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Debiasing through experience sampling: The case of myopic loss aversion☆

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ABSTRACT

We introduce a training intervention based on a novel tool to mitigate behavior consistent with myopic loss aversion (MLA). We present the results of a large-scale online experiment with 894 student participants. The study featured a two-step debiasing training intervention based on experience sampling and a subsequent elicitation of MLA. We found that participants in the baseline treatment exhibit behavior consistent with MLA, which was not the case for decision makers who underwent the debiasing training intervention. Nonetheless, we found no statistically significant difference-in-difference effect of the training intervention on the magnitude of MLA. However, when we focused on the more attentive participants, the magnitude of the difference-in-difference effect of the training intervention increased strongly and became statistically significant when controlling for age, gender, education, field of study, investment experience, and risk preferences.

1. Introduction

Myopic loss aversion (MLA) describes the behavior of individuals to frame financial decisions narrowly, i.e., to evaluate investments frequently or to segregate them, which is based on mental accounting (Kahneman and Tversky, 1984; Thaler, 1985; Kahneman and Lovallo, 1993; Thaler et al., 1997; Read et al., 1999), making individuals more vulnerable to existing loss aversion (Kahneman and Tversky, 1979). This narrow, myopic framing refers to the "inability to consider the long-term outcomes of an action when making a choice" (Christensen and Bickel, 2010, p. 118). MLA-compliant behavior has been demonstrated extensively not only among university students in individual decisions (Keren and Wagenaar, 1987; Gneezy and Potters, 1997; Thaler et al., 1997; Bellemare et al., 2005; Langer and Weber, 2005; Fellner and Sutter, 2009; Wendy and Asri, 2012) but also in experimental market situations (Gneezy et al., 2003) and among teams as decision makers (Sutter, 2007). Furthermore, it has been shown that not only students but also individuals from the general population (Van der Heijden et al., 2012), financial experts (Haigh and List, 2005; Eriksen and Kvaloy, 2010; Larson et al., 2016) and

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private investors (Wendy and Asri, 2012) behave according to MLA theory.[1] In a natural field experiment, financial professionals have been associated with MLA in asset markets–their everyday work environment (Larson et al., 2016). Moreover, there exists evidence of MLA-compliant behavior in the contexts of retirement planning and insurance (Benartzi and Thaler, 1999; Papon, 2008). The above literature on MLA has in common the observation that narrow framing, i.e., short-term information and decision horizons with respect to risky assets, leads to more conservative decisions that are, on average, associated with poorer financial results (Thaler et al., 1997; Looney and Hardin, 2009; Larson et al., 2016). However, from the perspective of a rational, utility-maximizing agent, the framing of decisions and outcomes should be irrelevant to his decisions. Venkatraman et al. (2006) have provided evidence for a channel through which conservative financial decisions among individuals exhibiting MLA-conforming behavior emerge. The authors have shown that short-term information horizons are associated with an increase in the perceived risk of the asset under consideration, resulting in a lower willingness to invest in that asset. Nonetheless, Benartzi and Thaler (1999) and Looney and Hardin (2009) found that MLA-compliant behavior can be mitigated by a more aggregate and distributional representation of the possible outcomes of assets, making them appear less risky.

We have built on these research findings and developed a novel interactive “debiasing” tool based on experience sampling to improve behavior associated with MLA. We experimentally tested its success in a training intervention with 894 student participants. The aim was to overcome the documented overcautious tendencies of participants with shorter information and decision horizons. This was done by graphically and numerically illustrating the consequences of higher vs. lower risk-taking on the associated aggregate financial outcomes, based on sampling from the underlying return distribution. Furthermore, we interactively communicated the consequences of investing in a risky asset with positive expected value in a broader frame. We did not aim to eliminate participants’ loss aversion or their myopic tendencies in general. Rather, we aimed to make participants more robust to induced narrow framing in a specific context. We hypothesized that this would lead participants with relatively short-term information and decision horizons to better resist the behavior associated with MLA, such that their risk-taking would catch up with that of other participants with already longer-term information and decision horizons. According to Muradoglu and Harvey (2012) the presentation of aggregated outcome diagrams of investment processes with otherwise frequent outcome feedback could reduce the susceptibility of individuals to MLA by distracting from myopic decisions. Furthermore, Bradbury et al. (2019) have argued that easy-to-read graphical representations such as histograms are important for risk communication. In addition to this finding, experience sampling and a risk instrument that combines experience sampling with graphical representations and numerical descriptions has been shown to influence risk preferences (Kaufmann et al., 2013). As a result we integrated these components into our tool presented in this paper. As such, the tool is based on experience sampling, with its insights communicated through easy-to-read, aggregating histograms and numerical-descriptive tables.

Addressing the behavior associated with MLA is important as its mechanism is particularly harmful to individuals who hold investments with relatively high short-term volatility, such as stocks, while pursuing a long-term investment horizon. Stocks are often accompanied by very positive long-term return expectations; therefore, they have been an important and successful way to build up wealth in the past (Jordà et al., 2018). Nevertheless, investors have a tendency to frequently evaluate financial outcomes. Based on survey data, Lee and Veld-Merkoulova (2016) have reported that 44% of investors from the general Dutch population examine their stock portfolio at least once a month. This trend can be explained by the strong preference of individuals for immediate and frequent outcome feedback (Fellner and Sutter, 2009). If investors were less inclined to evaluate their portfolios frequently or were provided with the outcomes in a more aggregated form, they would be more likely to observe positive results through statistical aggregation. This would make a stock investment subjectively more attractive compared to other financial asset classes, such as bonds and treasury bills (Gneezy et al., 2003; Jordà et al., 2018). Therefore, it may be important to make individuals more resilient to short-term outcomes to prevent them from building overly conservative portfolios. This is reflected, for example, in the expected increasing relevance of adequate private pension savings in the future due to lower projected available national pensions in Europe (Hülsewig and Hülsewig, 2017) and shifts from defined benefit plans to defined contribution plans in the U.S. (U.S. Department of Labor, 2014). A representative survey in the U.S. has shown that, on average, participants estimate a 45% probability that they will outlive their savings, and 41% of participants have not yet taken action against this (Northwestern Mutual, 2019).[2]

In order to precisely assess the potential of the developed tool to improve behavior consistent with MLA, the tool’s underlying investment process is based on a lottery introduced by Gneezy and Potters (1997), which we used to measure whether participants in this study display MLA-conform behavior. This lottery procedure is the foundation for the most frequently applied measure of MLA available (e.g., Bellemare et al., 2005; Haigh and List, 2005; Fellner and Sutter, 2009). This implies that in this study, the risky asset underlying the tool does not belong to the domain of equity investments. Nevertheless, the properties of the lottery are similar, and the tool is very flexible, so it can easily and meaningfully be

[1] MLA joins a large number of deviations from neoclassical predictions, which have been documented among students (Tversky and Kahneman, 1974; Svenson, 1981; Samuelson and Zeckhauser, 1988; Kahneman et al., 1990; Grosshans and Zeisberger, 2018) and among professionals from different fields (Roszkowski and Snelbecker, 1990; Haigh and List, 2005; Cipriani and Guarino, 2009; Deaves et al., 2010; Abdellaoui et al., 2013; Menkhoff and Schmeling, 2013; Pikulina et al., 2017; Kirchler et al., 2018; Sheffer et al., 2018; Huber et al., 2019; Schwaiger et al., 2020).

[2] Generally, the suitability of stock investments for retirement savings also depends crucially on the investment horizon, i.e., the time until retirement. If this investment horizon is relatively short, shares may not be the best option due to their relatively high short-term volatility (Zvi et al., 1992).

extended to other investments, such as stocks.[3] Furthermore, the tool can potentially be used in financial consulting and planning, as well.[4]

We set up a highly powered online experiment with 894 student participants from the University of Innsbruck. In a between-subjects design, participants were randomly assigned to either the baseline or the debiasing treatment with two experimental stages each. Only the first stage differed between the treatments. In the first stage of the baseline treatment, the participants played the game Minesweeper as a filler task. In the first stage of the debiasing treatment, the participants were confronted with a two-step training intervention to familiarize themselves with the underlying properties of the lottery introduced by Gneezy and Potters (1997) in a broader frame and the implications of different betting decisions in this lottery. In the second stage, which was identical for the baseline and debiasing treatment, we measured MLA according to Gneezy and Potters (1997).

In the baseline treatment, we found statistically significant evidence of behavior consistent with MLA. However, we did not find statistical evidence of MLA-consistent behavior in the debiasing treatment. When we directly tested for the difference-in-difference effect of the training intervention on MLA, we found no statistically significant reduction in MLA as a result of the training intervention, which was supported by randomization inference. Furthermore, in an exploratory approach, we excluded the participants with the 10% longest and 10% shortest processing times on the relevant instruction screens and repeated the main analyses with a sample comprised of more attentive participants. In contrast to the full sample, we found a stronger difference-in-difference effect. It was statistically significant when controlling for age, gender, education, field of study, investment experience, and risk preferences. Specifically, fractional regression analyses predicted that the training intervention reduces behavior consistent with MLA by 9.40 percentage points compared to the baseline. The statistical significance was confirmed by randomization inference and also held for most cut-off points regarding processing times other than 10%. We concluded that the developed tool can reduce susceptibility to MLA-conforming behavior in participants with more attention and focus. We attempted to determine the mechanism through which the intervention worked. Based on the results of additional experiments, we concluded that the broad framing of outcomes induced by the intervention reduced the perception of loss likelihood exclusively among those who were exposed to narrow-bracketing of lottery results in stage 2. The perception of loss likelihood was also highly significantly negatively associated with risk-taking, making this a plausible driver of the main results.

This study contributes to several strands in the literature. First, it contributes to the literature on the concept of MLA proposed by Benartzi and Thaler (1995) as an explanation for the equity premium puzzle (Mehra and Prescott, 1985); ever since, MLA has been manifoldly studied as already discussed.

In particular, we add to the literature by measuring MLA according to Gneezy and Potters (1997) among student participants in an online experiment, which provides evidence of the generalizability of the laboratory result to an online environment. We also contribute by targeting this bias in a training intervention, with the goal of mitigating the negative consequences of it.

Secondly, the study contributes to a nascent stream in the literature on systematic debiasing of existing cognitive biases. The literature distinguishes between three main categories of debiasing approaches namely (i) changing underlying incentives, (ii) improving the framing and the elicitation of decisions, and (iii) reducing biases through training (Morewedge et al., 2015). This study specifically adds to the last category. Kaustia and Perttula (2012) have presented evidence that the better-than-average type of overconfidence might be reduced by communicating explicit warnings to participants. Nevertheless, this approach does not work regarding overconfidence in probability assessments. Kučera (2020) has shown that confirmation bias can be statistically significantly reduced by presenting a video on confirmation bias and its impact and mitigation strategies. Fong and Nisbett (1991) have provided evidence for successfully improving statistical reasoning over a longer period of time by providing example problems in a training intervention. Morewedge et al. (2015) have achieved medium to large reductions of biases such as blind spot, confirmation bias, fundamental attribution error, anchoring, representativeness, and social projection. We expressly contribute by introducing an interactive debiasing tool to improve behavior consistent with the cognitive bias MLA.

Thirdly, the study contributes to the small but growing strand on experience sampling in finance. Prominently, Kaufmann et al. (2013) have shown that experience sampling and a risk tool combining experience sampling with graphical illustrations and numerical descriptions influence risk preferences. In particular, the authors have found that participants increase the allocation of funds in the risky asset after being able to sample from the distribution of the risky asset. Nevertheless, Bradbury et al. (2019) have only found weak support for persistent changes in investor behavior due to risk simulations. The authors argued that experience sampling might only influence the initial investment decision. Cason and Samek (2015) have reported that mispricing in experimental asset markets is reduced when participants are confronted with passive pre-market training and visual representations of trade prices before actively engaging in trading. Lusardi et al. (2017) have provided evidence that financial literacy and/or confidence in financial decision making improves when information is provided via videos or visual interactive tools using experience sampling. We specifically contribute by exploring the role of an experience sampling based tool in tackling MLA.

[3] It could also be used, in principle, to illustrate the adverse long-term consequences of investments with negative expected value (Haisley et al., 2008).

[4] Mullainathan et al. (2012) have demonstrated that investment advisors often fail to free their clients from biases and often even reinforce biases to promote their personal interests. The developed tool does not necessarily require the presence of a financial advisor, as it is self-explanatory and easy to use.

2. Experimental design and procedure

The experiment consisted of two main stages. In the first stage, participants were randomly assigned either to the training treatment, i.e., treatment DEBIASING, or the baseline treatment, i.e., treatment BASELINE. Participants in the treatment DEBIASING underwent a training intervention tailored to mitigate or eliminate behavior consistent with MLA. Participants in the treatment BASELINE played the game Minesweeper as an independent filler task for at least 10 min and 5 repetitions, which corresponded to the planned time for the training intervention.[5] This was to ensure that the expected processing time for the filler task was comparable to the expected processing time of the training intervention. Similar to the training intervention, the filler task required a certain amount of cognition and attention. In both treatments we informed the participants that, in contrast to the second stage, their decisions from the first stage of the experiment are not relevant to the payoff. In the second stage of the experiment, which was identical for participants in treatments DEBIASING and BASELINE, we measured whether participants' behavior was consonant with the theory of MLA according to Gneezy and Potters (1997) to investigate the effectiveness of the intervention.[6] In an exit questionnaire, we asked participants to provide information on their general and financial risk preferences; their individual experience with financial investments; and their demographic and socio-economic characteristics, such as age, gender, education, and field of study.[7] The training intervention in the DEBIASING treatment and the subsequent examination of MLA in both treatments were based on the following lottery originally introduced by Gneezy and Potters (1997):

> You have a chance of 2/3 (67%) to lose the amount you bet and a chance of 1/3 (33%) to win two and a half times the amount you bet.

2.1. Debiasing training intervention

In the DEBIASING treatment, we implemented the training tool, which consisted of two steps to familiarize participants with the implications of different decisions regarding the bet amount and the lottery results in a broader frame. Participants were endowed with 200 tokens for each of nine rounds and had to choose an amount $x(0 < x < 200)$ in tokens at the beginning of the first round, which was used to illustrate the characteristics of the lottery.[8]

We introduced two fictitious scenarios, *Chosen_Bet* and *Reduced_Bet*, which served as a basis for the illustration.[9] The two scenarios differed only in terms of the amount of tokens actually bet in the lottery in the specific rounds of the illustration to demonstrate the implications of behavior consistent with the theory of MLA. Specifically, in *Chosen_Bet*, the amount in tokens chosen by participants was bet throughout the nine rounds of the illustration, whereas in *Reduced_Bet*, the amount was reduced by 20% of the amount originally chosen by participants after a first loss was incurred.[10] This reduced amount was then bet in each subsequent round following that loss. Once a second loss occurred, the amount was further reduced by 20% of the originally chosen amount and bet in subsequent rounds following the second loss. This procedure was applied after each iterative loss in the lottery until five losses occurred. Then, an amount of zero was bet in all subsequent rounds. This resulted in lower average risk-taking over nine rounds in the latter scenario.

For a simple, understandable, and direct comparison of the two scenarios and the lottery results in a broader frame, participants were presented *Simulation A* in the experiment, i.e., a dynamic bar chart with bars showing the aggregated wealth in tokens over nine rounds. Figure 1 shows an example of *Simulation A*. The bar chart showed one bar for scenario *Chosen_Bet* and one bar for scenario *Reduced_Bet*. The bars developed gradually over nine rounds and represented the aggregated wealth in tokens after each of the nine lottery draws. Therefore, each bar after nine rounds showed the aggregated wealth in tokens after all nine rounds in each scenario. In parallel, participants were provided with a simultaneously evolving table that numerically displayed wealth, wealth differences between *Chosen_Bet* and *Reduced_Bet*, and the result of the random lottery draw determined by the computer, i.e., win or loss, in each of the nine rounds and in each scenario. The lottery results were highlighted in green and red, depending on whether a win (green) or a loss (red) was determined by

[5] After 10 min and 5 repetitions, a "Next" button appeared and participants could continue the experiment.

[6] As reported in the pre-registration, we initially started the experiment with the following adapted lottery properties (Charness and Gneezy, 2010): "*You have a chance of 1/2 (50%) to lose the amount you bet and a chance of 1/2 (50%) to win two and a half times the amount you bet*". This was done to ensure a higher expected value of the lottery, to clearly distinguish the prospects of a constant bet from reduced bets (more in *Chosen_Bet* and *Reduced_Bet* in Section 2.1). We deviated from these lottery characteristics after piloting the software and finding that the student participants in the online experiment did not exhibit behavior consistent with MLA in the baseline treatment. Evidence has indicated that MLA does not always appear to be robust to differences in the risk profiles of mixed gambles (Haisley et al., 2008; Langer and Weber, 2001; 2005; Beshears et al., 2017). Since MLA-consistent behavior is a prerequisite for measuring the effectiveness of the debiasing training intervention, we performed a robustness check and applied another pilot for the baseline treatment with the original properties by Gneezy and Potters (1997), finding behavior consistent with MLA. Thus, this paper is based on the original lottery properties by Gneezy and Potters (1997).

[7] The self-reported risk preferences were measured using the German SOEP questionnaire (Dohmen et al., 2011) on Likert scales from 0 to 10.

[8] We use tokens as our experimental currency unit in the paper. Note that we used the term "Taler" in the software to tailor the wording to the German speaking participants.

[9] At first, we planned a third scenario called "No-bet", which showed the consequences of betting an amount of zero in all rounds of the lottery, which simply equals total wealth per round corresponding to the original endowment. After receiving feedback from students in a pilot of the software that the instructions were too long and cumbersome to read, we decided to discard this scenario altogether, as it is the least important in targeting MLA.

[10] We have tested reductions at several levels. However, a 20% reduction after each loss resulted in a sufficiently noticeable difference in aggregate results over nine rounds on average. As a result, the consequences of the reduced risk appetite became clearly apparent.

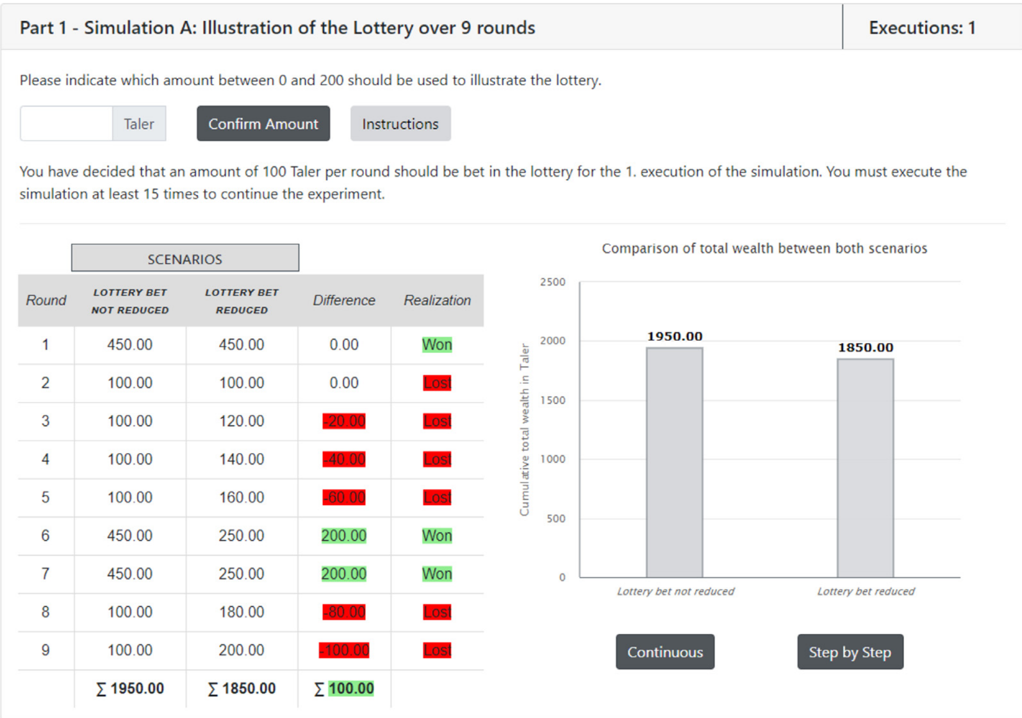

Fig. 1. Experimental screen of Simulation A (English translation). The figure shows the experimental screen of the first step of the debiasing training intervention. The right side of the screen showed a gradually evolving bar chart presenting aggregated wealth in tokens in each of the nine rounds. The left bar in this chart showed aggregated wealth in tokens in scenario *Chosen_Bet* while the right bar in this chart showed aggregated wealth in tokens in scenario *Reduced_Bet*. The numbers at the top of the bars displayed aggregated wealth after each of the nine rounds. On the left side, an additional table was displayed, which presented the numbers processed in the bar chart. In particular, wealth in each of the nine rounds was displayed in scenario *Chosen_Bet* and *Reduced_Bet*, the numerical difference between both scenarios and the lottery realizations drawn by the computer in the respective rounds were additionally shown and colored in green or red depending on which scenario resulted in higher wealth and whether the lottery realized a loss or a win in the respective round. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

the computer. The goal here was to make participants more resilient to short-term outcomes by showing them that, despite frequent individual losses (2/3 of the time), total wealth after nine rounds is on average higher when higher amounts are bet. Thus, in addition, wealth differences between the two scenarios were highlighted in green (or red) when, in a given round and accumulated over nine rounds, wealth in tokens in the *Chosen_Bet* scenario was higher (or lower) than wealth in tokens in the *Reduced_Bet* scenario. Therefore, participants were provided with the specific lottery results by both graphical and numerical representation, which also addressed differences in learning preferences (Fleming and Mills, 1992; Caligaris et al., 2015). There were possibilities to pause the process at any time to get an overview of the outcomes so far and also to go through the process without many single clicks. Specifically, the lottery simulation over nine rounds could be carried out either step by step by clicking on the respective button for each lottery draw individually, or continuously, by clicking once on the respective button to initialize automatic lottery draws over nine rounds in one run. Importantly, executing nine lottery draws corresponded to one iteration of *Simulation A*. Participants were required to perform at least 15 iterations of *Simulation A*. This requirement was established to provide a reasonable understanding of the link between differences in the amount bet, the results of the lottery, and the accumulated wealth after nine rounds between the two scenarios. After 15 iterations, a pop-up window displayed the average aggregated wealth in tokens after nine rounds over all 15 iterations in the *Chosen_Bet* and the *Reduced_Bet* scenario and a "Next" button appeared.

In a second step, participants were presented with *Simulation B*, adapted from (Kaufmann et al., 2013), containing two simultaneously evolving histograms, each showing the distribution of 15,000 draws[11] of aggregated wealth in tokens in the lottery over nine rounds in the *Chosen_Bet* and *Reduced_Bet* scenario, respectively. Figure 2 shows an example of *Simulation B*. In both scenarios, the gradual evolution of the distribution of aggregated wealth after nine rounds was based on a hypothetical amount $x(1 < x < 200)$ in tokens to be chosen by the participants. After the simulation of the 15,000 draws, both histograms showed final distributions and mean values of realized aggregated wealth after nine rounds for both scenarios *Chosen_Bet* and *Reduced_Bet*, respectively. As the simulations in both scenarios were based on such a large number of draws

[11] This number of draws was chosen through comprehensive testing to allow for a trade-off between processing capacity and time, and a sufficient number of draws to approximate the theoretical distributions of aggregate outcomes after nine rounds to minimize heterogeneity in the distributions across participants.

