. As an example, 3000 ECU equal 2.50€ in real money. You will be paid automatically by bank transfer very shortly after the study.

25-10C30 HIGH

This study consists of thirty successive rounds. You may take as much time as you need to make your choices.

You will start with a balance of 3000 Experimental Currency Units (ECU). You must decide which part of your balance (between 0% and 100%) you wish to bet in the following gamble whose outcome will be randomly determined by the computer in each round.

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At the end of each round, you will learn how much money you gained or lost from the gamble and your resulting balance.

After that, you will make your choice for the next round. Again you may choose to bet between 0% and 100% of your balance in the gamble. The same procedure as described above determines your earnings for this round. All subsequent rounds will also proceed in the same manner.

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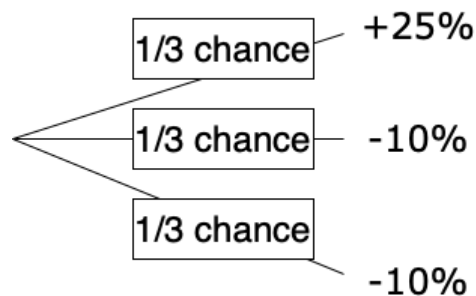
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25-10C30 LOW

This study consists of thirty successive rounds. You may take as much time as you need to make your choices.

You will start with a balance of 3000 Experimental Currency Units (ECU). You must decide which part of your balance (between 0% and 100%) you wish to bet in the following gamble whose outcome will be randomly determined by the computer in each round.

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Rene Schwaiger, Markus Strucks, Stefan Zeisberger

The Consequences of Narrow Framing for Risk-Taking: A Stress Test of Myopic Loss Aversion

Abstract

Narrow bracketing in combination with loss aversion has been shown to reduce individual risk-taking. This is known as myopic loss aversion (MLA) and has been corroborated by many studies. Recent evidence has contested this notion indicating that MLA's applicability is confined to highly artificial settings. Given the impact of these findings, we reevaluated the evidence on MLA involving a total of 2,245 university students, thereby achieving substantially higher statistical power than in almost all previous studies. To clarify inconsistencies in the literature, specifically under more realistic investment environments, we systematically modified the seminal study design by Gneezy and Potters (1997) to include five key adjustments. These involved realistic, down-scaled returns, return compounding, and extended investment horizons. Contrary to some prior studies that have raised doubts about the robustness of MLA, our results—which are highly robust to analytical heterogeneity—consistently document the presence of MLA across all experimental conditions. Our findings substantiate the widespread applicability of MLA and underscore the benefits of disclosing aggregated returns in practical financial decision-making contexts.

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