Fig. 2. Experimental screen of Simulation B (English translation). The figure shows the experimental screen of the second step of the debiasing training intervention. Both graphs represented a gradually evolving histogram showing the distributions of aggregated wealth after nine rounds based on 15,000 draws in scenario *Chosen_Bet* (left graph), and scenario *Reduced_Bet*, (right graph). The vertical dashed lines displayed mean aggregated wealth after nine rounds based on 15,000 draws for both scenarios.

of aggregated wealth after nine rounds, the mean values in the *Chosen_Bet* and *Reduced_Bet* scenarios approached the respective expected values of aggregated wealth after nine rounds for the initially chosen level of risk. Thus, the presentation of the distribution provided the participants with the expected wealth difference between the initially chosen risk level (i.e., *Chosen_Bet*) and a reduced risk level (i.e., *Reduced_Bet*). Furthermore, the histograms provided graphical information about the overall dispersion of the distribution of aggregated wealth after nine rounds in each of the two scenarios, which is higher in *Chosen_Bet* than in *Reduced_Bet*. The second step had to be performed at least twice to continue the experiment. Thus, *Simulation A* gave participants an impression of the associations between the lottery results and aggregated wealth after nine rounds. *Simulation B* provided the broader picture by conveying the theoretical properties of the lottery as it showed the distribution of outcomes over nine rounds in the two scenarios in the limit.

Therefore, the simulation based learning demonstrated the consequences of MLA-consistent behavior on wealth in order to implicitly make participants less sensitive to narrow framing. This was done by repeatedly drawing from the underlying lottery distribution and, at the same time, introducing a more aggregated graphical and numerical representation.[12]

2.2. Elicitation of MLA

The second stage of the experiment was identical for the treatments DEBIASING and BASELINE and was concerned with the measurement of MLA-consistent behavior. Participants were told that the decisions in stage 2 of the experiment are payoff relevant. Specifically, in each of the nine consecutive rounds, participants chose an amount $x(0 < x < 200)$ in tokens of an endowment per round of 200 tokens to be bet in the described lottery. Within treatments, participants were randomly assigned either to sub-treatment H or sub-treatment L, which only differed in terms of decision and feedback frequency. In the H sub-treatment, participants in each of the nine rounds decided how much they wanted to bet in the lottery and were informed after each round about the lottery result drawn by the computer and the payoff for that round. In sub-treatment L, participants decided on their preferred bet in rounds 1, 4 and 7 for the three consecutive rounds. In this sub-treatment, the amount bet remained unchanged for three consecutive rounds. After three rounds, participants were informed about the results of the lottery for each of the three rounds and were notified about their total payoff for these three consecutive rounds (i.e., round 1–3 in round 3, round 4–6 in round 6, round 7–9 in round 9).[13]

[12] For details on the training intervention, see the screenshots in the Appendix Section Appendix B.

[13] Studies that have looked at the causes of MLA-conforming behavior, i.e., feedback and/or decision frequency, have provided mixed results (Bellemare et al., 2005; Langer and Weber, 2008; Fellner and Sutter, 2009).

2.3. Hypothesized mechanisms

The first hypothesized mechanism by which the training intervention might mitigate behavior consistent with MLA is based on the illustration of the differences in consequences between the two scenarios. The scenarios should mimic the typical differences in risk-taking between participants in sub-treatment H and L. Here, individuals with higher feedback and decision frequency tend to invest reduced amounts relative to individuals with less frequent feedback and decision frequency (see, e.g., Keren and Wagenaar, 1987; Gneezy and Potters, 1997; Thaler et al., 1997; Bellemare et al., 2005; Langer and Weber, 2005; Fellner and Sutter, 2009; Wendy and Asri, 2012). Showing the adverse consequences of lower average bets, which typically corresponds to the behavior of participants in sub-treatment H compared to participants in sub-treatment L, should make the former participants more sensitive to overcautious actions in stage 2 of the experiment. Of course, we also expected a potential effect of this on participants in the L sub-treatment. However, we hypothesized that this way of contrasting the two scenarios would have a stronger effect on participants in sub-treatment H, as they have more to catch up with relative to treatment BASELINE in terms of their overall risk preferences than participants in sub-treatment L. These overall risk preferences should not systematically differ between participants in L and H due to the random treatment assignment.

This would not have required the dynamic component of scenario *Reduced_Bet*. In general, the literature shows mixed results when it comes to risk-taking conditional on past outcomes (gains or losses). Some studies have found that individuals increase their risk-taking after losses and reduce it after gains (see, e.g., Andrade and Iyer, 2009; Heimer et al., 2021). In contrast, other studies have found the opposite behavior in both domains (see, e.g., Liu et al., 2010), and only after losses (see, e.g., Kaufmann et al., 2013). Yet, these studies are not directly related to MLA. Beshears et al. (2017) have correctly noted that the experimental literature on MLA does not provide strong evidence that individuals in sub-treatment H reduce their risk-taking over time based on past outcomes. They rather take less risk from the outset than individuals in sub-treatment L. The authors have argued that individuals in the narrow frame (H) might prospectively reduce risk-taking to avoid the negative utility associated with experiencing losses (which is more likely in the narrow than the broad frame). However, the authors also noted that it is possible, in principle, that decision makers may not initially recognize how short-term outcome disclosure in the experiment would affect their utility and instead gradually learn as they are exposed to these outcomes. This would then lead to a relative decrease in the risk-taking of the group confronted with the narrow framing over time.[14] As Thaler et al. (1997, p. 650) have put it: "If losses cause more mental anguish than equivalent gains cause pleasure, the experienced utility associated with owning stocks is lower for the more myopic investor [...]. Over time, the myopic investor is expected to gravitate to a lower level of risk". There are also a few studies supporting this conjecture (see, e.g., Shiv et al., 2005). The reason we designed the *Reduced_Bet* scenario dynamically in terms of risk reduction after negative feedback, i.e., after losses, is to capture this channel as a second potential mechanism.

The third hypothesized mechanism by which the training intervention might mitigate MLA is based on general statistical aggregation. Participants in the H sub-treatment are exposed to narrow framing of lottery results in stage 2. That is, they receive the lottery results in segregated rather than aggregated form. The simulation in stage 1 was designed to show these participants what the results of the same lottery would look like if they were more broadly framed (over nine rounds). This was done by experience sampling and aggregating the results into graphs and tables. We expected that this experience would carry over to stage 2 and make participants more robust to the effects of narrow framing in the actual task. Of course, again, we also expected an effect of this on participants in the L sub-treatment. However, we expected the effect to be statistically significantly stronger for participants in the H group. This is because they would likely be more influenced by experience and learning of the aggregate lottery results in stage 1 when they face the actual task in stage 2 than those who receive more aggregate feedback in stage 2 anyway. Based on the findings by Venkatraman et al. (2006), we hypothesized that the broad framing of the lottery results through the training intervention decreases the perceived riskiness or perceived likelihood of losses regarding the lottery and lead to higher favourable risk-taking in stage 2, especially for the decision makers who are confronted with this lottery in a narrow frame (sub-treatment H).

2.4. Implementation

Based on the variations described above, we obtained a 2×2 factorial experimental design. For both treatments, (BASELINE and DEBIASING), there were two sub-treatments, (H and L), which were implemented to examine the presence and magnitude of MLA in both treatments. To assess the success of the training intervention in reducing MLA-consistent behavior, we followed a difference-in-difference comparison of the H and L sub-treatments between the BASELINE and DEBIASING treatments.

We conducted online experiments with 894 student participants from the University of Innsbruck.[15] The average age of the participants was 24 years and 59% were female. The average payoff was EUR 4.97 (sd: EUR 1.52) across treatments for an expected processing time of approximately 25–30 min. The experimental online sessions took place between May and July

[14] Some work also has shown that both groups start with very similar levels of risk-taking, and only those exposed to a comparably broad frame tend to increase risk-taking over time, or at least relatively more compared to the other group, which results in an average difference in risk-taking (Thaler et al., 1997; Larson et al., 2016; Lee and Veld-Merkoulova, 2016).

[15] See the pre-registration for detailed power calculations. The experiments were conducted online due to the COVID-19 pandemic.

2020. The software was programmed using oTree (Chen et al., 2016) and participants were recruited via hroot (Bock et al., 2014). Participants received Amazon vouchers in the denomination of their experimental payoff as compensation. The digital vouchers were sent to the e-mail address that the participants had to provide at the end of the experiment. Participants were informed at the beginning of the experiment that payment would only be made if the experiment was completed.[16] Screenshots of the English translation of the experiment are provided in Section Appendix B in the Appendix.[17]

3. Results

> **Result 1:** *The decision makers in treatment* BASELINE*displayed behavior that is consistent with MLA, which was not the case among decision makers in treatment* DEBIASING. *Overall, the average risk-taking of decision makers in* DEBIASING*was higher than that of participants in treatment* BASELINE.

Figure 3 shows a comparison of the average lottery bets over nine rounds as a percentage of the endowment in stage 2 of the experiment between treatments BASELINE and DEBIASING and sub-treatments H and L, respectively.[18] "*p*" on top of the bars indicates *p*-values of two-sided unpaired sample *t*-tests between sub-treatments H and L. Letters, i.e., *a, b*, and *c* indicate significance groupings with respect to the average amounts bet in the lottery over nine rounds as a percentage of the endowment. Conditions with a distinct letter differed statistically significantly (two-sided unpaired samples *t*-test, $\alpha = 0.05$). In the BASELINE treatment, we found a statistically significant difference in the average amount bet in the lottery as percentage of endowment between participants in L and H. Specifically, decision makers in sub-treatment L bet on average 8.30 percentage points more in the lottery compared to their peers in the H sub-treatment, corresponding to a Cohen's *d* of 0.28. This is highly statistically significant, as can be seen at the top of the corresponding first pair of bars in Fig. 3 (H: 39.00% - L: 47.30% = −8.30 pp.; $p = 0.003$; $N = 439$, see the upper half of Table A.4 in the Appendix for details). Thus, we found MLA-consistent behavior in the BASELINE treatment. Next, we analyzed the participants who underwent the training treatment, i.e., participants in treatment DEBIASING. As can be seen from the top of the second pair of bars in Fig. 3, participants in the L sub-treatment did not bet statistically significantly higher portions of their endowment compared to decision makers in the H sub-treatment, with the effect corresponding to a Cohen's *d* of 0.18 (H: 56.90% - L: 62.40% = −5.50 pp.; $p = 0.054$; $N = 455$, see the upper half of Table A.4 in the Appendix for details). However, the difference approached conventional levels of statistical significance. Furthermore, from the significance groupings in Fig. 3, i.e., letters *a, b*, and *c*, it is visible that general risk-taking measured over both sub-treatments was higher among participants in treatment DEBIASING than in treatment BASELINE. We found that the difference is highly statistically significant. In particular, decision makers in DEBIASING bet on average 17 percentage points more in the lottery compared to their peers in BASELINE. (BASELINE: 43.00% - DEBIASING: 60.00% = −17.00 pp.; $p < 0.005$; $N = 894$, see the lower half of Table A.4 in the Appendix for details).

This level effect is not surprising as participants in the training treatment learned that on average betting higher amounts leads to a higher aggregated wealth after nine rounds when comparing the two scenarios. This translated into different average payoffs between treatments. Participants in BASELINE earned an average of EUR 4.88 in stage 2 of the experiment and decision makers in the DEBIASING treatment earned an average of EUR 5.05. The result is consistent with Kaufmann et al. (2013) who have found that experience sampling increases risk-taking. Similarly, our debiasing tool graphically illustrated also the respective dispersion of aggregate wealth after nine rounds in the lottery. Therefore, participants further learned that increased risk-taking is associated with higher standard deviation of aggregate lottery outcomes. This effect of increased risk-taking in DEBIASING seemed to be slightly more associated with participants in sub-treatment H (BASELINE: 39.00% - DEBIASING: 56.90% = −17.90 pp.; $p < 0.005$; $N = 431$) than with participants in sub-treatment L (BASELINE: 47.30% - DEBIASING: 62.40% = −15.10 pp.; $p < 0.005$; $N = 463$). See the lower half of Table A.4 in the Appendix for details.

In the next step, we tested for an interaction effect between treatments and sub-treatments as the mere presence of MLA-consistent behavior in treatment BASELINE but not in treatment DEBIASING is insufficient evidence of success of the training intervention. Thus, to test for a difference-in-differences treatment effect, we applied multivariate marginal effects fractional regression models with the proportional lottery bets over nine rounds as the dependent variable along with clustered standard errors at the subject level. We reported the results in Table 1.

> **Result 2:** *Based on the difference-in-difference effect, we found no statistically significant difference in the degree of MLA between treatment* BASELINE*and treatment* DEBIASING.

As a robustness check, we first tested for the general treatment effects in model (I) in Table 1. The coefficient DEBIASING is a binary dummy variable that takes the value of 0 for participants in treatment BASELINE and 1 for participants in treat-

[16] Since physical payment was not allowed at the university and to avoid requesting participants' sensitive banking information, this method of payment offered a viable alternative.

[17] The English version of the software can be found using the following link.

[18] We applied significance levels of 5%, 1%, and 0.5% for all statistical tests in this paper and took a conservative approach by conducting two-sided tests. Furthermore, we examined whether the randomization procedure worked by testing for differences in the self-reported participant characteristics between treatments and sub-treatments. The results are displayed in Table A.3 in the Appendix. For no self-reported characteristics, we found statistically significant differences between treatments or sub-treatments. However, for our main analyses we followed a cautious approach and estimated additional econometric specifications controlling for all self-reported participant characteristics.

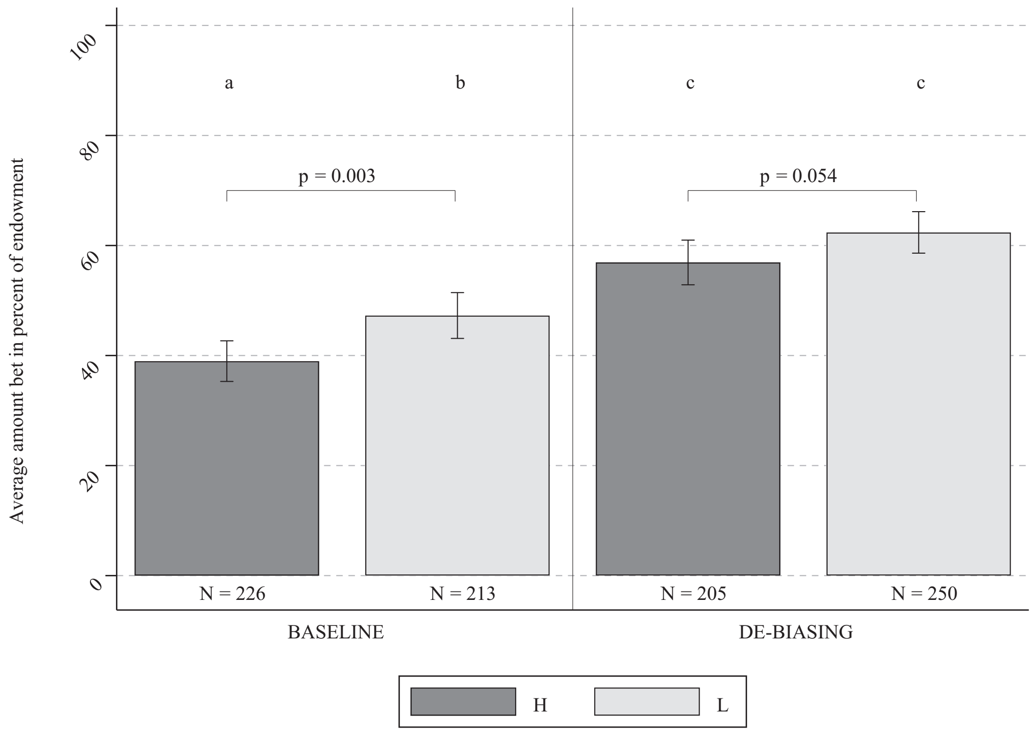

Fig. 3. Average bets over nine rounds in percent of endowment. The graph shows the average amounts bet in the lottery over nine rounds as a percentage of the endowment of 200 tokens for each treatment (BASELINE and DEBIASING) and sub-treatment (H and L). p indicates p-values of two-sided unpaired sample t-tests between sub-treatments H and L. Letters, i.e., a, b, and c indicate significance groupings with respect to the average amounts bet in the lottery over nine rounds as a percentage of the endowment. Conditions with a distinct letter differed statistically significantly (two-sided unpaired samples t-test, $\alpha = 0.05$). The whiskers represent 95% confidence intervals.

ment DEBIASING. L is a binary dummy variable that takes the value of 1 for decision makers in the low-frequency feedback sub-treatment, i.e., L, and 0 for participants in the high-frequency feedback group, i.e., H. DEBIASING#LOW_FREQUENCY(L) represents an interaction term between DEBIASING and L. AGE indicates the age of the participants in years, MALE is a binary dummy variable that takes the value of 0 for female participants and the value of 1 for male participants. STUDY_ECONOMICS is a binary variable that takes the value of 1 for participants enrolled in economics, business administration, or business law, and 0 for all other programs. INVESTMENT_EXPERIENCE is a dummy that takes the value of 1 for decision makers who have already invested in financial products and 0 for participants who have not yet done so. RISK_FINANCIAL is an ordinal scaled variable that represents self-reported risk preferences on a 10-point Likert scale in the financial domain. RISK_GENERAL is an ordinal scaled variable that represents self-reported risk preferences on a 10-point Likert scale in the general domain. GRADUATE is a binary dummy taking a value of 1 for graduate students and 0 for undergraduate students. ROUND is an ordinal variable indicating the specific round for which bet was made. From the coefficient DEBIASING it can be inferred that participants who completed the training intervention in the first stage of the experiment took higher risks in the lottery in the second stage of the experiment, confirming the visual impression presented in Fig. 3 and Result 1. When aggregating both treatments, we could discern from the coefficient L that decision makers in the L sub-treatment took higher risks than participants in the H sub-treatment. This indicates the general presence of MLA-consistent behavior among the participants. Secondly, to test whether the training intervention influenced the degree of MLA, we estimated the following specification in model (II) of Table 1, where y denotes the bet relative to the endowment, i denotes the participant, and $t = \{1, \ldots, 9\}$ represents the respective round:

$$y_{i,t} = \alpha + \beta_1 \text{DEBIASING}_{i,t} + \beta_2 \text{L}_{i,t} + \beta_3 \text{DEBIASING}_i \# \text{L}_{i,t} + \epsilon_{i,t} \tag{1}$$

Apparent by the coefficient DEBIASING#LOW_FREQUENCY(L), we find an expected negative sign, which shows that the regression predicted the difference in risk-taking between participants in L and H to be lower in DEBIASING than in BASELINE. This is consistent with the discussed slightly stronger effect of the intervention on participants in the sub-treatment H. Nevertheless, the influence of the training intervention on the existing MLA-consistent behavior is not statistically significant. In model (III) we included the participants' financial and general risk preferences; their individual experience with financial investments; and their demographic and socio-economic characteristics. We found a statistically significant association between students' age and their lottery decision. In particular, older students bet slightly higher amounts.

Table 1

Multivariate marginal effects fractional regression models. The dependent variable (FRACTION_BET) represents the round-specific lottery bets relative to the endowments over nine rounds in stage 2 of the experiment. Clustered standard errors on the subject level are shown in parentheses. The variable DEBIASING is a binary dummy taking on the value 0 for participants in treatment BASELINE and 1 for participants in treatment DEBIASING. L represents a binary dummy variable taking the value 1 for decision makers in the low-frequency feedback sub-treatment and 0 for their peers in the high-frequency feedback group, i.e., H. DEBIASING#LOW_FREQUENCY(L) represents an interaction term between DEBIASING and L. The variable AGE indicates the participants' age in years, MALE is a binary dummy taking the value of 0 for female participants and 1 for male participants. STUDY_ECONOMICS is a binary variable, which equals 1 for participants enrolled in economics, business, or business law and 0 for all other study programs. INVESTMENT_EXPERIENCE is a dummy taking the value of 1 for decision makers who had already invested in financial products and 0 for participants who had not. GRADUATE is a binary dummy taking a value of 1 for graduate students and 0 for undergraduate students. RISK_FINANCIAL is an ordinal variable representing self-reported risk preferences on a 10-point Likert scale in the financial domain. RISK_GENERAL is an ordinal variable representing self-reported risk preferences on a 10-point Likert scale in the general domain. ROUND is an ordinal variable indicating the specific round for which a bet was made. "Permute *p*" reported the *p*-values of the corresponding coefficient, obtained from permutation tests with 1000 random draws.

	Model (I)	Model (II)	Model (III)
DEBIASING	0.161***	0.175***	0.182***
	(0.019)	(0.027)	(0.025)
LOW_FREQUENCY(L)	0.068***	0.082***	0.099***
	(0.020)	(0.028)	(0.026)
ROUND	0.008***	0.008***	0.008***
	(0.001)	(0.001)	(0.001)
DEBIASING#LOW_FREQUENCY(L)		−0.027	−0.049
		(0.040)	(0.037)
AGE			0.006*
			(0.002)
MALE			0.096***
			(0.021)
GRADUATE			−0.000
			(0.032)
STUDY_ECONOMICS			0.006
			(0.020)
RISK_FINANCIAL			0.015***
			(0.005)
RISK_GENERAL			0.019***
			(0.005)
INVESTMENT_EXPERIENCE			0.026
			(0.022)
Permute p DEBIASING#LOW_FREQUENCY(L)		0.487	0.196
Observations	8046	8046	8046
N. of Subjects	894	894	894
Prob > Chi^2	0.000	0.000	0.000
Pseudo R^2	0.026	0.026	0.061

$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.005$. Dependent variable: Amount bet relative to the endowment (FRACTION_BET); Clustered standard errors on the subject level in parentheses.

Further, we found a statistically significant and large influence of gender on risk appetite. In particular, the regression predicted that male participants bet on average 9.60 percentage points more in the lottery than female participants. This is not surprising, as the literature on financial risk-taking has shown that men prefer to take higher risks than women (Charness and Gneezy, 2012). Further, it is unsurprising that participants who described themselves as risk-seeking in financial and general matters bet statistically significantly higher amounts in the lottery (see coefficients RISK_FINANCIAL and RISK_GENERAL in model (III) of Table 1).

Although the impact of the training intervention seemed to be estimated stronger in model (III), the coefficient DEBIASING#LOW_FREQUENCY(L) is not statistically significant.[19,20] Consequently, the results pointed to either a true null effect or a lack of statistical power or data quality to detect a true effect of the training intervention on MLA of the given magnitude.

[19] In addition, we applied randomization inference and performed permutation tests with the relevant interaction term in models (II) and (III) in Table 1.

[20] We used the user-written program "ritest" in Stata (Heß, 2017). We tested the null hypothesis that there is no effect of the training intervention on behavior consistent with MLA by simulating 1000 draws of differences in fractional amounts bet between H and L based on ex-post randomized treatment assignments in BASELINE and DEBIASING and recording the 1000 interaction effects. The rarer the simulated interaction effects are greater than the actual interaction effect, the lower the permutation *p*-values for the interaction term DEBIASING#LOW_FREQUENCY(L) (line "Permute *p* DEBIASING#LOW_FREQUENCY(L)" in Table 1). The lower these *p*-values, the higher the probability ($1 - p$) that the actual treatment allocation caused the observed effect. This probability is clearly lower than 95% in both specifications, which confirms the statistical insignificance of the training intervention on MLA. We tested for multicollinearity by calculating variance inflation factors (VIFs), which indicated that multicollinearity was not a primary concern (the VIFs of all independent variables in model (III) were below 3.50).

Recent evidence on the replicability of social science experiments has provided an estimate of the average relative effect size of true positives, which is around 71% (Camerer et al., 2018). Nevertheless, in contrast to the original study (Gneezy and Potters, 1997), we ran the experiment online; thus, having to differ slightly from the original instructions. Therefore, for this study, we applied an even more conservative approach. We based the power calculations of the interaction term on an expected difference in risk-taking between participants in L and H, amounting to about 67% of the original difference of 16.90 percentage points in Gneezy and Potters (1997). Consequently, we ensured a sufficient number of participants to guarantee 80% power to reliably detect an 11.30 percentage point reduction in MLA-compliant behavior through the training intervention.[21] However, the actual difference between L and H (8.30 percentage points) measured in this study in the BASELINE treatment corresponds to only about 49% of the original effect size in Gneezy and Potters (1997).

Thus, we tested whether the statistical insignificance of the interaction was due to a lack of statistical power or data quality or whether the effect was virtually equivalent to zero. To do so, we performed an equivalence test (TOST regression) to the specifications in models (II) and (III) in Table 1.[22] We set a minimum relevant effect size of $\beta = \pm\ 0.083$. This is rather conservative, as this minimum relevant interaction effect size corresponds to the actual difference between sub-treatments L and H in the BASELINE treatment, which the intervention was intended to correct. Nevertheless, we could not provide strong statistical support for the null hypothesis with respect to the coefficient DEBIASING#LOW_FREQUENCY(L) (model (II): $p(T > t_1) = 0.003$, $p(T > t_2) = 0.085$; model (III): $p(T > t_1) < 0.005$, $p(T > t_2) = 0.193$). We concluded that we are statistically indeterminate and would need more data or better data quality to detect a difference or an equivalence with the null (Tryon and Lewis, 2008). Regarding the latter, Oppenheimer et al. (2009) have shown that experimental participants fail attention checks more often when no supervisor is present compared to supervised experimental sessions. The authors inferred that the presence of less attentive participants reduces the signal-to-noise ratio. Thus in the next step, we addressed this point and applied an exploratory approach by checking whether the result was driven by inattentive participants and, thus, noisy data, as the experiment was conducted online due to the COVID-19 pandemic and not in a controlled, supervised laboratory setting.

4. The role of attention

First, as a proxy for attentiveness, we analyzed the time each participant spent on the instruction screens.[23] Sufficient attention and seriousness is a prerequisite for successfully treating participants with the training intervention, as the intervention provided the relevant information only implicitly through experience sampling. Based on Oppenheimer et al. (2009), we argue that non-attentive participants who did not take enough time to read the instructions for stage 1 and stage 2 of the experiment could have been a source of noise in the data. This could be a possible reason for the ambiguity regarding the hypothesis and the equivalence test. On the other hand, participants who spent an excessively long time on the instruction screens could also have been a problem, and we were cautious in assuming that these participants performed the experiment with the necessary diligence and without being distracted. For example, 76 out of 894 participants (8.50%) spent a total of less than 2 min on both instruction screens in stage 1 and stage 2 and 153 out of 894 participants (17.11%) spent a total of more than 1 h on these screens. Participants had to read on average 1196 words in total over all treatment and sub-treatment combinations on both instruction screens. This should take a native German speaker around 6.68 min on average (Trauzettel-Klosinski and Dietz, 2012).

We followed Downs et al. (2010) who have found that the exclusion of participants in the top decile of processing times in an MTurk sample statistically significantly distinguishes attentive from non-attentive participants. Although the authors indicated that the prediction quality of this cut-off point is far from perfect, it still provided us with a validated reference for our data cleaning process. Furthermore, Downs et al. (2010) have argued that unmotivated and inattentive participants might not always click quickly, but rather act distracted and simultaneously do something else. Combined with the detection of disproportionately long processing times in the data and the rather uncontrolled environment, we decided to trim the sample symmetrically by excluding participants with the 10% shortest and 10% longest processing times on the task relevant instruction screens in stage 1 and stage 2 from the analyses. This left us with a total of 716 observations. From now on, we refer to this sample as the "high attentives". In a next step, we repeated our analyses from Section 3.

> **Result 3:** *When excluding the participants with the 10% shortest and longest processing times on the instruction screens from the analyses, we found a stronger corrective effect of the training intervention on MLA-consistent behavior, which was statistically significant when controlled for age, gender, education, field of study, investment experience, and risk preferences.*

[21] See the pre-registration for details. Note that we based our power calculations on Tobit regression models. However, in this study, we used fractional regression models because they are more appropriate for proportional data as the dependent variable. Thus, we performed robustness checks by running all regression analyses using Tobit regressions (not shown), which qualitatively yielded the same results.

[22] We used the user-written program "tostregress" in Stata (Dinno, 2017).

[23] Because of considerations between data quality and statistical power, we did not include the processing times on the screens that were not directly relevant to the main tasks in both stages of the experiment in the data quality checks. For the main tasks themselves, we implemented minimum time requirements or a minimum number of iterations, as discussed previously.

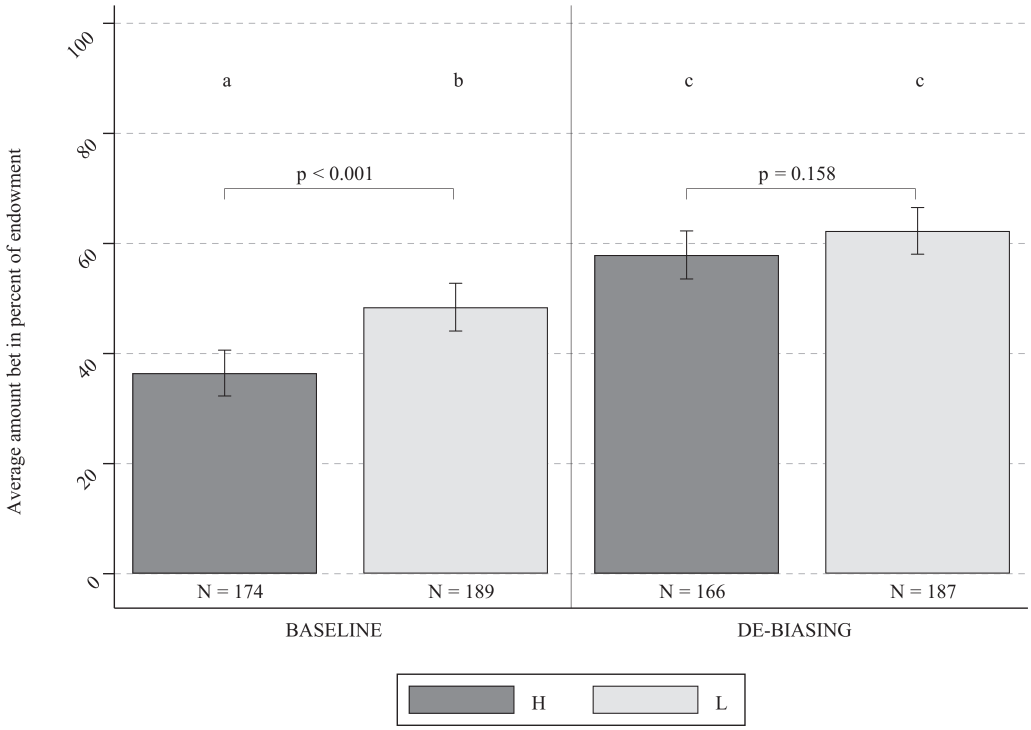

Fig. 4. Average amount bet in percent of endowment (high attentives). The graph shows the average amounts bet in the lottery over nine rounds as a percentage of the endowment of 200 tokens for each treatment (BASELINE and DEBIASING) and sub-treatment (H and L). p indicates p-values of two-sided unpaired sample t-tests between sub-treatments H and L. Letters, i.e., *a*, *b*, and *c* indicate significance groupings with respect to the average amounts bet in the lottery over nine rounds as a percentage of the endowment. Conditions with a distinct letter differed statistically significantly (two-sided unpaired samples t-test, $\alpha = 0.05$). The whiskers represent 95% confidence intervals.

Figure 4 shows the comparison of the average lottery bet in percent of the endowment in stage 2 of the experiment between treatments BASELINE and DEBIASING and sub-treatments H and L. The overall patterns remain similar to Fig. 3, representing the full sample.

To test statistically for the presence of MLA-consistent behavior under both treatments among the more attentive participants, we again applied two-sided unpaired sample t-tests. We indicated the corresponding p-values on top of the bars in Fig. 4 and reported the results in more detail in the upper half of Table A.5 in the Appendix. In the BASELINE treatment, we found even more statistically significant evidence for MLA-consistent behavior than in the full sample. Here, decision makers in sub-treatment L bet on average 11.90 percentage points more in the lottery than decision makers in sub-treatment H, which corresponds to a Cohen's d of 0.41 (H: 36.50% - L: 48.40% $= -11.90$ pp.; $p < 0.001$; $N = 363$). More attentive participants in treatment DEBIASING and sub-treatment L did not bet statistically significantly higher amounts compared to their counterparts in the H sub-treatment, which constituted an even more insignificant difference compared to the full sample, corresponding to a Cohen's d of 0.15; thus, clearly indicating no evidence of MLA-consistent behavior (H: 57.90% - L: 62.30% $= -4.40$ pp.; $p = 0.158$; $N = 353$). It seemed that among the more attentive participants, the difference in risk appetite between L and H in the DEBIASING treatment was greatly reduced compared to the BASELINE treatment. This was partly due to a slightly smaller difference between L and H in the DEBIASING treatment compared to the full sample, but even more due to stronger MLA-compliant behavior in BASELINE among the attentive participants. One reason for this could be that inattentive participants who clicked through or were distracted did not display the higher risk perceptions associated with more narrow framing found in the literature (Venkatraman et al., 2006) to such a marked degree, which may explain the less MLA-compliant behavior in the full sample.

In addition, we repeated the previous analyses on overall risk-taking, indicating the results with significance groupings in Fig. 4. We reported these results in more detail in the lower half of Table A.5 in the Appendix. Overall, we found a similarly large and as large a statistically significant difference as in the full sample. decision makers in the DEBIASING treatment bet on average 17.50 percentage points more in the lottery compared to participants in the BASELINE treatment (BASELINE: 42.70% - DEBIASING: 60.20% $= -17.50$ pp.; $p < 0.005$; $N = 716$). Among the more attentive participants, the positive effect of the training intervention on risk-taking was clearly more strongly associated with participants in sub-treatment H (BASELINE: 36.50% - DEBIASING: 57.90% $= -21.40$ pp.; $p < 0.005$; $N = 340$), than with participants in sub-treatment L (BASELINE: 48.40% - DEBIASING: 62.30% $= -13.90$ pp.; $p < 0.005$; $N = 376$), which is observable in detail from the bottom half of Table A.5. This points to a specifically corrective impact of the intervention on participants with a higher decision and feedback frequency compared to participants with lower frequency. Since participants in L were already relatively more inclined to take higher risk in BASELINE because their investment outcomes were presented to them in more aggregate form, it makes perfect sense that the aggregate presentation of outcomes and scenario comparisons through the training intervention would affect participants in the H sub-treatment to a relatively greater extent. To explicitly test for the difference-in-difference effect among the more attentive participants, we repeated the multivariate fractional regression analyses from Table 1 with the sample of high attentives. Model (I) in Table 2 yields results regarding the coefficients DEBIASING and L that are consistent with the results in Table 1, (the results with the full sample). We tested whether the training intervention had a statistically significant effect on MLA and again estimated the specification in Eq. (1) in model (II) of Table 2.

As can be seen from the coefficient DEBIASING#LOW_FREQUENCY(L), there was a stronger estimated MLA reducing effect of the training intervention than in the full sample. However, the effect was not statistically significant. When adding in the participants' reported financial and general risk preferences; their individual experience with financial investments; and their demographic and socio-economic characteristics, we found a statistically significant, corrective effect of the training intervention on behavior consistent with MLA, even though we lost statistical power when we trimmed the sample. Specifically, the fractional regression predicted that the training intervention reduces the H vs. L difference in risk-taking by about 9.40 percentage points in treatment DEBIASING compared to treatment BASELINE. Additionally, this significant regression result was confirmed by the results of randomization inference (line "Permute *p* DEBIASING#LOW_FREQUENCY(L)" in Table 2).[24] Interestingly, the main difference between the sample of more attentive participants and the full sample appears to be the difference-in-difference effect, but not the level effect in overall risk appetite between treatments, as the difference in overall risk-taking between BASELINE and DEBIASING amounted to 17.00 percentage points in the full sample and 17.50 percentage points in the sample with more attentive participants (see Table A.5 in the Appendix). We conclude that an adequate level of attention is required to successfully correct MLA-consistent behavior through the developed training tool. Participants who did not read the instructions carefully and with focus or were distracted might have been a source of noisy data.

Furthermore, we conducted a detailed analysis of the impact of percentile cut-off points on processing times other than 10% on the results. Specifically, we calculated corresponding marginal effect sizes and *p*-values of the variable DEBIASING#LOW_FREQUENCY(L), which represents the difference-in-difference effect, for all symmetric percentile cut-off points starting with 99/1 and ending with 55/45. As can be seen from Figs. A.1 and A.2 in the Appendix, we found that symmetrically trimming the sample based on the processing times clearly has a consistently positive effect on the strength of the effect size. Additionally, we found a U-shaped relationship between the corresponding *p*-values and the cut-off points.[25] In summary, this suggests that the associated results in model (III) in Table 2 are not limited to the specific cut-off point of 10%, and that there were structural differences in behavior between more and less attentive participants.

5. Possible mechanisms

In a next step, we addressed the identification of mechanisms by which the intervention might have triggered the difference-in-difference effect. We started with the first potential effect described–the communication of the negative consequences associated with MLA-compliant behavior via the two scenarios. Thus, first, we tested whether the overall display of higher average aggregate wealth in tokens after nine rounds in Simulation A in scenario *Chosen_Bet* compared to scenario *Reduced_Bet* could potentially explain the reduction in MLA through treatment DEBIASING. We recorded for all participants in DEBIASING what the average aggregate wealth in tokens was after nine rounds across all 15 iterations in scenario *Chosen_Bet* and scenario *Reduced_Bet*, i.e., what participants saw individually. A differential impact of the displayed average total wealth differences between scenarios in the simulation on risk-taking between the H and L sub-treatments would be given by a statistically significant interaction effect LOW_FREQUENCY(L)#SIM_OUTCOME on bet amounts. This is an interaction effect between the variable indicating sub-treatment L and the displayed average aggregate wealth differences in tokens between scenarios after 15 rounds of Simulation A (SIM_OUTCOME equals the average aggregate wealth in tokens after 9 rounds and 15 iterations in *Chosen_Bet* minus the average aggregate wealth in tokens after 9 rounds and 15 iterations in *Reduced_Bet*). We ran multivariate marginal effects fractional regression models to estimate the interaction effect and reported the results in the Appendix. Table A.16 shows the results for the full sample and Table A.17 for the more attentive participants. We found that the differences in average aggregate wealth in tokens between scenarios did not affect participants in the H and L sub-treatments differently in their propensity to bet in the lottery. Furthermore, as a robustness check, we also coded a binary variable that is equal to 1 if the average aggregate wealth in tokens after 9 rounds and 15 iterations in *Chosen_Bet* was greater than the average aggregate wealth in tokens after 9 rounds and 15 iterations in *Reduced_Bet* and equal to 0 otherwise. Two-sided unpaired sample *t*-tests showed that there was no statistically significant difference in risk-taking between participants in H and L when this variable is equal to 1 (full sample: H: 59.56% - L: 65.40% = −5.84 pp., $p = 0.071$, $N = 332$; high attentives: H: 59.56% - L: 65.23% = −5.67 pp., $p = 0.115$, $N = 95$) or when this variable is equal to 0 (H: 49.55% - L: 55.24% = −5.69 pp., $p = 0.300$, $N = 332$; high attentives: H: 52.91% - L: 55.06% = −2.14 pp., $p = 0.720$, $N = 95$).[26]

[24] We re-tested for multicollinearity by considering variance inflation factors (VIFs) that suggested that multicollinearity was not a primary concern (the VIFs of all independent variables in model (III) were again below 3.50).

[25] Consequently, trimming the sample increases the effect sizes, which, *ceteris paribus*, would reduce the *p*-values. This is, however, simultaneously accompanied by a loss of statistical power, and this seems to counteract the *p*-value-lowering effect of increasing effect sizes at some point.

[26] Using this binary variable instead of the variable SIM_OUTCOME in the difference-in-difference analysis above did not change the results qualitatively.

Table 2
Multivariate marginal effects fractional regression models (high attentives). The dependent variable (FRACTION_BET) represents the round-specific lottery bets relative to the endowments over nine rounds in stage 2 of the experiment among the high attentives. Clustered standard errors on the subject level are shown in parentheses. The variable DEBIASING is a binary dummy taking on the value 0 for participants in treatment BASELINE and 1 for participants in treatment DEBIASING. L represents a binary dummy variable taking the value 1 for decision makers in the low-frequency feedback sub-treatment and 0 for their peers in the high-frequency feedback group, i.e., H. DEBIASING#LOW_FREQUENCY(L) represents an interaction term between DEBIASING and L. AGE indicates the participants' age in years, MALE is a binary dummy taking the value of 0 for female participants and 1 for male participants. STUDY_ECONOMICS is a binary variable, which equals 1 for participants enrolled in economics, business, and business law and 0 for all other study programs. INVESTMENT_EXPERIENCE is a dummy taking the value of 1 for decision makers who had already invested in financial products and 0 for participants who had not. GRADUATE is a binary dummy taking a value of 1 for graduate students and 0 for undergraduate students. RISK_FINANCIAL is an ordinal variable representing self-reported risk preferences on a 10-point Likert scale in the financial domain. RISK_GENERAL is an ordinal variable representing self-reported risk preferences on a 10-point Likert scale in the general domain. ROUND is an ordinal variable indicating the specific round for which a bet was made. "Permute p" reports the p-values of the corresponding coefficient, obtained from permutation tests with 1000 random draws.

	Model (I)	Model (II)	Model (III)
DEBIASING	0.171***	0.210***	0.221***
	(0.020)	(0.029)	(0.027)
LOW_FREQUENCY(L)	0.082***	0.118***	0.130***
	(0.021)	(0.030)	(0.028)
ROUND	0.008***	0.008***	0.008***
	(0.002)	(0.002)	(0.002)
DEBIASING#LOW_FREQUENCY(L)		−0.074	−0.094*
		(0.043)	(0.039)
AGE			0.006*
			(0.003)
MALE			0.103***
			(0.023)
GRADUATE			0.005
			(0.034)
STUDY_ECONOMICS			0.023
			(0.021)
RISK_FINANCIAL			0.012*
			(0.006)
RISK_GENERAL			0.025***
			(0.005)
INVESTMENT_EXPERIENCE			0.012
			(0.024)
Permute p DEBIASING#LOW_FREQUENCY(L)		0.094	0.027
Observations	6444	6444	6444
N. of Subjects	716	716	716
Prob > Chi^2	0.000	0.000	0.000
Pseudo R^2	0.029	0.030	0.073

$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.005$. Dependent variable: Amount bet relative to the endowment (FRACTION_BET); Clustered standard errors on the subject level in parentheses.

Accordingly, we consider it highly implausible that this mechanism was a relevant driver of the MLA reduction caused by the intervention.[27]

Second, we tested the potential mechanism of highlighting the negative consequences of applying a dynamic reduction strategy of lottery bets conditional on losses via the two scenarios *Chosen_Bet* and *Reduced_Bet*. Figures A.3 (full sample) and A.4 (high attentives) in the Appendix show the average amounts bet in the lottery in percent of the endowment in each of the nine rounds for both treatments and sub-treatments. Tables A.6 (full sample) and A.7 (high attentives) additionally show the results of pairwise two-tailed unpaired-sample t-tests for differences in average bet amounts in percent of the endowment between sub-treatment H and L in each of the nine rounds. We found no statistically significant differences between the two groups in the first round in BASELINE. The statistical differences emerged only as the rounds progressed (see the top half of Tables A.6 and A.7 in the Appendix), what would be compatible with this second hypothesized mechanism. Furthermore, we also found that the intervention worked across virtually all rounds and led to non-significant differences between H and L in treatment DEBIASING. However, it is interesting to see that participants in sub-treatment H exhibited risk-taking without any clear up- or down-trend over time. Participants in sub-treatment L, on the other hand, seem to have increased risk-taking over the course of the nine rounds, leading to stronger differences in risk-taking compared to group H toward the middle or end of the task (see Figs. A.3 for the full sample and A.4 for the high attentives in the Appendix). This seems to contradict our hypothesized mechanism of displaying the negative consequences of a dynamic risk reduction conditional on the experience of losses that we considered in our tool. To test this in more detail, we analyzed how participants' bets changed on average conditional on the lottery outcomes of the previous round in H or the aggregated last three rounds in L (Δ BET). The results are reported in Figs. A.5 and A.6 in the Appendix for participants in group H and L in the full sample, and in Figs. A.7 and A.8 in the Appendix for participants in group H and L among the high attentives.

[27] In Simulation B, all participants saw virtually the same average difference between the two scenarios for the same amount entered, which is the reason we did not record this.

We applied OLS regressions on the constant (α) with clustered standard errors on the subject level and with Δ BET as the dependent variable (not shown). In treatment BASELINE we found that participants in the H sub-treatment increased their risk-taking after losses statistically significantly (full sample: $\alpha = 0.069$, $p < 0.005$, $N = 226$; high attentives: $\alpha = 0.065$, $p < 0.005$, $N = 226$) and decreased it statistically significantly to a greater extent after gains (full sample: $\alpha = -0.121$, $p < 0.005$, $N = 174$; high attentives: α = -0.110, $p < 0.005$, $N = 167$). The weaker positive effect of losses on risk-taking appears to have counteracted the stronger negative effect of gains due to the more frequent occurrence of losses in two-thirds of the cases, resulting in relatively constant bets over the nine rounds on average (e.g., in the full sample: average bet in rounds 1–3 = 0.380; average bet in rounds 4–6 = 0.378; average bet in rounds 7–9: 0.412). However, in sub-treatment L we found that participants increased their risk-taking after gains statistically significantly (full sample: $\alpha = 0.053$, $p < 0.005$, $N = 197$; high attentives: $\alpha = 0.052$, $p < 0.005$, $N = 177$) but did not react conditional on past losses (full sample: $\alpha = 0.012$, $p = 0.496$, $N = 110$; high attentives: $\alpha = 0.011$, $p = 0.588$, $N = 94$), leading to an overall increase in risk-taking over time. This is consistent with Figs. A.3 and A.4 (e.g., in the full sample: average bet in rounds 1–3 = 0.428; average bet in rounds 4–6 = 0.481; average bet in rounds 7–9: 0.509). Therefore, the difference in behavior between the two groups in treatment BASELINE was driven by the general increase in risk-taking over the nine rounds, especially in rounds 4–6, in group L, compared to the relatively constant bets in group H. This is broadly consistent with Thaler et al. (1997), Larson et al. (2016), Lee and Veld-Merkoulova (2016). Therefore, we consider it implausible that the explicit illustration of the negative consequences of the dynamic strategy to reduce bets after losses is a mechanism that led to less consistent behavior with MLA in treatment DEBIASING compared to treatment BASELINE. This behavior did not characterize participants' behavior in the BASELINE treatment and sub-treatment H–the opposite was true.

In treatment DEBIASING and sub-treatment H we found similar patterns compared to treatment BASELINE. Participants in sub-treatment H started with virtually the same level of risk as participants in sub-treatment L, however, seemed to exhibit a slightly increasing risk-taking pattern over the nine rounds (e.g., in the full sample: average bet in rounds 1–3 = 0.561; average bet in rounds 4–6 = 0.575; average bet in rounds 7–9: 0.602). Furthermore, similar to the treatment BASELINE, participants increased their risk-taking after losses statistically significantly (full sample: $\alpha = 0.029$, $p < 0.005$, $N = 205$; high attentives: $\alpha = 0.030$, $p < 0.005$, $N = 166$) and decreased it to a greater extent after gains (full sample: α = -0.049, $p < 0.005$, $N = 197$; high attentives: α = -0.048, $p < 0.005$, $N = 159$). Importantly, bets seem to have been less dependent on the past lottery outcomes. This was true for gains as well as for losses. Tables A.8 and A.10 in the Appendix show the results of multivariate OLS regressions, which indicate that this reduction was statistically significant (see the coefficient DEBIASING#PREV_WIN). Thus, the intervention made participants in H more robust with respect to past outcomes in general. This is somewhat consistent with Kaufmann et al. (2013), who have shown that reactivity to losses (decrease in risk taking after a loss) is lower after an experience-sampling treatment compared to a descriptive treatment.[28]

For participants in sub-treatment L and treatment DEBIASING we found slightly different patterns compared to their counterparts in treatment BASELINE, but, not for average risk-taking over the nine rounds (e.g., in the full sample: average bet in rounds 1–3 = 0.589; average bet in rounds 4–6 = 0.623; average bet in rounds 7–9: 0.657). However, in treatment DEBIASING participants seemed to also increase risk-taking after losses statistically significantly (full sample: $\alpha = 0.044$, $p = 0.013$, $N = 131$; high attentives: $\alpha = 0.046$, $p = 0.028$, $N = 101$). This was also the case for prior gains (full sample: $\alpha = 0.026$, $p = 0.021$, $N = 131$; high attentives: $\alpha = 0.029$, $p = 0.043$, $N = 168$). Furthermore, in contrast to participants in sub-treatment H, we did not observe a reduction in reactivity to past outcomes through treatment DEBIASING, which is visible from the coefficient DEBIASING#PREV_WIN in Tables A.9 and A.11 in the Appendix. Our general findings of higher risk taking after prior losses are consonant with the discussion in Imas (2016). The author has identified the framing of losses as either a paper loss or a realized loss as a distinguishing feature of the mixed literature on risk-taking conditional on past losses.

The last mechanism to be examined, which we considered as a possible factor driving the main results, is the broad frame of lottery outcomes generally induced by the simulations. Specifically, according to findings by Venkatraman et al. (2006) such broad framing could reduce perceptions of riskiness and loss likelihood of the asset under consideration. We hypothesized that such an effect might be stronger in sub-treatment H than in sub-treatment L due to the differences in the frame of the actual investment task between the two groups. To test this, we collected additional data from 429 student participants from the University of Innsbruck. For the additional experiments, we ran the original protocol plus a questionnaire at the end of stage 2.[29] This questionnaire was based on Venkatraman et al. (2006) and in part on Kaufmann et al. (2013). On 7-point Likert scales we asked about the perceived risk of the lottery and the perceived likelihood of losses when betting in the lottery. Furthermore, on 7-point Likert scales, we also asked questions regarding understanding of the lottery properties and asked about satisfaction with the betting decisions.[30] We asked these questions

[28] All of these results also show that the generally higher risk-taking due to the intervention in both sub-treatments was likely not due to simple learning effects that would occur in treatment BASELINE over time anyway due to actually betting in the lottery. This is because we found no lower bets in treatment BASELINE at the beginning of the nine rounds compared to subsequent rounds and, in general, no increase in overall risk taking (learning) in treatment BASELINE over time in group H. In group L, the increase in risk-taking over time in treatment BASELINE was not stronger than the increase in treatment DEBIASING.

[29] It was necessary that we placed the questionnaire after stage 2, that is, after the actual investment task, because only there the differences in the sub-treatments arise, i.e., narrow vs. broad framing. Therefore, we always performed additional specifications to control for the betting decisions in the task as well as the results that occurred in the lottery.

[30] The exact translation of the wording of the questions can be found in the screenshots of the instructions in the Appendix and in the captions of Tables A.18 and A.19 in the Appendix.

in each treatment (BASELINE and DEBIASING) and each sub-treatment (H and L) to allow for a proper analysis. The average age of the participants in the additional sample was 23 years and 61% were female. The average payoff was EUR 5.13 (sd: EUR 1.41) across treatments.

First, we found qualitatively similar results with respect to our main findings in the additionally collected data (for details see Tables A.12 and A.13 in the Appendix). The interaction coefficient DEBIASING#LOW_FREQUENCY(L) in the additional sample was not statistically significant (not shown), which held true for the full sample (model (II): DEBIASING#LOW_FREQUENCY(L): −0.087 pp., $p = 0.107$, $N = 429$; model (III): DEBIASING#LOW_FREQUENCY(L): −0.070 pp., $p = 0.183$, $N = 429$) as well as the attentive sample (model (II): DEBIASING#LOW_FREQUENCY(L): −0.077 pp., $p = 0.201$, $N = 343$, model (III): DEBIASING#LOW_FREQUENCY(L): −0.060 pp., $p = 0.302$, $N = 343$). However, based on the results reported in Tables A.12 and A.13, this could likely be a power issue. When we added the data of attentive participants from the additionally collected sample to the original attentive sample, the results remained qualitatively robust, which can be seen in Table A.14 in the Appendix.[31] Due to the very similar main results between the full sample and the high attentives in the new data, we focus in the following on the full sample. The results among the high attentives in the new data are qualitatively identical and are available upon request.[32]

Second, visible from Table A.19 in the Appendix, the intervention did not appear to have a statistically significant effect on risk perceptions (question 1), the worrying about the consequences of betting (question 3), the perception of the likelihood of a great loss (question 4), the understanding of the lottery characteristics (questions 5–10), or the satisfaction with the betting decisions (question 10).[33] Yet, visible from Table A.19, the training intervention influenced perceptions of the general loss likelihood (question 2) exclusively and strongly in sub-treatment H. Specifically, decision makers in BASELINE estimated this likelihood on a 7-point scale statistically significantly lower than decision makers in DEBIASING. A multivariate OLS regression (clustered standard errors on the subject level) with the perceived probability of loss as the dependent and the treatment allocation DEBIASING as independent variable, controlling for all personal characteristics of the decision makers as well as their betting decisions and payoffs,[34] indicated that this result is robust (DEBIASING = −0.546, $p = 0.005$, $N = 231$) –an effect we did not find for participants in sub-treatment L. Thus, in terms of the perceptions of the general loss likelihood when betting in the lottery, the simulation only affected participants who made their decisions in a narrower frame in stage 2. Table A.18 indicates that there was a highly statistically significant difference in the assessment of this question between participants in both sub-treatments in treatment BASELINE. This was again robust to all control variables in a multivariate OLS regression (L = −0.607, $p = 0.004$, $N = 225$). In treatment DEBIASING, however, this effect was non-significant.[35] Furthermore as a final step, we tested whether the perceptions of loss likelihood had a statistically significant and robust influence on risk-taking in stage 2. The results can be seen in Table A.15 in the Appendix. We found across the board that participants who perceived lottery losses to be more likely took less risk. Overall, this argues for our third hypothesized mechanism and here for an influence of the intervention through a reduction in the perceived likelihood of a loss (not perceived riskiness).

6. Conclusion

In this paper, we presented a novel tool to reduce or eliminate behavior consonant with the theory of myopic loss aversion (MLA) in a training intervention. Specifically, we conducted a large-scale online experiment with 894 student participants which consisted of two main stages. In the first stage, participants in the debiasing treatment underwent the training intervention. We used experience sampling and graphical and numerical representations as a means to illustrate the consequences of the behavior associated with MLA. Specifically, we illustrated the results of different betting decisions in the lottery originally introduced by Gneezy and Potters (1997) in a more aggregate way. In the baseline treatment, participants played the game Minesweeper as a filler task. In the second experimental stage, in which treatments did not differ, the susceptibility of participants to MLA was determined. We found behavior consistent with MLA in the baseline treatment, whereas we did not find behavior consistent with MLA in the debiasing training treatment. Nonetheless, we found no statistically significant difference-in-difference effect of the training intervention on participants' susceptibility to MLA.

[31] The interaction coefficient DEBIASING#LOW_FREQUENCY(L) for the entire untrimmed data (original plus additional sample) remained non-significant (not shown), although approaching conventional levels of significance (model (II): DEBIASING#LOW_FREQUENCY(L): −0.047 pp., $p = 0.145$, $N = 1323$; model (III): DEBIASING#LOW_FREQUENCY(L): −0.056 pp., $p = 0.064$, $N = 1323$).

[32] There was one exception among high attentives: participants in sub-treatment L were more satisfied with their decisions in the lottery in treatment DEBIASING than in treatment BASELINE.

[33] Although in general it certainly depends on the underlying asset and the specific scope of application whether the impact of an overall increased risk appetite is to be considered positive or negative, the results of the new data led us to reconsider the side effect of overall increased risk-taking as a result of the intervention as a non-negative effect. Similar to Kaufmann et al. (2013), participants in both sub-treatments did not appear to regret their significantly higher risk-taking in DEBIASING compared to BASELINE as measured by self-reported satisfaction with their betting decisions.

[34] With the latter, it is possible to isolate the direct effect of the intervention on loss probability perceptions, since indirect effects, e.g., through higher risk taking and thus higher payoffs in DEBIASING, can be ruled out.

[35] We also estimated an interaction effect DEBIASING#LOW_FREQUENCY(L) in multivariate OLS regressions (not shown) with clustered standard errors on the subject level and the perceived probability of loss as the dependent variable. The difference-in-difference effect was not statistically significant but approached conventional levels of significance (DEBIASING#LOW_FREQUENCY(L) = 0.540, $p = 0.106$, $N = 429$). Based on the data in Tables A.18 and A.19, we consider power-issues to be very likely.

This result was also supported by randomization inference. Nevertheless, we found that the training intervention increased overall risk-taking among participants.

In an exploratory approach, we analyzed whether the (in)attention of participants was driving the result. We found that a considerable number of participants spent a disproportionately long or short period of time on the instruction screens. Therefore, we trimmed the sample and excluded participants with the 10% shortest and 10% longest processing times on the instruction screens from the analyses. Based on this sample of more attentive participants, we found a statistically significant effect of the training intervention on the susceptibility of participants to MLA when we controlled for age, gender, field of study, education investment experience, and risk preferences. The results also held for most cut-off points with respect to processing times other than 10%. We concluded that given appropriate participant attention, experience sampling using graphical and numerical representations corrects behavior that is consistent with MLA. We also proposed several possible mechanisms and tested how the intervention worked. A plausible candidate was found to be the inducement of a broad frame of lottery outcomes via the intervention selectively influencing perceptions of loss probability.

We consider these findings to be important because, especially in some European countries, a shift from public pension savings to private pension savings might be foreseeable. Therefore, the relevance of investments in financial products with higher short-term volatility for private individuals might increase due to the minimum/negative interest rate policy in the most important financial markets. The tool presented provides a self-explanatory alternative to being debiased by financial advisors who are not always able to correct biases of their clients or even reinforce them (Mullainathan et al., 2012). As such, the tool can be used as a standardized, stand-alone tool to mitigate MLA-compliant behavior, with the goal of improving people's investment decisions toward a variety of risky assets. For a possible application of the tool in other domains, the underlying risky asset can be replaced by real historical market data (e.g. time series of indices or funds). Thus, the tool has the potential to be applied to different contexts. This study demonstrated its effectiveness for a risky lottery introduced by Gneezy and Potters (1997). An alternative way to make individuals less sensitive to short-term outcomes would simply be to limit feedback and/or decision frequency. However, the tool presented in this study bypasses the interference with decision freedom and the documented preference for frequent feedback. Instead, the negative consequences of investment decisions associated with narrow framing are highlighted, improving decisions in a more subtle way.

The results in this paper also emphasize the importance of shrewd attention and a lack of long interruptions among participants in training interventions to ensure a full understanding of the implications conveyed by the intervention. Future research should rely on highly controlled environments when training interventions are conducted that are tailored to mitigate cognitive biases, i.e., supervised laboratory settings where high attention and absence of distraction are guaranteed. Future research on the effectiveness of training interventions in reducing MLA-consistent behavior could include experiments with different pools of participants. In particular, financial professionals, as well as individuals from the general population could be invited to participate.

In this study, the effectiveness of the debiasing tool was tested immediately after the implementation of the debiasing intervention. This was a first step to investigate the general effect of such a tool. In a future step, it would be interesting to examine the effect of the training intervention when it is temporally separated from the measurement of MLA. Ideally, the training intervention would have long-term alleviating effects on participants' susceptibility to MLA.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Additional tables and figures

Table A1
Randomization checks of self-reported characteristics across treatments and sub-treatments. AGE represents the participants age in years. MALE represents a dummy variable for gender taking a value of 1 for male participants and 0 for female participants. AGE indicates the participants' age in years, MALE is a binary dummy taking the value of 0 for female participants and 1 for male participants. STUDY_ECONOMICS is a binary variable, which equals 1 for participants enrolled in economics, business, and business law and 0 for all other study programs. INVESTMENT_EXPERIENCE is a dummy taking the value of 1 for decision makers who already have invested in financial products and 0 for participants who have not. GRADUATE is a binary dummy taking a value of 1 for graduate students and 0 for undergraduate students. RISK_FINANCIAL is an ordinal variable representing self-reported risk preferences on a 10-point Likert scale in the financial domain. RISK_GENERAL is an ordinal variable representing self-reported risk preferences on a 10-point Likert scale in the general domain.

Comparison	Variable	Test	Test-Statistic	*N*
Treatment	MALE	Pearsons χ^2 Test	$chi^2 = 0.012$	894
Sub-treatment	MALE	Pearsons χ^2 Test	$chi^2 = 0.085$	894
Treatment	AGE	Kruskal-Wallis Test	$chi^2 = 1.749$	894
Sub-treatment	AGE	Kruskal-Wallis Test	$chi^2 = 0.234$	894
Treatment	INVESTMENT_EXPERIENCE	Pearsons χ^2 Test	$chi^2 = 1.509$	894
Sub-treatment	INVESTMENT_EXPERIENCE	Pearsons χ^2 Test	$chi^2 = 0.067$	894
Treatment	STUDY_ECONOMICS	Pearsons χ^2 Test	$chi^2 = 0.011$	894
Sub-treatment	STUDY_ECONOMICS	Pearsons χ^2 Test	$chi^2 = 0.400$	894
Treatment	GRADUATE	Pearsons χ^2 Test	$chi^2 = 0.663$	894
Sub-treatment	GRADUATE	Pearsons χ^2 Test	$chi^2 = 0.363$	894
Treatment	RISK_FINANCIAL	Kruskal-Wallis Test	$chi^2 = 0.410$	894
Sub-treatment	RISK_FINANCIAL	Kruskal-Wallis Test	$chi^2 = 0.250$	894
Treatment	RISK_GENERAL	Kruskal-Wallis Test	$chi^2 = 0.222$	894
Sub-treatment	RISK_GENERAL	Kruskal-Wallis Test	$chi^2 = 0.547$	894

$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.005$.

Table A2
Differences in treatments and sub-treatments. The table shows pairwise differences in the average bet amount over nine rounds in percent of the endowment between sub-treatments H and L in treatments BASELINE and DEBIASING using two-sided unpaired sample *t*-tests. The table also shows pairwise differences in the average bet amount over nine rounds in percent of the endowment between treatments BASELINE and DEBIASING in sub-treatments H and L, separately and jointly (H + L).

Treatments	obs	Sub-Treatment Difference: H-L		std. err.	pr(| T | > | t |)
BASELINE	439	-0.083^{***}	(0.390 - 0.473)	0.028	0.003
DEBIASING	455	-0.055	(0.569 - 0.624)	0.028	0.054
Sub-Treatments	**obs**	**Treatment Difference: BASELINE - DEBIASING**		**std. err.**	**pr(| T | > | t |)**
H	431	-0.179^{***}	(0.390 - 0.569)	0.028	0.000
L	463	-0.151^{***}	(0.473 - 0.624)	0.028	0.000
H + L	894	-0.170^{***}	(0.430 - 0.600)	0.020	0.000

Note: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.005$.

Table A3
Differences in treatments and sub-treatments (high attentives). The table shows pairwise differences in the average bet amount over nine rounds in percent of the endowment between sub-treatments H and L in treatments BASELINE and DEBIASING using two-sided unpaired sample *t*-tests. The table also shows pairwise differences in the average bet amount over nine rounds in percent of the endowment between treatments BASELINE and DEBIASING in sub-treatments H and L, separately and jointly (H + L).

Treatments	obs	Sub-Treatment Difference: H-L		std. err.	pr(| T | > | t |)
BASELINE	363	-0.119^{***}	(0.365 - 0.484)	0.031	0.000
DEBIASING	353	-0.044	(0.579 - 0.623)	0.031	0.158
Sub-Treatment	**obs**	**Treatment Difference: BASELINE − DEBIASING**		**std. err.**	**pr(| T | > | t |)**
H	340	-0.214^{***}	(0.365 - 0.579)	0.031	0.000
L	376	-0.139^{***}	(0.484 - 0.623)	0.031	0.000
H + L	716	-0.175^{***}	(0.427 - 0.602)	0.022	0.000

Note: $^{*}\ p < 0.05$, $^{**}\ p < 0.01$, $^{***}\ p < 0.005$.

Table A4

Differences between sub-treatments across rounds. The table shows pairwise differences in the average bet amount over nine rounds in percent of the endowment in the full sample between sub-treatments H and L in treatments BASELINE and DEBIASING using two-sided unpaired sample *t*-tests.

Treatments	Round	obs	Sub-Treatment Difference: H-L		std. err.	pr(| T | > | t |)
BASELINE	1	439	−0.032	(0.396 - 0.428)	0.031	0.300
BASELINE	2	439	−0.068*	(0.360 - 0.428)	0.031	0.030
BASELINE	3	439	−0.044	(0.384 - 0.428)	0.032	0.176
BASELINE	4	439	−0.091**	(0.390 - 0.481)	0.034	0.009
BASELINE	5	439	−0.110***	(0.371 - 0.481)	0.033	0.001
BASELINE	6	439	−0.110***	(0.371 - 0.481)	0.034	0.001
BASELINE	7	439	−0.126***	(0.383 - 0.509)	0.035	<0.001
BASELINE	8	439	−0.107***	(0.402 - 0.509)	0.036	0.003
BASELINE	9	439	−0.059	(0.451 - 0.509)	0.036	0.106
DEBIASING	1	455	−0.011	(0.581 - 0.591)	0.031	0.729
DEBIASING	2	455	−0.050	(0.542 - 0.591)	0.032	0.117
DEBIASING	3	455	−0.053	(0.538 - 0.591)	0.032	0.097
DEBIASING	4	455	−0.059	(0.565 - 0.624)	0.033	0.071
DEBIASING	5	455	−0.059	(0.565 - 0.624)	0.032	0.070
DEBIASING	6	455	−0.064	(0.560 - 0.624)	0.033	0.051
DEBIASING	7	455	−0.084*	(0.571 - 0.656)	0.033	0.011
DEBIASING	8	455	−0.051	(0.605 - 0.656)	0.033	0.122
DEBIASING	9	455	−0.060	(0.596 - 0.656)	0.033	0.072

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.005$.

Table A5

Differences between sub-treatments across rounds (high attentives). The table shows pairwise differences in the average bet amount over nine rounds in percent of the endowment in the attentive sample between sub-treatments H and L in treatments BASELINE and DEBIASING using two-sided unpaired sample *t*-tests.

Treatments	Round	obs	Sub-Treatment Difference: H-L		std. err.	pr(| T | > | t |)
BASELINE	1	363	−0.062	(0.378 - 0.440)	0.034	0.067
BASELINE	2	363	−0.092**	(0.348 - 0.440)	0.034	0.007
BASELINE	3	363	−0.073*	(0.367 - 0.440)	0.035	0.039
BASELINE	4	363	−0.135***	(0.356 - 0.491)	0.036	< 0.001
BASELINE	5	363	−0.152***	(0.339 - 0.491)	0.036	< 0.001
BASELINE	6	363	−0.131***	(0.360 - 0.491)	0.037	< 0.001
BASELINE	7	363	-0.173***	(0.348 - 0.522)	0.039	< 0.001
BASELINE	8	363	−0.165***	(0.356 - 0.522)	0.039	< 0.001
BASELINE	9	363	−0.095*	(0.427 - 0.522)	0.040	0.018
DEBIASING	1	353	−0.006	(0.582 - 0.589)	0.034	0.850
DEBIASING	2	353	−0.036	(0.552 - 0.589)	0.035	0.303
DEBIASING	3	353	−0.041	(0.548 - 0.589)	0.036	0.252
DEBIASING	4	353	−0.040	(0.583 - 0.623)	0.036	0.274
DEBIASING	5	353	−0.047	(0.576 - 0.623)	0.036	0.191
DEBIASING	6	353	−0.059	(0.564 - 0.623)	0.037	0.103
DEBIASING	7	353	−0.074*	(0.583 - 0.657)	0.037	0.044
DEBIASING	8	353	−0.040	(0.617 - 0.657)	0.036	0.273
DEBIASING	9	353	−0.050	(0.606 - 0.657)	0.036	0.174

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.005$.

Table A6

Multivariate OLS regression models on lottery bet changes in sub-treatment H. The dependent variable (Δ BET) represents the change in the lottery bet from previous round in percentage points in stage 2 of the experiment. Clustered standard errors on the subject level are shown in parentheses. The variable DEBIASING is a binary dummy taking on the value 0 for participants in treatment BASELINE and 1 for participants in treatment DEBIASING. PREV_WIN is a dummy variable indicating whether participants faced a win (1) or loss (0) in the previous round of the lottery. DEBIASING#PREV_WIN represents an interaction term between DEBIASING and PREV_WIN. AGE indicates the participants' age in years, MALE is a binary dummy taking the value of 0 for female participants and 1 for male participants. STUDY_ECONOMICS is a binary variable, which equals 1 for participants enrolled in economics, business, and business law and 0 for all other study programs. INVESTMENT_EXPERIENCE is a dummy taking the value of 1 for decision makers who had already invested in financial products and 0 for participants who had not. GRADUATE is a binary dummy taking a value of 1 for graduate students and 0 for undergraduate students. RISK_FINANCIAL is an ordinal variable representing self-reported risk preferences on a 10-point Likert scale in the financial domain. RISK_GENERAL is an ordinal variable representing self-reported risk preferences on a 10-point Likert scale in the general domain. ROUND is an ordinal variable indicating the specific round for which a bet was made.

	Model (I)	Model (II)
PREV_WIN	−0.190***	−0.191***
	(0.020)	(0.020)
DEBIASING	−0.040***	−0.040***
	(0.009)	(0.009)
DEBIASING#PREV_WIN	0.111***	0.113***
	(0.026)	(0.026)
ROUND		0.006***
		(0.001)
AGE		0.002***
		(0.001)
MALE		−0.004
		(0.005)
GRADUATE		−0.012
		(0.007)
STUDY_ECONOMICS		0.000
		(0.005)
RISK_FINANCIAL		−0.001
		(0.001)
RISK_GENERAL		0.001
		(0.001)
INVESTMENT_EXPERIENCE		−0.007
		(0.006)
Constant	0.069***	0.022
	(0.007)	(0.020)
Observations	3448	3448
N. of Subjects	431	431
Prob > F	0.000	0.000
R^2	0.061	0.064

$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.005$. Dependent variable: Change in lottery bet from previous round in percentage points (Δ BET); Clustered standard errors on the subject level in parentheses.

Table A7

Multivariate OLS regression models on lottery bet changes in sub-treatment L. The dependent variable (Δ BET) represents the change in the lottery bet from previous round in percentage points in stage 2 of the experiment. Clustered standard errors on the subject level are shown in parentheses. The variable DEBIASING is a binary dummy taking on the value 0 for participants in treatment BASELINE and 1 for participants in treatment DEBIASING. PREV_WIN is a dummy variable indicating whether participants faced a win (1) or loss (0) in the previous round of the lottery. DEBIASING#PREV_WIN represents an interaction term between DEBIASING and PREV_WIN. AGE indicates the participants' age in years, MALE is a binary dummy taking the value of 0 for female participants and 1 for male participants. STUDY_ECONOMICS is a binary variable, which equals 1 for participants enrolled in economics, business, and business law and 0 for all other study programs. INVESTMENT_EXPERIENCE is a dummy taking the value of 1 for decision makers who had already invested in financial products and 0 for participants who had not. GRADUATE is a binary dummy taking a value of 1 for graduate students and 0 for undergraduate students. RISK_FINANCIAL is an ordinal variable representing self-reported risk preferences on a 10-point Likert scale in the financial domain. RISK_GENERAL is an ordinal variable representing self-reported risk preferences on a 10-point Likert scale in the general domain. ROUND is an ordinal variable indicating the specific round for which a bet was made.

	Model (I)	Model (II)
PREV_WIN	0.040	0.041
	(0.022)	(0.022)
DEBIASING	0.032	0.033
	(0.025)	(0.026)
DEBIASING#PREV_WIN	−0.058	−0.058
	(0.032)	(0.033)
ROUND		−0.004
		(0.006)
AGE		0.000
		(0.001)
MALE		−0.017
		(0.014)
GRADUATE		−0.003
		(0.019)
STUDY_ECONOMICS		−0.023
		(0.013)
RISK_FINANCIAL		−0.002
		(0.003)
RISK_GENERAL		0.005
		(0.003)
INVESTMENT_EXPERIENCE		0.009
		(0.015)
Constant	0.012	0.043
	(0.018)	(0.050)
Observations	926	926
N. of Subjects	463	463
Prob > F	0.205	0.152
R^2	0.004	0.012

$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.005$. Dependent variable: Change in lottery bet from previous round in percentage points (Δ BET); Clustered standard errors on the subject level in parentheses.

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Table A8

Multivariate OLS regression models on lottery bet changes in sub-treatment H (high attentives). The dependent variable (Δ BET) represents the change in the lottery bet from previous round in percentage points in stage 2 of the experiment. Clustered standard errors on the subject level are shown in parentheses. The variable DEBIASING is a binary dummy taking on the value 0 for participants in treatment BASELINE and 1 for participants in treatment DEBIASING. PREV_WIN is a dummy variable indicating whether participants faced a win (1) or loss (0) in the previous round of the lottery. DEBIASING#PREV_WIN represents an interaction term between DEBIASING and PREV_WIN. AGE indicates the participants' age in years, MALE is a binary dummy taking the value of 0 for female participants and 1 for male participants. STUDY_ECONOMICS is a binary variable, which equals 1 for participants enrolled in economics, business, and business law and 0 for all other study programs. INVESTMENT_EXPERIENCE is a dummy taking the value of 1 for decision makers who had already invested in financial products and 0 for participants who had not. GRADUATE is a binary dummy taking a value of 1 for graduate students and 0 for undergraduate students. RISK_FINANCIAL is an ordinal variable representing self-reported risk preferences on a 10-point Likert scale in the financial domain. RISK_GENERAL is an ordinal variable representing self-reported risk preferences on a 10-point Likert scale in the general domain. ROUND is an ordinal variable indicating the specific round for which a bet was made.

	Model (I)	Model (II)
PREV_WIN	−0.176***	−0.177***
	(0.022)	(0.022)
DEBIASING	−0.036***	−0.036***
	(0.011)	(0.011)
DEBIASING#PREV_WIN	0.099***	0.099***
	(0.029)	(0.029)
ROUND		0.006***
		(0.002)
AGE		0.002*
		(0.001)
MALE		−0.001
		(0.006)
GRADUATE		−0.016*
		(0.008)
STUDY_ECONOMICS		−0.002
		(0.006)
RISK_FINANCIAL		−0.003
		(0.001)
RISK_GENERAL		0.002
		(0.001)
INVESTMENT_EXPERIENCE		−0.005
		(0.006)
Constant	0.066***	0.009
	(0.008)	(0.024)
Observations	2720	2720
N. of Subjects	340	340
Prob > F	0.000	0.000
R^2	0.055	0.059

$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.005$. Dependent variable: Change in lottery bet from previous round in percentage points (Δ BET); Clustered standard errors on the subject level in parentheses.

Table A9

Multivariate OLS regression models on lottery bet changes in sub-treatment L (high attentives). The dependent variable (Δ BET) represents the change in the lottery bet from previous round in percentage points in stage 2 of the experiment. Clustered standard errors on the subject level are shown in parentheses. The variable DEBIASING is a binary dummy taking on the value 0 for participants in treatment BASELINE and 1 for participants in treatment DEBIASING. PREV_WIN is a dummy variable indicating whether participants faced a win (1) or loss (0) in the previous round of the lottery. DEBIASING#PREV_WIN represents an interaction term between DEBIASING and PREV_WIN. AGE indicates the participants' age in years, MALE is a binary dummy taking the value of 0 for female participants and 1 for male participants. STUDY_ECONOMICS is a binary variable, which equals 1 for participants enrolled in economics, business, and business law and 0 for all other study programs. INVESTMENT_EXPERIENCE is a dummy taking the value of 1 for decision makers who had already invested in financial products and 0 for participants who had not. GRADUATE is a binary dummy taking a value of 1 for graduate students and 0 for undergraduate students. RISK_FINANCIAL is an ordinal variable representing self-reported risk preferences on a 10-point Likert scale in the financial domain. RISK_GENERAL is an ordinal variable representing self-reported risk preferences on a 10-point Likert scale in the general domain. ROUND is an ordinal variable indicating the specific round for which a bet was made.

	Model (I)	Model (II)
PREV_WIN	0.041	0.042
	(0.024)	(0.025)
DEBIASING	0.034	0.034
	(0.029)	(0.030)
DEBIASING#PREV_WIN	−0.058	−0.056
	(0.037)	(0.038)
ROUND		−0.003
		(0.006)
AGE		0.000
		(0.001)
MALE		−0.019
		(0.016)
GRADUATE		0.002
		(0.023)
STUDY_ECONOMICS		−0.022
		(0.015)
RISK_FINANCIAL		−0.002
		(0.004)
RISK_GENERAL		0.007
		(0.004)
INVESTMENT_EXPERIENCE		0.006
		(0.018)
Constant	0.011	0.016
	(0.021)	(0.060)
Observations	752	752
N. of Subjects	376	376
Prob > F	0.322	0.288
R^2	0.004	0.012

$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.005$. Dependent variable: Change in lottery bet from previous round in percentage points (Δ BET); Clustered standard errors on the subject level in parentheses.

Table A10

Differences in treatments and sub-treatments in the additional sample. The table shows pairwise differences in the average bet amount over nine rounds in percent of the endowment between sub-treatments H and L in treatments BASELINE and DEBIASING using two-sided unpaired sample t-tests in the additional sample. The table also shows pairwise differences in the average bet amount over nine rounds in percent of the endowment between treatments BASELINE and DEBIASING in sub-treatments H and L, separately and jointly (H + L).

Treatments	obs	Sub-Treatment Difference: H-L		std. err.	pr(| T | > | t |)
BASELINE	225	-0.116^{***}	(0.363 - 0.480)	0.036	0.002
DEBIASING	204	−0.028	(0.582 - 0.610)	0.041	0.490
Sub-Treatments	**obs**	**Treatment Difference: BASELINE − DEBIASING**		**std. err.**	**pr(| T | > | t |)**
H	231	-0.220^{***}	(0.363 - 0.582)	0.037	0.000
L	198	-0.131^{***}	(0.479 - 0.611)	0.041	0.000
H + L	429	-0.176^{***}	(0.419 - 0.595)	0.027	0.000

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.005$.

Table A11

Differences in treatments and sub-treatments in the additional sample (high attentives). The table shows pairwise differences in the average bet amount over nine rounds in percent of the endowment between sub-treatments H and L in treatments BASELINE and DEBIASING using two-sided unpaired sample *t*-tests in the additional sample among the high attentives. The table also shows pairwise differences in the average bet amount over nine rounds in percent of the endowment between treatments BASELINE and DEBIASING in sub-treatments H and L, separately and jointly (H + L).

Treatments	obs	Sub-Treatment Difference: H-L		std. err.	pr(| T | > | t |)
BASELINE	187	−0.106**	(0.365 - 0.471)	0.040	0.010
DEBIASING	156	−0.026	(0.599 - 0.625)	0.046	0.565
Sub-Treatment	obs	Treatment Difference: BASELINE − DEBIASING		std. err.	pr(| T | > | t |)
H	186	−0.234***	(0.365 - 0.599)	0.040	0.000
L	157	−0.155***	(0.471 - 0.625)	0.046	0.000
H + L	343	−0.192***	(0.418 - 0.610)	0.031	0.000

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.005$.

Table A12

Multivariate marginal effects fractional regression models including the observations from the additional sample (high attentives). The dependent variable (FRACTION_BET) represents the round-specific lottery bets relative to the endowments over nine rounds in stage 2 of the experiment among the high attentives. Clustered standard errors on the subject level are shown in parentheses. The variable DEBIASING is a binary dummy taking on the value 0 for participants in treatment BASELINE and 1 for participants in treatment DEBIASING. L represents a binary dummy variable taking the value 1 for decision makers in the low-frequency feedback sub-treatment and 0 for their peers in the high-frequency feedback group, i.e., H. DEBIASING#LOW_FREQUENCY(L) represents an interaction term between DEBIASING and L. AGE indicates the participants' age in years, MALE is a binary dummy taking the value of 0 for female participants and 1 for male participants. STUDY_ECONOMICS is a binary variable, which equals 1 for participants enrolled in economics, business, and business law and 0 for all other study programs. INVESTMENT_EXPERIENCE is a dummy taking the value of 1 for decision makers who had already invested in financial products and 0 for participants who had not. GRADUATE is a binary dummy taking a value of 1 for graduate students and 0 for undergraduate students. RISK_FINANCIAL is an ordinal variable representing self-reported risk preferences on a 10-point Likert scale in the financial domain. RISK_GENERAL is an ordinal variable representing self-reported risk preferences on a 10-point Likert scale in the general domain. ROUND is an ordinal variable indicating the specific round for which a bet was made. "Permute *p*" reports the *p*-values of the corresponding coefficient, obtained from permutation tests with 1000 random draws.

	Model (I)	Model (II)	Model (III)
DEBIASING	0.178***	0.217***	0.213***
	(0.016)	(0.023)	(0.022)
LOW_FREQUENCY(L)	0.077***	0.114***	0.113***
	(0.017)	(0.024)	(0.022)
ROUND	0.008***	0.008***	0.008***
	(0.001)	(0.001)	(0.001)
DEBIASING#LOW_FREQUENCY(L)		−0.076*	−0.081*
		(0.035)	(0.033)
AGE			0.005*
			(0.003)
MALE			0.086***
			(0.019)
GRADUATE			0.018
			(0.030)
STUDY_ECONOMICS			0.017
			(0.017)
RISK_FINANCIAL			0.008
			(0.005)
RISK_GENERAL			0.026***
			(0.004)
INVESTMENT_EXPERIENCE			−0.001
			(0.020)
Permute *p* DEBIASING#LOW_FREQUENCY(L)		0.042	0.015
Observations	9531	9531	9531
N. of Subjects	1059	1059	1059
Prob > Chi^2	0.000	0.000	0.000
Pseudo R^2	0.029	0.031	0.066

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.005$. Dependent variable: Amount bet relative to the endowment (FRACTION_BET); Clustered standard errors on the subject level in parentheses.

Table A13

Multivariate marginal effects fractional regression models on the influence of perceptions of loss likelihood in the lottery in the additional sample. The dependent variable (FRACTION_BET) represents the round-specific lottery bets relative to the endowments over nine rounds in stage 2 of the experiment. Clustered standard errors on the subject level are shown in parentheses. The variable L represents a binary dummy variable taking the value 1 for decision makers in the low-frequency feedback sub-treatment and 0 for their peers in the high-frequency feedback group, i.e., H. The variable PERCEPTION_LOSS is an ordinal variable on the individual answers on a 7-point Likert scale and the following question: "I could incur a great loss if I decide to bet in the lottery". AGE indicates the participants' age in years, MALE is a binary dummy taking the value of 0 for female participants and 1 for male participants. STUDY_ECONOMICS is a binary variable, which equals 1 for participants enrolled in economics, business, and business law and 0 for all other study programs. INVESTMENT_EXPERIENCE is a dummy taking the value of 1 for decision makers who had already invested in financial products and 0 for participants who had not. GRADUATE is a binary dummy taking a value of 1 for graduate students and 0 for undergraduate students. RISK_FINANCIAL is an ordinal variable representing self-reported risk preferences on a 10-point Likert scale in the financial domain. RISK_GENERAL is an ordinal variable representing self-reported risk preferences on a 10-point Likert scale in the general domain. ROUND is an ordinal variable indicating the specific round for which a bet was made. "Permute p" reports the p-values of the corresponding coefficient, obtained from permutation tests with 1000 random draws.

	Model (I)	Model (II)	Model (III)
PERCEPTION_LOSS	-0.037^{***}	-0.029^{***}	-0.024^{***}
	(0.009)	(0.009)	(0.008)
ROUND	0.008^{***}	0.008^{***}	0.008^{***}
	(0.002)	(0.002)	(0.002)
DEBIASING		0.163^{***}	0.160^{***}
		(0.025)	(0.025)
LOW_FREQUENCY(L)		0.062^{*}	0.063^{*}
		(0.027)	(0.026)
AGE			0.004
			(0.003)
MALE			0.032
			(0.029)
GRADUATE			0.013
			(0.047)
STUDY_ECONOMICS			0.008
			(0.028)
RISK_FINANCIAL			0.004
			(0.008)
RISK_GENERAL			0.021^{***}
			(0.007)
INVESTMENT_EXPERIENCE			−0.035
			(0.030)
Permute p PERCEPTION_LOSS	0.000	0.000	0.002
Observations	3861	3861	3861
N. of Subjects	429	429	429
Prob > Chi^2	0.000	0.000	0.000
Pseudo R^2	0.013	0.035	0.055

$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.005$. Dependent variable: Amount bet relative to the endowment (FRACTION_BET); Clustered standard errors on the subject level in parentheses.

Table A14

Multivariate marginal effects fractional regression models on the influence of displayed average aggregate wealth levels in tokens in the simulation in Treatment DEBIASING . The dependent variable (FRACTION_BET) represents the round-specific lottery bets relative to the endowments over nine rounds in stage 2 of the experiment. Clustered standard errors on the subject level are shown in parentheses. The variable L represents a binary dummy variable taking the value 1 for decision makers in the low-frequency feedback sub-treatment and 0 for their peers in the high-frequency feedback group, i.e., H. The variable SIM_OUTCOME indicates the displayed average aggregate wealth differences in tokens between scenarios after 15 rounds of Simulation A (SIM_OUTCOME = Average aggregate wealth in tokens after 9 rounds and 15 iterations in *Chosen_Bet* - Average aggregate wealth in tokens after 9 rounds and 15 iterations in *Reduced_Bet*). *LOW_FREQUENCY(L)#SIM_OUTCOME* represents an interaction term between L and SIM_OUTCOME. AGE indicates the participants' age in years, MALE is a binary dummy taking the value of 0 for female participants and 1 for male participants. STUDY_ECONOMICS is a binary variable, which equals 1 for participants enrolled in economics, business, and business law and 0 for all other study programs. INVESTMENT_EXPERIENCE is a dummy taking the value of 1 for decision makers who had already invested in financial products and 0 for participants who had not. GRADUATE is a binary dummy taking a value of 1 for graduate students and 0 for undergraduate students. RISK_FINANCIAL is an ordinal variable representing self-reported risk preferences on a 10-point Likert scale in the financial domain. RISK_GENERAL is an ordinal variable representing self-reported risk preferences on a 10-point Likert scale in the general domain. ROUND is an ordinal variable indicating the specific round for which a bet was made. "Permute *p*" reports the *p*-values of the corresponding coefficient, obtained from permutation tests with 1000 random draws.

	Model (I)	Model (II)	Model (III)
SIM_OUTCOME	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)
ROUND	0.008***	0.008***	0.008***
	(0.002)	(0.002)	(0.002)
LOW_FREQUENCY(L)		0.048	0.036
		(0.033)	(0.030)
LOW_FREQUENCY(L)#SIM_OUTCOME		0.000	0.000
		(0.000)	(0.000)
AGE			0.005
			(0.004)
MALE			0.090***
			(0.029)
GRADUATE			0.012
			(0.047)
STUDY_ECONOMICS			0.005
			(0.028)
RISK_FINANCIAL			0.020**
			(0.007)
RISK_GENERAL			0.015*
			(0.007)
INVESTMENT_EXPERIENCE			0.015
			(0.033)
Permute *p* LOW_FREQUENCY(L)#SIM_OUTCOME		0.638	0.384
Observations	4095	4095	4095
N. of Subjects	455	455	455
Prob > Chi^2	0.000	0.000	0.000
Pseudo R^2	0.020	0.023	0.059

$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.005$. Dependent variable: Amount bet relative to the endowment (FRACTION_BET); Clustered standard errors on the subject level in parentheses.

Table A15

Multivariate marginal effects fractional regression models on the influence of displayed average aggregate wealth levels in tokens in the simulation in Treatment DEBIASING (high attentives). The dependent variable (FRACTION_BET) represents the round-specific lottery bets relative to the endowments over nine rounds in stage 2 of the experiment. Clustered standard errors on the subject level are shown in parentheses. The variable L represents a binary dummy variable taking the value 1 for decision makers in the low-frequency feedback sub-treatment and 0 for their peers in the high-frequency feedback group, i.e., H. The variable SIM_OUTCOME indicates the displayed average aggregate wealth differences in tokens between scenarios after 15 rounds of Simulation A (SIM_OUTCOME = Average aggregate wealth in tokens after 9 rounds and 15 iterations in *Chosen_Bet* - Average aggregate wealth in tokens after 9 rounds and 15 iterations in *Reduced_Bet*). *LOW_FREQUENCY(L)#SIM_OUTCOME* represents an interaction term between L and SIM_OUTCOME. AGE indicates the participants' age in years, MALE is a binary dummy taking the value of 0 for female participants and 1 for male participants. STUDY_ECONOMICS is a binary variable, which equals 1 for participants enrolled in economics, business, and business law and 0 for all other study programs. INVESTMENT_EXPERIENCE is a dummy taking the value of 1 for decision makers who had already invested in financial products and 0 for participants who had not. GRADUATE is a binary dummy taking a value of 1 for graduate students and 0 for undergraduate students. RISK_FINANCIAL is an ordinal variable representing self-reported risk preferences on a 10-point Likert scale in the financial domain. RISK_GENERAL is an ordinal variable representing self-reported risk preferences on a 10-point Likert scale in the general domain. ROUND is an ordinal variable indicating the specific round for which a bet was made. "Permute *p*" reports the *p*-values of the corresponding coefficient, obtained from permutation tests with 1000 random draws.

	Model (I)	Model (II)	Model (III)
SIM_OUTCOME	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)
ROUND	0.008***	0.008***	0.008***
	(0.002)	(0.002)	(0.002)
LOW_FREQUENCY(L)		0.045	0.030
		(0.036)	(0.031)
LOW_FREQUENCY(L)#SIM_OUTCOME		0.000	0.000
		(0.000)	(0.000)
AGE			0.006
			(0.005)
MALE			0.109***
			(0.032)
GRADUATE			0.011
			(0.046)
STUDY_ECONOMICS			0.031
			(0.030)
RISK_FINANCIAL			0.013
			(0.008)
RISK_GENERAL			0.024***
			(0.008)
INVESTMENT_EXPERIENCE			−0.015
			(0.036)
Permute *p* LOW_FREQUENCY(L)#SIM_OUTCOME		0.867	0.652
Observations	3177	3177	3177
N. of Subjects	353	353	353
Prob > Chi^2	0.000	0.000	0.000
Pseudo R^2	0.017	0.018	0.070

$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.005$. Dependent variable: Amount bet relative to the endowment (FRACTION_BET); Clustered standard errors on the subject level in parentheses.

Table A16

Differences in answers to additional questionnaire between sub-treatments in the additional sample. The table shows pairwise differences in the average answers to each question in the questionnaire at the end of stage 2 on 7-point Likert scales between both sub-treatments H and L in both treatments BASELINE and DEBIASING using two-sided unpaired sample *t*-tests.

Treatment	obs	Sub-Treatment Difference: H-L		std. err.	pr(| T | > | t |)
1. How risky is this lottery?					
BASELINE	225	0.110	(5.573 - 5.463)	0.209	0.490
DEBIASING	204	−0.129	(5.316- 5.444)	0.217	0.554
2. How much do you agree: *It is very likely that I will lose money when I bet in the lottery.*					
BASELINE	225	0.660***	(5.966 - 5.306)	0.213	0.002
DEBIASING	204	0.120	(5.298 - 5.178)	0.256	0.638
3. How much do you agree: *If I decide to bet in the lottery, I would worry about the consequences.*					
BASELINE	225	0.030	(4.752 - 4.722)	0.263	0.910
DEBIASING	204	0.144	(4.754 - 4.611)	0.133	0.593
4. How much do you agree: *I could incur a great loss if I decide to bet in the lottery.*					
BASELINE	225	−0.385	(4.957 - 5.343)	0.262	0.143
DEBIASING	204	−0.067	(5.000 - 5.067)	0.272	0.806
5. How certain are you about the distribution of outcomes of the lottery?					
BASELINE	225	−0.180	(0.371 - 0.389)	0.243	0.461
DEBIASING	204	−0.503*	(3.553 - 4.056)	0.243	0.040
6. How much do you agree: *I fully understand the distribution of outcomes of the lottery.*					
BASELINE	225	0.291	(4.846 - 4.556)	0.272	0.2874
DEBIASING	204	0.006	(4.684 - 4.678)	0.262	0.980
7. How much do you agree: *I am confident that I know the expected outcomes of the lottery.*					
BASELINE	225	−0.260	(3.376 - 3.630)	0.259	0.329
DEBIASING	204	−0.446	(3.590 - 4.033)	0.276	0.109
8. How much do you agree: *I have all the relevant information I need to bet in the lottery.*					
BASELINE	225	−0.472	(4.214 - 4.685)	0.272	0.084
DEBIASING	204	−0.157	(4.632 - 4.789)	0.266	0.556
9. How much do you agree: *I have sufficient information to make a sound betting decision*					
BASELINE	225	0.009	(4.436 - 4.444)	0.2666	0.974
DEBIASING	204	−0.250	(4.561 - 4.811)	0.275	0.365
10. How much do you agree: *I need more information to make a good betting decision.*					
BASELINE	225	0.117	(4.043 - 3.926)	0.275	0.672
DEBIASING	204	0.113	(3.824 - 3.711)	0.273	0.678
11. How much do you agree: *How satisfied are you with the results of your bets in the lottery?*					
BASELINE	225	−0.279	(3.240 - 3.519)	0.232	0.229
DEBIASING	204	−0.537*	(3.430 - 3.967)	0.237	0.025
12. *If you bet the complete initial endowment of 200 tokens in each of the nine rounds in the lottery, in how many of 100 total runs of the lottery (each over nine rounds) would the total wealth (over all nine rounds) be less than 1800 tokens?*					
BASELINE	225	−1.583	(53.444 - 55.028)	3.820	0.679
DEBIASING	204	−1.416	(48.728 - 50.144)	3.933	0.719
13. *If you bet the complete initial endowment of 200 tokens in each of the nine rounds in the lottery, in how many of 100 total runs of the lottery (each over nine rounds) would the total wealth (over all nine rounds) be over 2700 tokens?*					
BASELINE	225	0.603	(25.872 - 25.269)	2.982	0.840
DEBIASING	204	3.141	(24.263 - 21.122)	2.893	0.279

Table A17
Differences in answers to additional questionnaire between sub-treatments in the additional sample. The table shows pairwise differences in the average answers to each question in the questionnaire at the end of stage 2 on 7-point Likert scales between sub-treatments H and L using two-sided unpaired sample t-tests.

Sub-Treatment	obs	Treatment Difference: BASELINE − DEBIASING		std. err.	pr(| T | > | t |)
1. How risky is this lottery?					
H	231	0.257	(5.573 - 5.316)	0.210	0.223
L	198	0.019	(4.462 - 5.455)	0.213	0.931
H + L	429	0.147	(5.520 - 5.372)	0.150	0.326
2. How much do you agree: *It is very likely that I will lose money when I bet in the lottery.*					
H	231	0.668***	(5.966 - 5.298)	0.205	0.001
L	198	0.128	(5.306 - 5.178)	0.265	0.630
H + L	429	0.404*	(5.649 - 5.247)	0.167	0.015
3. How much do you agree: *If I decide to bet in the lottery, I would worry about the consequences.*					
H	231	−0.020	(4.752 - 4.754)	0.255	0.993
L	198	0.111	(4.722 - 4.611)	0.276	0.687
H + L	429	0.047	(4.738 - 4.691)	0.187	0.803
4. How much do you agree: *I could incur a great loss if I decide to bet in the lottery.*					
H	231	−0.043	(4.957 - 5.000)	0.260	0.870
L	198	0.276	(5.342 - 5.067)	0.273	0.313
H + L	429	0.113	(5.142 - 5.029)	0.188	0.549
5. How certain are you about the distribution of outcomes of the lottery?					
H	231	0.157	(3.709 - 3.552)	0.233	0.501
L	198	−0.017	(3.889 - 4.056)	0.254	0.513
H + L	429	0.021	(3.796 - 3.775)	0.172	0.903
6. How much do you agree: *I fully understand the distribution of outcomes of the lottery.*					
H	231	0.162	(4.846 - 4.684)	0.255	0.526
L	198	−0.122	(4.556 - 4.678)	0.283	0.666
H + L	429	0.0253	(4.707 - 4.681)	0.189	0.894
7. How much do you agree: *I am confident that I know the expected outcomes of the lottery.*					
H	231	−0.212	(3.376 - 3.588)	0.253	0.404
L	198	−0.404	(3.630 - 4.033)	0.283	0.155
H + L	429	−0.287	(3.498 - 3.784)	0.189	0.130
8. How much do you agree: *I have all the relevant information I need to bet in the lottery.*					
H	231	−0.418	(4.214 - 4.632)	0.268	0.120
L	198	−0.104	(4.685 - 4.789)	0.269	0.700
H + L	429	−0.261	(4.440 - 4.701)	0.191	0.172
9. How much do you agree: *I have sufficient information to make a sound betting decision*					
H	231	−0.126	(4.436 - 4.561)	0.267	0.638
L	198	−0.037	(4.444 - 4.811)	0.273	0.181
H + L	429	−0.232	(4.440 - 4.672)	0.191	0.225
10. How much do you agree: *I need more information to make a good betting decision*					
H	231	0.218	(4.043 - 3.824)	0.270	0.420
L	198	0.215	(3.926 - 3.711)	0.278	0.440
H + L	429	0.212	(3.987 - 3.775)	0.193	0.273
11. How much do you agree: *How satisfied are you with the results of your bets in the lottery?*					
H	231	−0.191	(3.239 - 3.430)	0.236	0.421
L	198	−0.448	(3.519 - 3.967)	0.229	0.052
H + L	429	−0.293	(3.373 - 3.667)	0.166	0.078
12. *If you bet the complete initial endowment of 200 tokens in each of the nine rounds in the lottery, in how many of 100 total runs of the lottery (each over nine rounds) would the total wealth (over all nine rounds) be less than 1800 tokens?*					
H	231	4.716	(53.444 - 48.723)	3.800	0.216
L	198	4.883	(55.028 - 50.144)	3.934	0.216
H + L	429	4.852	(54.204 - 49.353)	2.728	0.076
13. *If you bet the complete initial endowment of 200 tokens in each of the nine rounds in the lottery, in how many of 100 total runs of the lottery (each over nine rounds) would the total wealth (over all nine rounds) be over 2700 tokens?*					
H	231	1.609	(25.872 - 24.263)	2.995	0.592
L	198	4.146	(25.269 - 21.122)	2.843	0.146
H + L	429	2.705	(25.582 - 22.877)	2.076	0.193

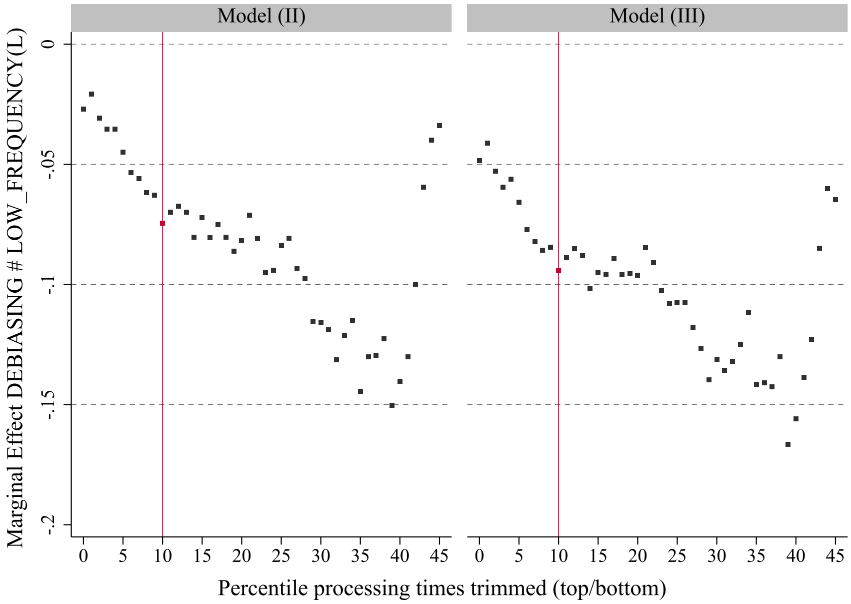


Fig. A.1. Marginal effects for different percentiles of trimmed processing times (top/bottom). The graph shows the relationship between the coefficient (marginal effect) DEBIASING#LOW_FREQUENCY(L) and different cut-off points. For example, for the 20th percentile, we excluded the participants with the 20% slowest and 20% fastest processing times on the two task relevant instruction screens in both treatments BASELINE and DEBIASING. Model (II) and model (III) show the respective results for the according specifications in Tables 1 and 2.

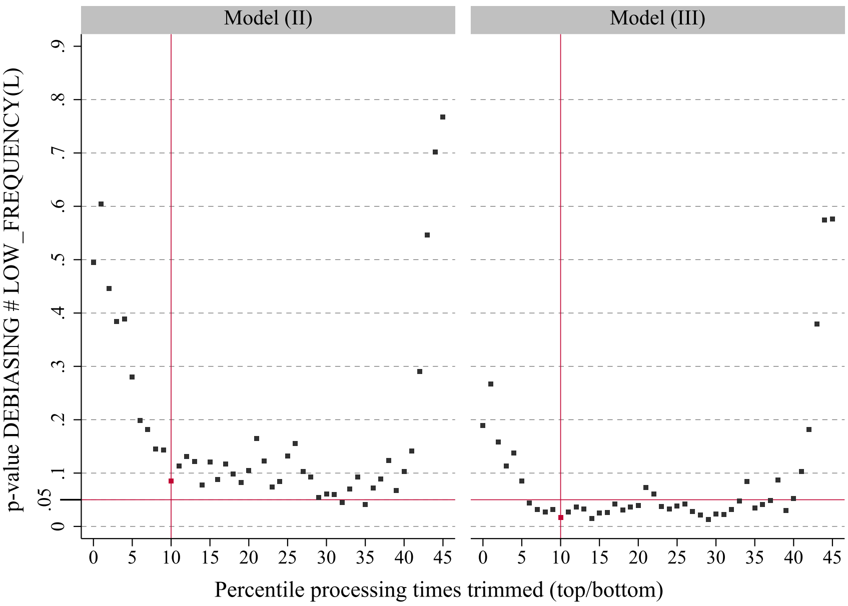
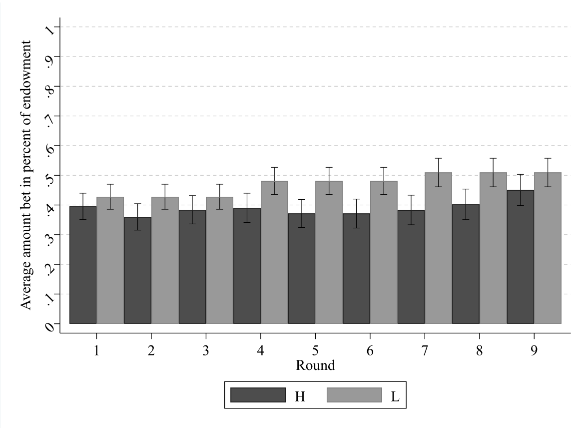
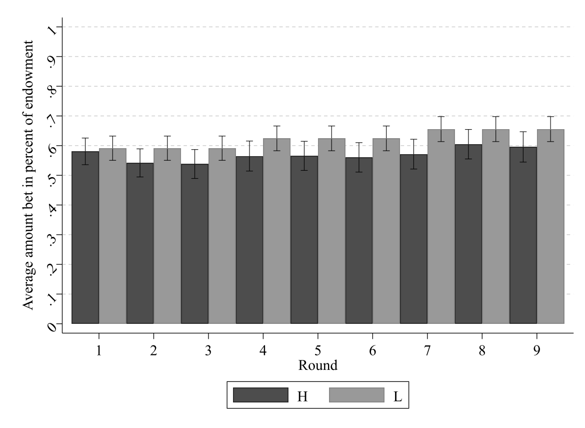


Fig. A.2. P-values for different percentiles of trimmed processing times (top/bottom). The graph shows the relationship between the p-value of the coefficient DEBIASING#LOW_FREQUENCY(L) and different cut-off points. For example, for the 20th percentile, we excluded the participants with the 20% slowest and 20% fastest processing times on the two task relevant instruction screens in both treatments BASELINE and DEBIASING. Model (II) and model (III) show the respective results for the according specifications in Tables 1 and 2.

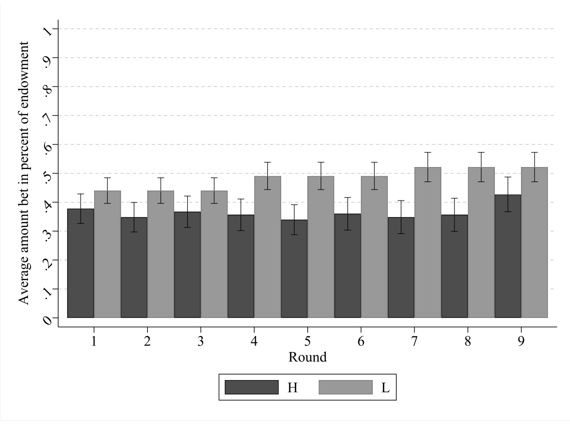


(a) Average amount bet in percent of endowment in each of the nine rounds in BASELINE.

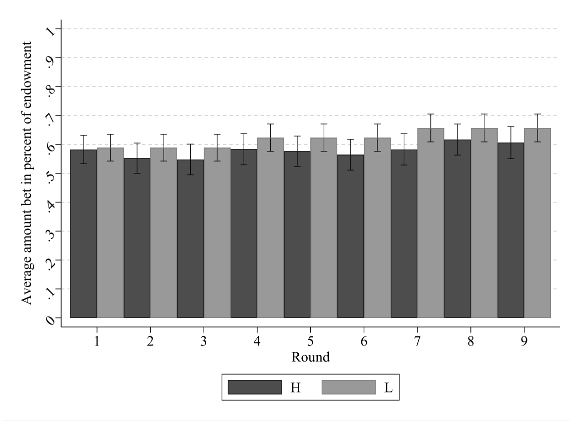


(b) Average amount bet in percent of endowment in each of the nine rounds in DEBIASING.

Fig. A.3. The graph shows the average amounts bet in the lottery in each of the nine rounds in the full sample as a percentage of the endowment of 200 tokens. Results are shown for both sub-treatments (H and L) in the baseline condition (BASELINE) in sub-figure (a) and in the debiasing treatment (DEBIASING) in sub-figure (b). The whiskers represent 95% confidence intervals.



(a) Average amount bet in percent of endowment in each of the nine rounds in BASELINE.



(b) Average amount bet in percent of endowment in each of the nine rounds in DEBIASING.

Fig. A.4. The graph shows the average amounts bet in the lottery in each of the nine rounds in the attentive sample as a percentage of the endowment of 200 tokens. Results are shown for both sub-treatments (H and L) in the baseline condition (BASELINE) in sub-figure (a) and in the debiasing treatment (DEBIASING) in sub-figure (b). The whiskers represent 95% confidence intervals.

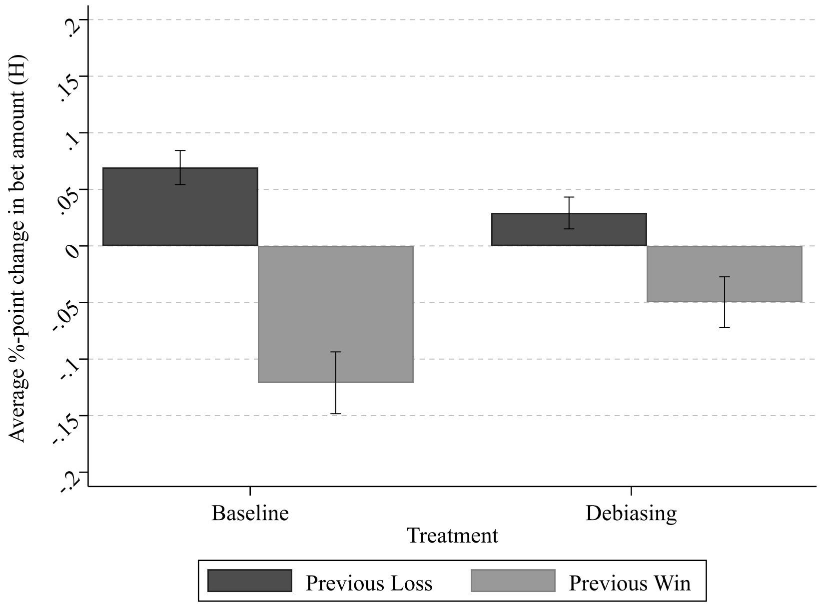


Fig. A.5. Average conditional △bets in sub-treatment H. The graph shows the average percentage point change in the amount bet in the lottery conditional on the lottery outcome of the previous round (win or loss) for each treatment (BASELINEand DEBIASING) and sub-treatment H. The whiskers represent 95% confidence intervals.

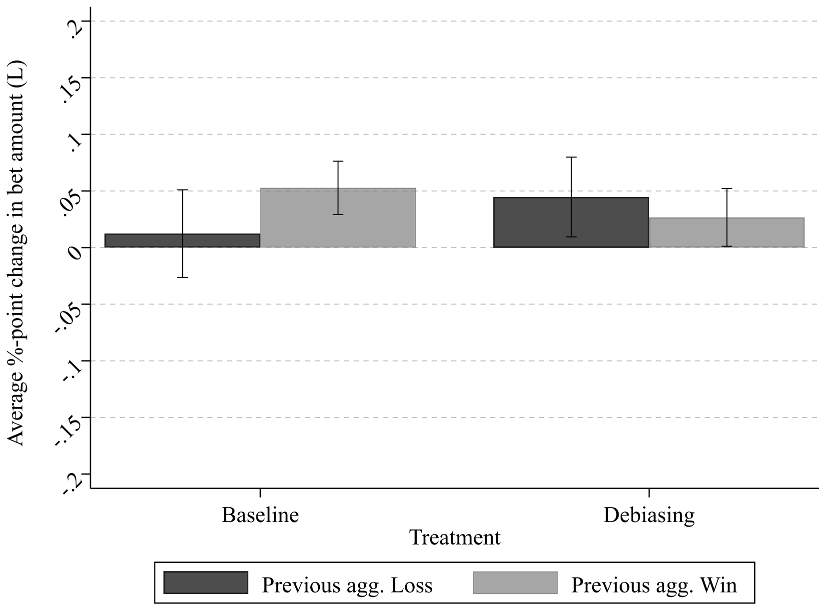


Fig. A.6. Average conditional △bets in sub-treatment L. The graph shows the average percentage point change in the amount bet in the lottery conditional on the aggregate lottery outcome of the previous 3 rounds (aggregate win or aggregate loss) for each treatment (BASELINE and DEBIASING) and sub-treatment L. The whiskers represent 95% confidence intervals.

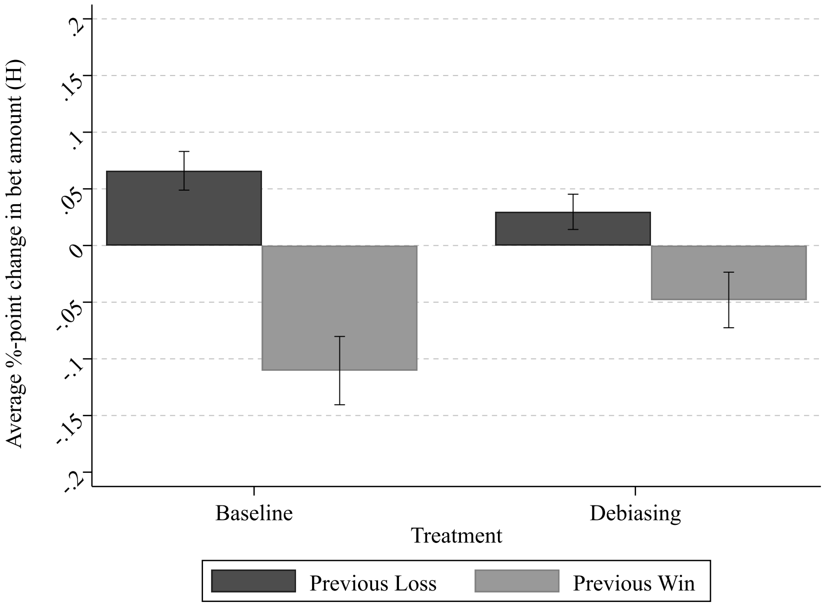


Fig. A.7. Average conditional △bets in sub-treatment H (high attentives). The graph shows the average percentage point change in the amount bet in the lottery conditional on the lottery outcome of the previous round (win or loss) for each treatment (BASELINE and DEBIASING) and sub-treatment H. The whiskers represent 95% confidence intervals.

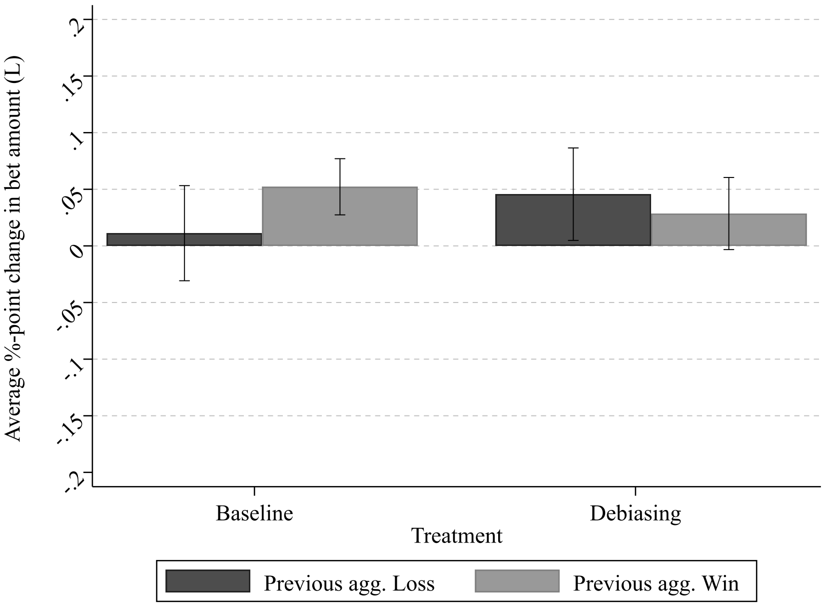


Fig. A.8. Average conditional △bets in sub-treatment L (high attentives). The graph shows the average percentage point change in the amount bet in the lottery conditional on the lottery outcome of the previous round (win or loss) for each treatment (BASELINE and DEBIASING) and sub-treatment L. The whiskers represent 95% confidence intervals.

Appendix B. Screenshots of the software

B1. Intro

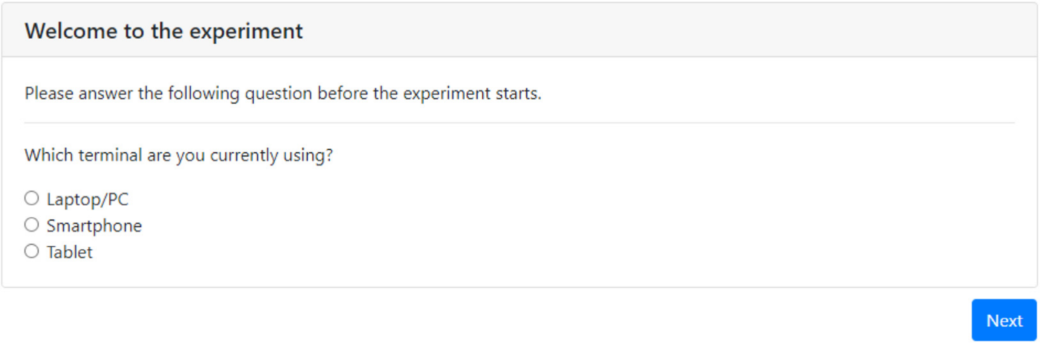


Fig. B.1. Question on terminal device.

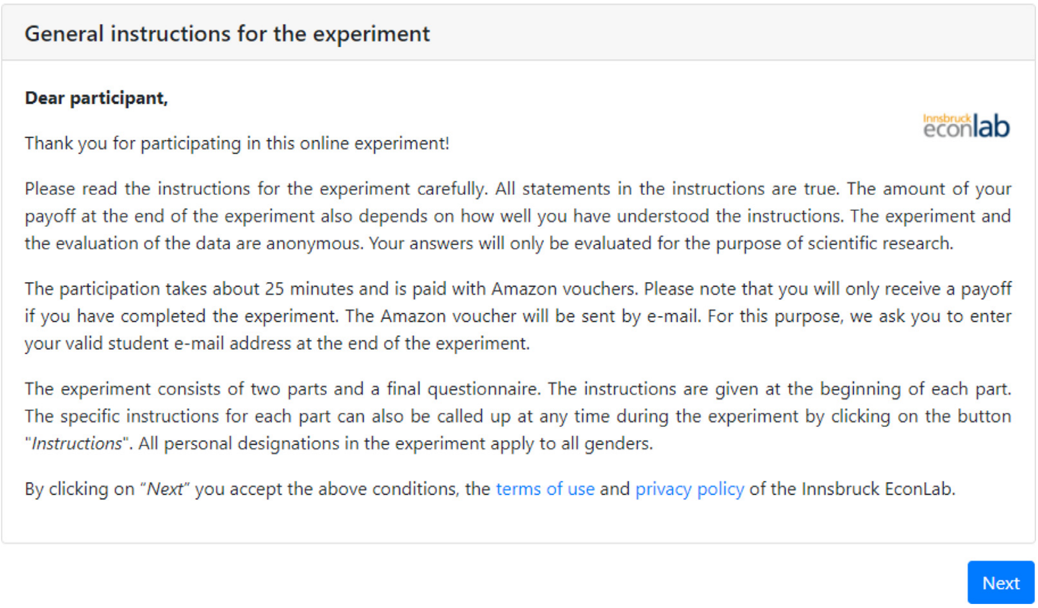


Fig. B.2. General Instructions.

B2. Treatment: BASELINE

Instructions for Part 1

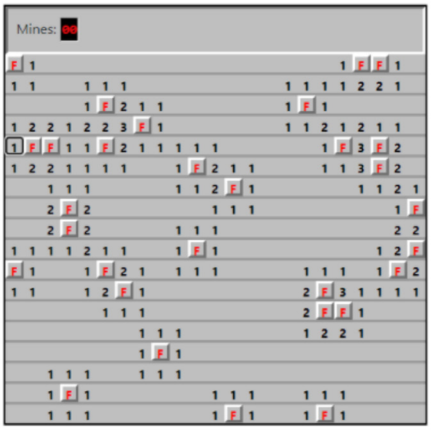
In Part 1 of the experiment you will play the game "Minesweeper". Note that your success in this game will **not** affect your payout. The game starts when you click on the button "*Start New Game*".
Your task is to mark all 30 fields under which there is a mine. A game ends when you uncover a field under which a mine is located or when you correctly mark all fields under which a mine is located. If you assume that a mine is hidden under a field, you can click on it with the **right mouse button** to mark the field with a flag. By right-clicking on the field again, you can unmark it.
Analyze the patterns. For example, if a 2 is displayed in a field, then there is a mine under 2 of the 8 adjacent fields. For example, if a field displays the number 8, then there is a mine under each of the adjacent 8 fields. If you do not know which field to click on, you should enter unexplored territory. It is better to click in the middle of an area of unmarked fields than in an area where you think there might be mines. During the game, you will be shown in the upper left corner how many mines are left according to your marking.
If you have solved a minefield or the game has ended because you uncovered a field with a mine, please click again on the button "*Start New Game*" to start a new game.

Regardless of your results in this game, you can continue the experiment by clicking on the "*Next*" button, which will be displayed after 10 minutes and at least 5 repetitions of the game.
Below you can see an example of the game with a solved minefield. You can trace the marking logic by looking at the individual numbers next to the fields.

Part 1 - Minesweeper	Time: 02:27	Repetitions: 1

Start the game by clicking on "*Start New Game*".

Instructions



Start New Game

Next

Fig. B.3. Instructions Filler Task.

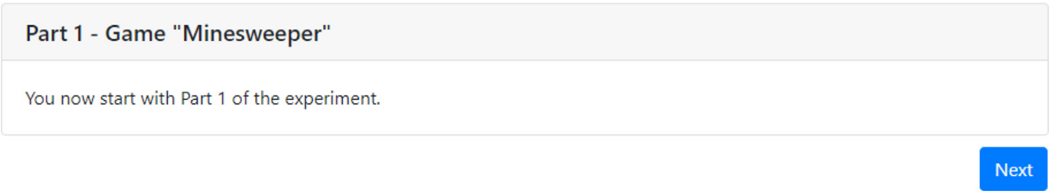


Fig. B.4. Transition Filler Task.

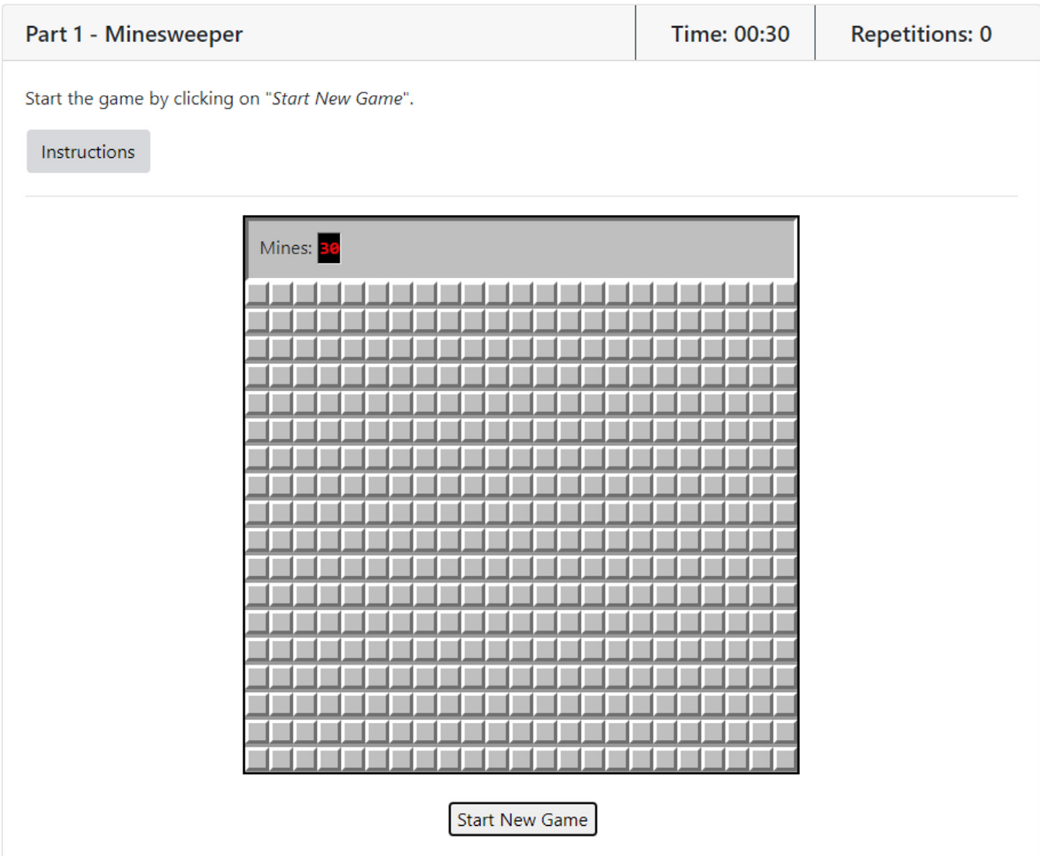


Fig. B.5. Filler Task.

B3. Treatment: DEBIASING

General Simulation A Simulation B

Instructions for Part 1

In Part 1 of the experiment you will see two simulations, A and B, of a lottery. To illustrate the lottery over 9 rounds, a **fictitious** initial endowment of 200 Taler per round is available. You can choose an amount "*x*" in Taler between 0 or 1 and 200, which will be used to illustrate the lottery. In Part 1 of the experiment, all amounts are **fictitious** and will affect **not** your payout. Part 1 is intended solely to illustrate the characteristics of the lottery. Please note, however, that in Part 2 of the experiment, you can bet payout relevant amounts into the same lottery and your understanding from Part 1 of the experiment can affect your decisions in Part 2 and thus the amount of your payout in Part 2. Both simulations deal with the same lottery, which has the following characteristics:

With a probability of 2/3 (67%) you will lose the amount you bet and with a probability of 1/3 (33%) you will win two and a half times (2.5 times) the amount you bet.

If you win the lottery in a round, you will receive $+\ 2.5 \cdot x$ for that round from the lottery. If you lose in a round in the lottery, you will receive $-\ x$ from the lottery for that round. The **total wealth per round** corresponds to the win ($+2.5 \cdot x$) or loss ($-\ x$) from the lottery and the initial endowment of 200 Taler that you receive in each round.

SCENARIOS

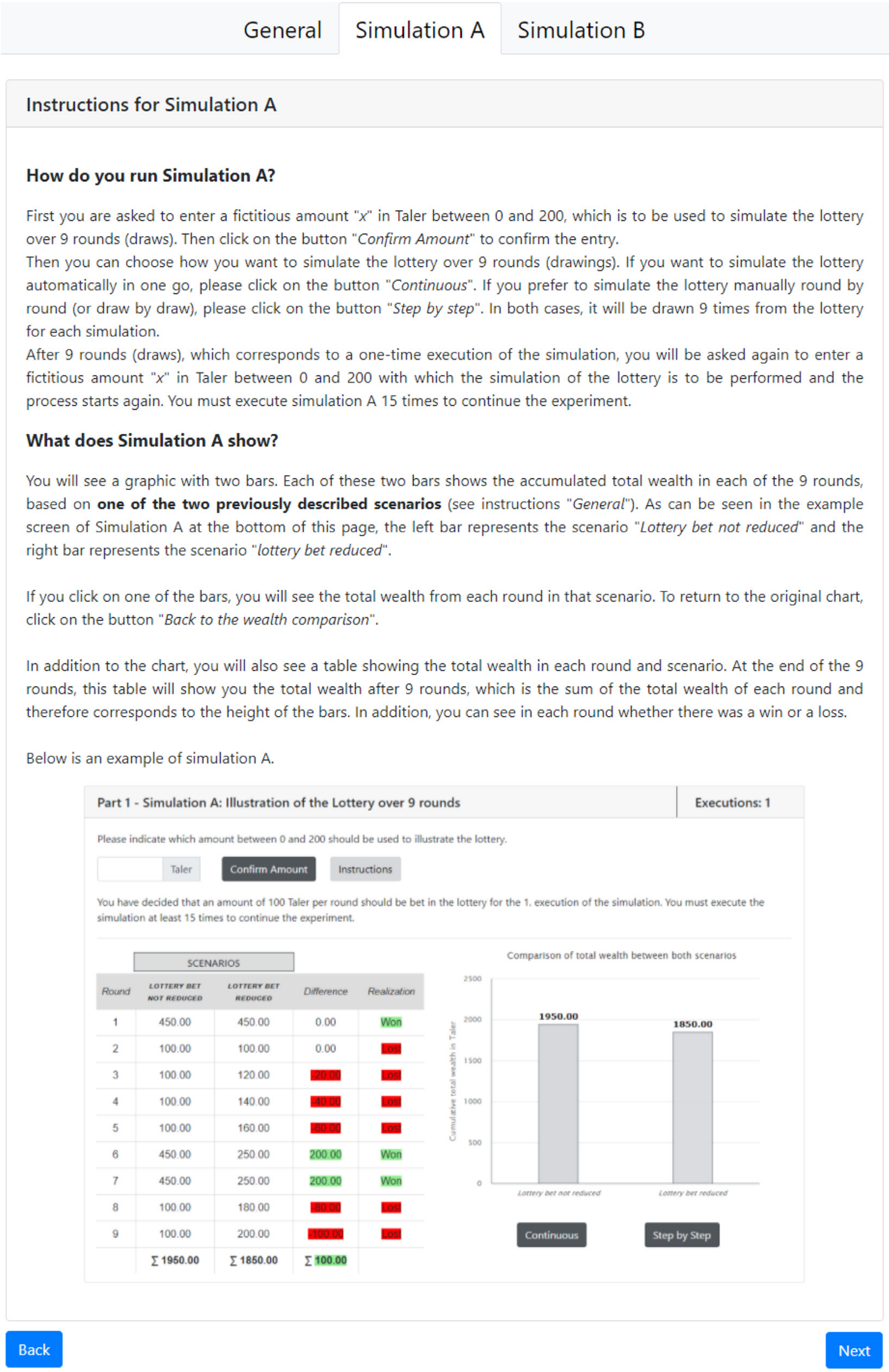
Both simulations, A and B, are based on the same two scenarios, whereby these two scenarios **differ only in the amount bet into the lottery described above**. In the following, the two scenarios are described.

Scenario 1: "*Lottery bet not reduced*"
In the first scenario, marked "*Lottery bet not reduced*", the amount "*x*" you have chosen will be bet in the lottery. The amount bet remains constant in each of the 9 rounds.

Scenario 2: "*Lottery bet reduced*"
In the second scenario, which is marked with "*Lottery bet reduced*", the amount "*x*" you have chosen will be bet into the lottery, as in scenario 1. The bet amount remains constant. However, if a loss occurs in one of the 9 lottery draws, **the amount "*x*" you originally selected will be reduced by 20%**. This new reduced amount (80% of the originally chosen amount) will then be bet into the lottery in each round following this loss. If a loss occurs again in later rounds, the **originally selected amount "*x*" is reduced again by 20%**. This further reduced amount (60% of the originally chosen amount) is then bet into the lottery in each round following the second loss. This principle is also applies after each further loss. Thus, if five or more losses occur, an amount of zero is bet into the lottery in all subsequent rounds. In summary, this means that after each loss, 20% less will be bet into the lottery than you originally chose.

Next

Fig. B.6. General Instructions Intervention.



General | Simulation A | Simulation B

Instructions for Simulation A

How do you run Simulation A?

First you are asked to enter a fictitious amount "*x*" in Taler between 0 and 200, which is to be used to simulate the lottery over 9 rounds (draws). Then click on the button "*Confirm Amount*" to confirm the entry.
Then you can choose how you want to simulate the lottery over 9 rounds (drawings). If you want to simulate the lottery automatically in one go, please click on the button "*Continuous*". If you prefer to simulate the lottery manually round by round (or draw by draw), please click on the button "*Step by step*". In both cases, it will be drawn 9 times from the lottery for each simulation.
After 9 rounds (draws), which corresponds to a one-time execution of the simulation, you will be asked again to enter a fictitious amount "*x*" in Taler between 0 and 200 with which the simulation of the lottery is to be performed and the process starts again. You must execute simulation A 15 times to continue the experiment.

What does Simulation A show?

You will see a graphic with two bars. Each of these two bars shows the accumulated total wealth in each of the 9 rounds, based on **one of the two previously described scenarios** (see instructions "*General*"). As can be seen in the example screen of Simulation A at the bottom of this page, the left bar represents the scenario "*Lottery bet not reduced*" and the right bar represents the scenario "*lottery bet reduced*".

If you click on one of the bars, you will see the total wealth from each round in that scenario. To return to the original chart, click on the button "*Back to the wealth comparison*".

In addition to the chart, you will also see a table showing the total wealth in each round and scenario. At the end of the 9 rounds, this table will show you the total wealth after 9 rounds, which is the sum of the total wealth of each round and therefore corresponds to the height of the bars. In addition, you can see in each round whether there was a win or a loss.

Below is an example of simulation A.

Part 1 - Simulation A: Illustration of the Lottery over 9 rounds | Executions: 1

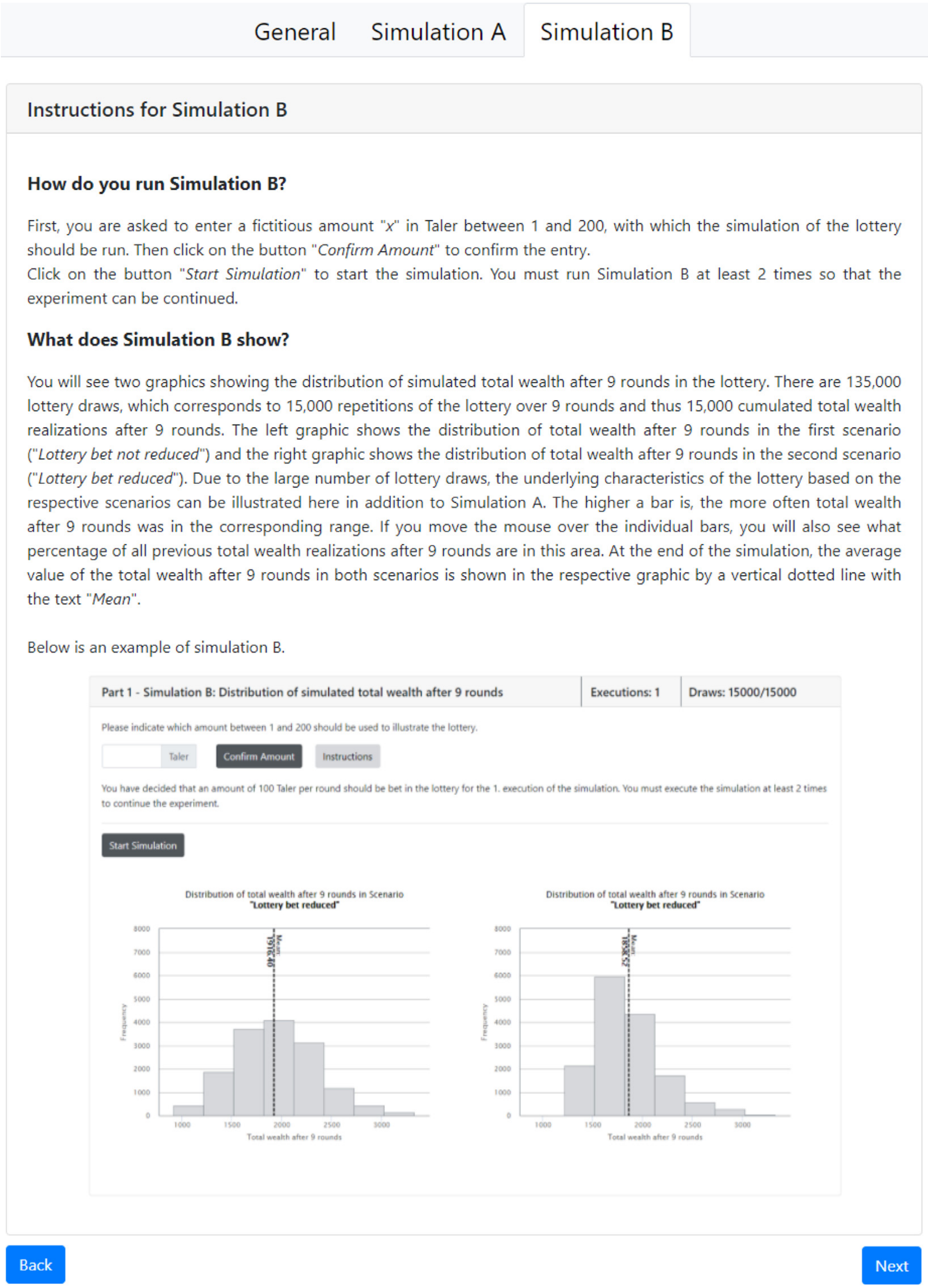
Please indicate which amount between 0 and 200 should be used to illustrate the lottery.

Taler | Confirm Amount | Instructions

You have decided that an amount of 100 Taler per round should be bet in the lottery for the 1. execution of the simulation. You must execute the simulation at least 15 times to continue the experiment.

	SCENARIOS			
Round	LOTTERY BET NOT REDUCED	LOTTERY BET REDUCED	Difference	Realization
1	450.00	450.00	0.00	Won
2	100.00	100.00	0.00	Lost
3	100.00	120.00	-20.00	Lost
4	100.00	140.00	-40.00	Lost
5	100.00	160.00	-60.00	Lost
6	450.00	250.00	200.00	Won
7	450.00	250.00	200.00	Won
8	100.00	180.00	-80.00	Lost
9	100.00	200.00	-100.00	Lost
	∑ 1950.00	∑ 1850.00	∑ 100.00	

Fig. B.7. Instructions Simulation A.



General Simulation A Simulation B

Instructions for Simulation B

How do you run Simulation B?

First, you are asked to enter a fictitious amount "*x*" in Taler between 1 and 200, with which the simulation of the lottery should be run. Then click on the button "*Confirm Amount*" to confirm the entry.
Click on the button "*Start Simulation*" to start the simulation. You must run Simulation B at least 2 times so that the experiment can be continued.

What does Simulation B show?

You will see two graphics showing the distribution of simulated total wealth after 9 rounds in the lottery. There are 135,000 lottery draws, which corresponds to 15,000 repetitions of the lottery over 9 rounds and thus 15,000 cumulated total wealth realizations after 9 rounds. The left graphic shows the distribution of total wealth after 9 rounds in the first scenario ("*Lottery bet not reduced*") and the right graphic shows the distribution of total wealth after 9 rounds in the second scenario ("*Lottery bet reduced*"). Due to the large number of lottery draws, the underlying characteristics of the lottery based on the respective scenarios can be illustrated here in addition to Simulation A. The higher a bar is, the more often total wealth after 9 rounds was in the corresponding range. If you move the mouse over the individual bars, you will also see what percentage of all previous total wealth realizations after 9 rounds are in this area. At the end of the simulation, the average value of the total wealth after 9 rounds in both scenarios is shown in the respective graphic by a vertical dotted line with the text "*Mean*".

Below is an example of simulation B.

Part 1 - Simulation B: Distribution of simulated total wealth after 9 rounds | Executions: 1 | Draws: 15000/15000

Please indicate which amount between 1 and 200 should be used to illustrate the lottery.

Taler | Confirm Amount | Instructions

You have decided that an amount of 100 Taler per round should be bet in the lottery for the 1. execution of the simulation. You must execute the simulation at least 2 times to continue the experiment.

Start Simulation

Back Next

Fig. B.8. Instructions Simulation B.

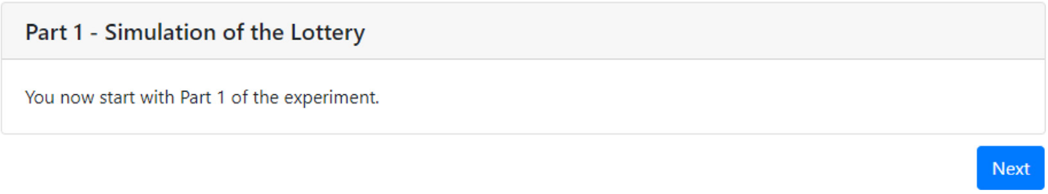


Fig. B.9. Transition Intervention.

Part 1 - Simulation A: Illustration of the Lottery over 9 rounds | Executions: 1

Please indicate which amount between 0 and 200 should be used to illustrate the lottery.

Taler | Confirm Amount | Instructions

You have decided that an amount of 100 Taler per round should be bet in the lottery for the 1. execution of the simulation. You must execute the simulation at least 15 times to continue the experiment.

	SCENARIOS			
Round	LOTTERY BET NOT REDUCED	LOTTERY BET REDUCED	Difference	Realization
1	450.00	450.00	0.00	Won
2	100.00	100.00	0.00	Lost
3	100.00	120.00	-20.00	Lost
4	100.00	140.00	-40.00	Lost
5	100.00	160.00	-60.00	Lost
6	450.00	250.00	200.00	Won
7	450.00	250.00	200.00	Won
8	100.00	180.00	-80.00	Lost
9	100.00	200.00	-100.00	Lost
	∑ 1950.00	∑ 1850.00	∑ 100.00	

Fig. B.10. Example of Simulation A.

Fig. B.11. Example of Simulation B.

B4. MLA elicitation

B4.1. Low frequency feedback

Instructions for Part 2

Part 2 of this experiment consists of 9 consecutive rounds. In each of the 9 rounds, you will receive 200 Taler as initial endowment. You must decide in **every third round** what amount "*x*" of your initial 200 Taler you wish to bet in a lottery with the following characteristics:

With a probability of 2/3 (67%) you lose the amount you bet and with a probability of 1/3 (33%) you receive two and a half times (2.5 times) the amount you bet.

Be aware that you make your decision for the current round as well as for the 2 following rounds. So if you decide to bet an amount "*x*" in round 1 in the lottery described above, you automatically decide to bet the same amount "*x*" in this lottery in rounds 2 and 3. Therefore your decision is always valid for 3 consecutive rounds.

If you win in the lottery in one round, you will receive $+2.5 \cdot x$ from the lottery for that round. If you lose in a round in the lottery, you will receive $-x$ from the lottery for that round. Your **total wealth per round** is equal to the win ($+2.5 \cdot x$) or loss ($-x$) from the lottery plus the initial endowment of 200 Taler you receive in each round.

In the following table you will see a general example of how to calculate your total wealth for the first 3 rounds.

Bet amount	Realization of the Lottery Round 1 - Round 2 - Round 3	Total wealth after 3 rounds
x $(0 \le x \le 200)$	*Won-Won-Won*	$600 + 2{,}5 \cdot 3 \cdot x$
x $(0 \le x \le 200)$	*Won-Won-Lost*	$600 - x + 2{,}5 \cdot 2 \cdot x$
x $(0 \le x \le 200)$	*Won-Lost-Won*	$600 - x + 2{,}5 \cdot 2 \cdot x$
x $(0 \le x \le 200)$	*Won-Lost-Lost*	$600 - 2 \cdot x + 2{,}5 \cdot x$
x $(0 \le x \le 200)$	*Lost-Won-Won*	$600 - x + 2{,}5 \cdot 2 \cdot x$
x $(0 \le x \le 200)$	*Lost-Won-Lost*	$600 - 2 \cdot x + 2{,}5 \cdot x$
x $(0 \le x \le 200)$	*Lost-Lost-Won*	$600 - 2 \cdot x + 2{,}5 \cdot x$
x $(0 \le x \le 200)$	*Lost-Lost-Lost*	$600 - 3 \cdot x$

At the end of the third round, your cumulative total wealth from the last 3 rounds (1 to 3) is displayed. At the beginning of the fourth round you will be asked to make your decision for the next 3 rounds (4 to 6). Your initial endowment for each of these 3 rounds is again 200 Taler, of which you can again bet an amount in the lottery described above for rounds 4 to 6. At the end of the sixth round you will be shown your cumulative total wealth from the last 3 rounds (4 to 6). This process is repeated in the following 3 rounds (7 to 9). Your total wealth from round 4 to 6 and round 7 to 9 is also calculated according to the calculation example above (see table).

Note that your total wealth from all rounds is collected. This means that any wealth already accumulated will not be available for use in the lottery in later rounds. At the end of this part, your total wealth over all nine rounds is added up and displayed in a ratio **1:400** converted to Euro. This sum determines the value of your Amazon voucher for this experiment.

Next

Fig. B.12. Instructions Elicitation - Low Frequency.

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Part 2 - Betting in the Lottery

The experiment is now continued with Part 2. Note that the decisions in this part are **payoff relevant**.

Next

Fig. B.13. Transition Elicitation.

Round 1 von 9

Part 2 - Betting in the Lottery

Please specify in the field below, which amount "*x*" of your initial endowment of 200 Taler per round you would like to bet for this round as well as for the next 2 rounds in a lottery with the following characteristics

With a probability of 2/3 (67%) you will lose the amount you bet and with a probability of 1/3 (33%) you will win two and a half times (2.5 times) the amount you bet.

x =

Instructions

Next

Fig. B.14. Example of First Three Rounds.

Round 3 of 9

Part 2 - Your total wealth

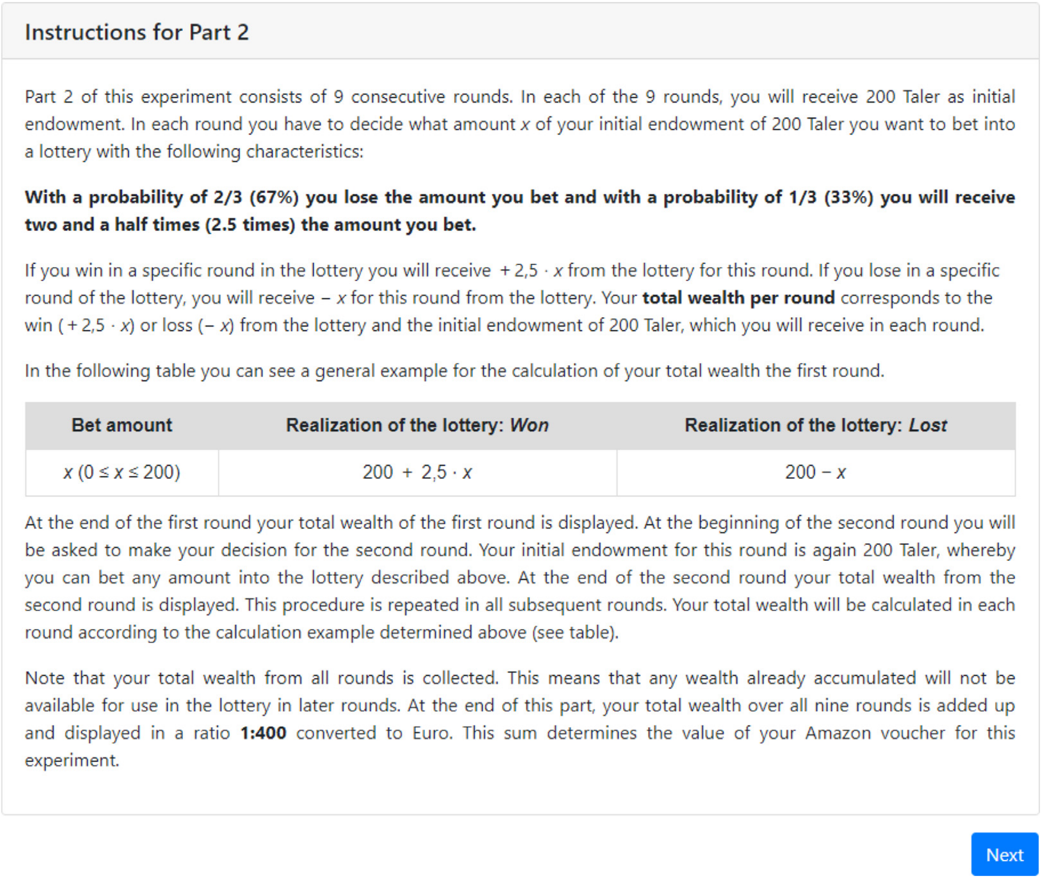
The following table shows the realizations of the lottery draws in rounds 1, 2 and 3 and your total wealth in Taler from these three rounds.

Round	Realization of the lottery	Total wealth
1	Won	1000.0 Taler
2	Lost	
3	Won	

Next

Fig. B.15. Example of First Three Rounds (History).

B4.2. High frequency feedback



Instructions for Part 2

Part 2 of this experiment consists of 9 consecutive rounds. In each of the 9 rounds, you will receive 200 Taler as initial endowment. In each round you have to decide what amount x of your initial endowment of 200 Taler you want to bet into a lottery with the following characteristics:

With a probability of 2/3 (67%) you lose the amount you bet and with a probability of 1/3 (33%) you will receive two and a half times (2.5 times) the amount you bet.

If you win in a specific round in the lottery you will receive $+2{,}5 \cdot x$ from the lottery for this round. If you lose in a specific round of the lottery, you will receive $-x$ for this round from the lottery. Your **total wealth per round** corresponds to the win ($+2{,}5 \cdot x$) or loss ($-x$) from the lottery and the initial endowment of 200 Taler, which you will receive in each round.

In the following table you can see a general example for the calculation of your total wealth the first round.

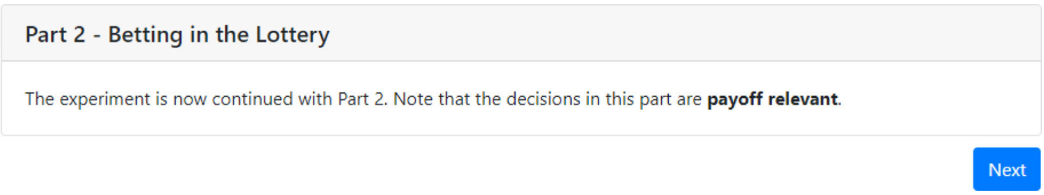
Bet amount	Realization of the lottery: *Won*	Realization of the lottery: *Lost*
x $(0 \le x \le 200)$	$200 + 2{,}5 \cdot x$	$200 - x$

At the end of the first round your total wealth of the first round is displayed. At the beginning of the second round you will be asked to make your decision for the second round. Your initial endowment for this round is again 200 Taler, whereby you can bet any amount into the lottery described above. At the end of the second round your total wealth from the second round is displayed. This procedure is repeated in all subsequent rounds. Your total wealth will be calculated in each round according to the calculation example determined above (see table).

Note that your total wealth from all rounds is collected. This means that any wealth already accumulated will not be available for use in the lottery in later rounds. At the end of this part, your total wealth over all nine rounds is added up and displayed in a ratio **1:400** converted to Euro. This sum determines the value of your Amazon voucher for this experiment.

Next

Fig. B.16. Instructions stage 2.



Part 2 - Betting in the Lottery

The experiment is now continued with Part 2. Note that the decisions in this part are **payoff relevant**.

Next

Fig. B.17. Transition Elicitation.

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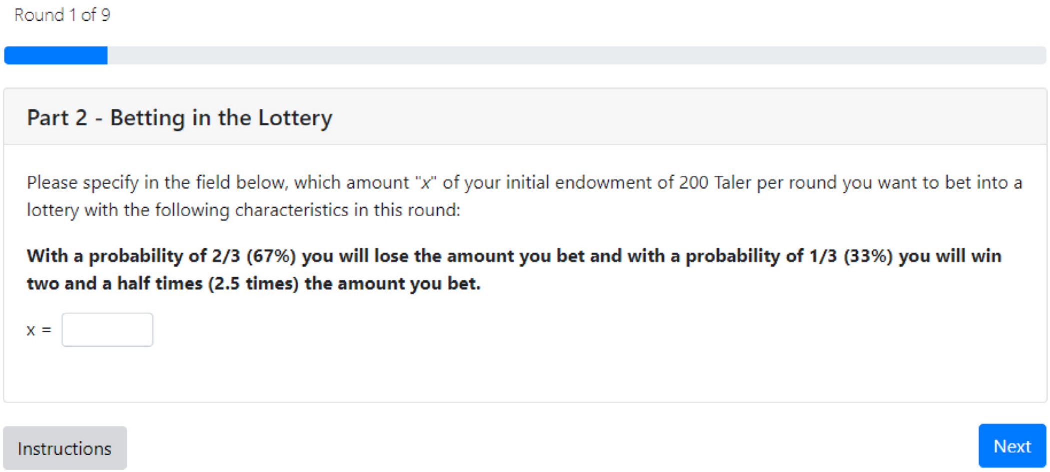


Fig. B.18. Example of First Round.

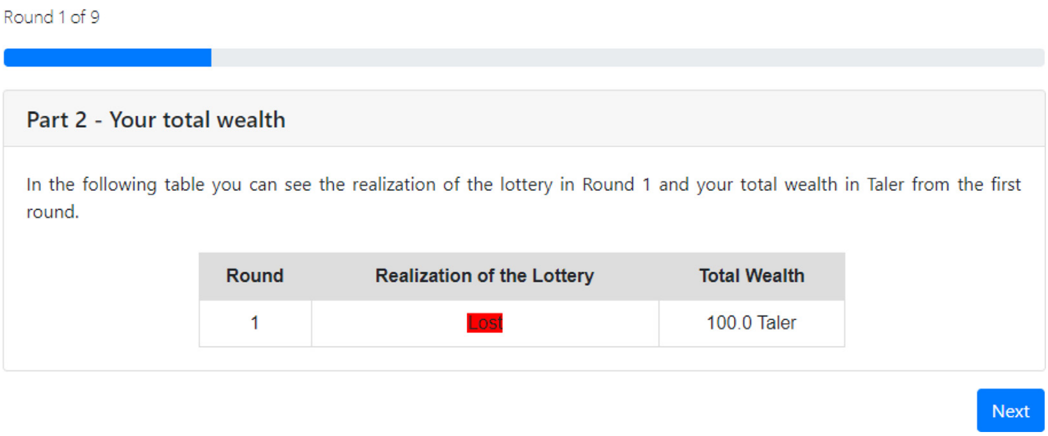


Fig. B.19. Example of First Round (History).

B5. Exit questionnaire and payoff

Assessment of the lottery

The following questions on this page and the next page refer to the lottery that this experiment was about and that you could bet into.

How *risky* is the lottery?

not risky at all ○ ○ ○ ○ ○ ○ ○ very risky

How much do you agree with the following statements?

It is *very likely* that I will lose money when I bet in the lottery.

don't agree at all ○ ○ ○ ○ ○ ○ ○ fully agree

If I decide to bet in the lottery, I would *worry* about the consequences.

don't agree at all ○ ○ ○ ○ ○ ○ ○ fully agree

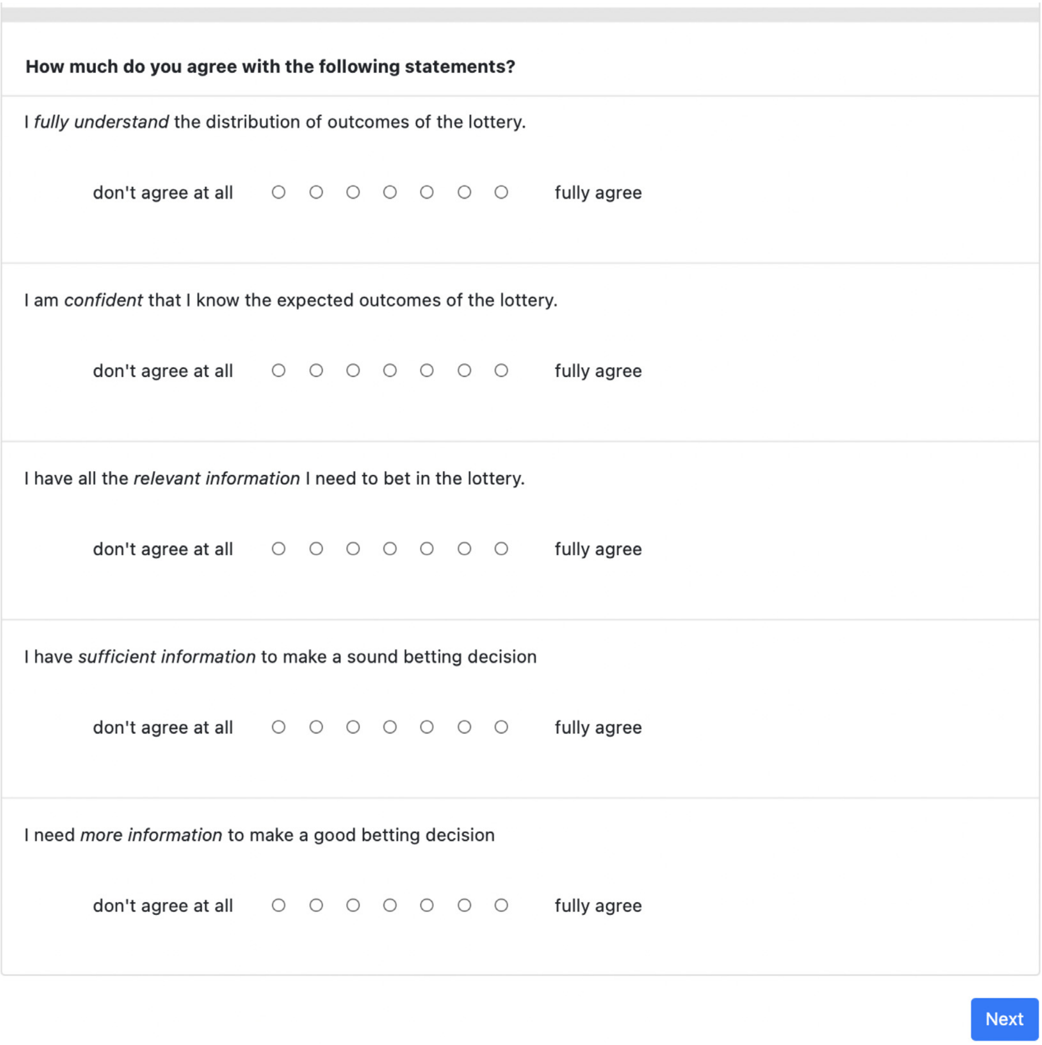
I could incur a *great loss* if I decide to bet in the lottery.

don't agree at all ○ ○ ○ ○ ○ ○ ○ fully agree

How *certain* are you about the distribution of outcomes of the lottery?

not certain at all ○ ○ ○ ○ ○ ○ ○ very certain

Fig. B.20. New Questionnaire in Additional Sample 1.



How much do you agree with the following statements?

I *fully understand* the distribution of outcomes of the lottery.

don't agree at all ○ ○ ○ ○ ○ ○ ○ fully agree

I am *confident* that I know the expected outcomes of the lottery.

don't agree at all ○ ○ ○ ○ ○ ○ ○ fully agree

I have all the *relevant information* I need to bet in the lottery.

don't agree at all ○ ○ ○ ○ ○ ○ ○ fully agree

I have *sufficient information* to make a sound betting decision

don't agree at all ○ ○ ○ ○ ○ ○ ○ fully agree

I need *more information* to make a good betting decision

don't agree at all ○ ○ ○ ○ ○ ○ ○ fully agree

Next

Fig. B.21. New Questionnaire in Additional Sample 2.

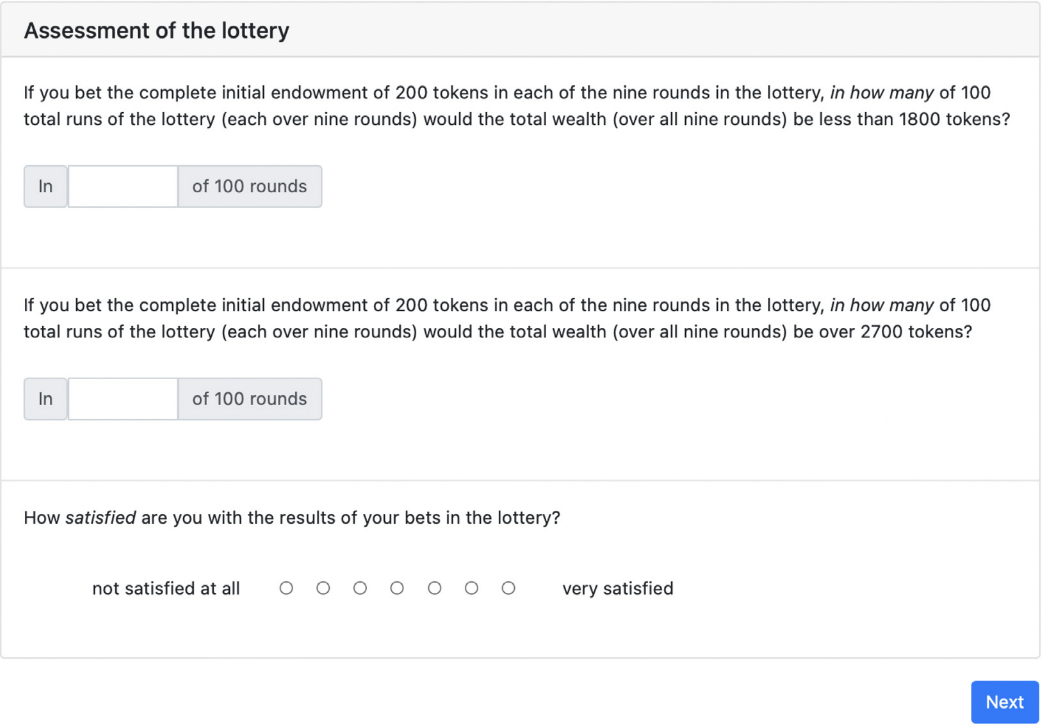


Fig. B.22. New Questionnaire in Additional Sample 3.

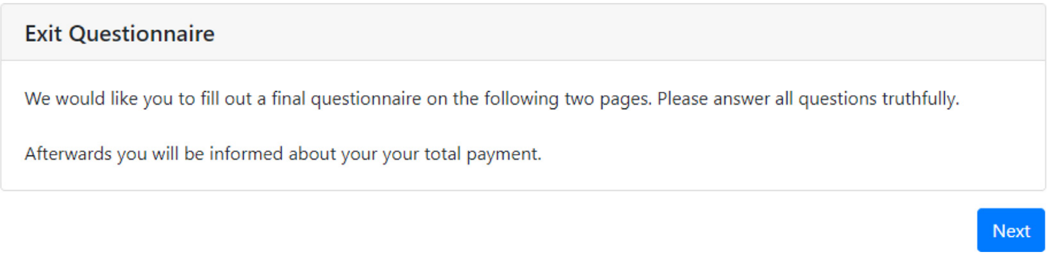


Fig. B.23. Transition Exit Questionnaire.

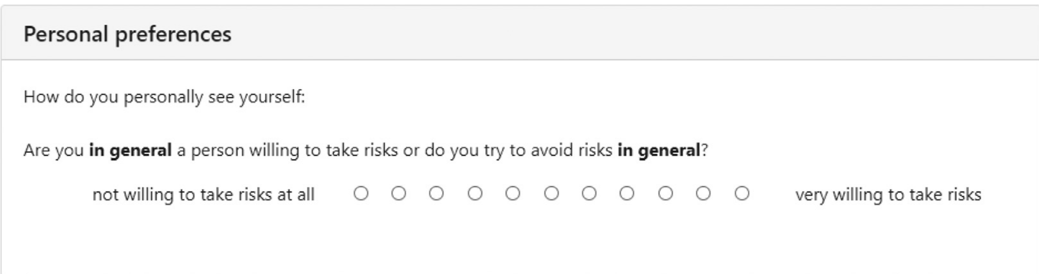
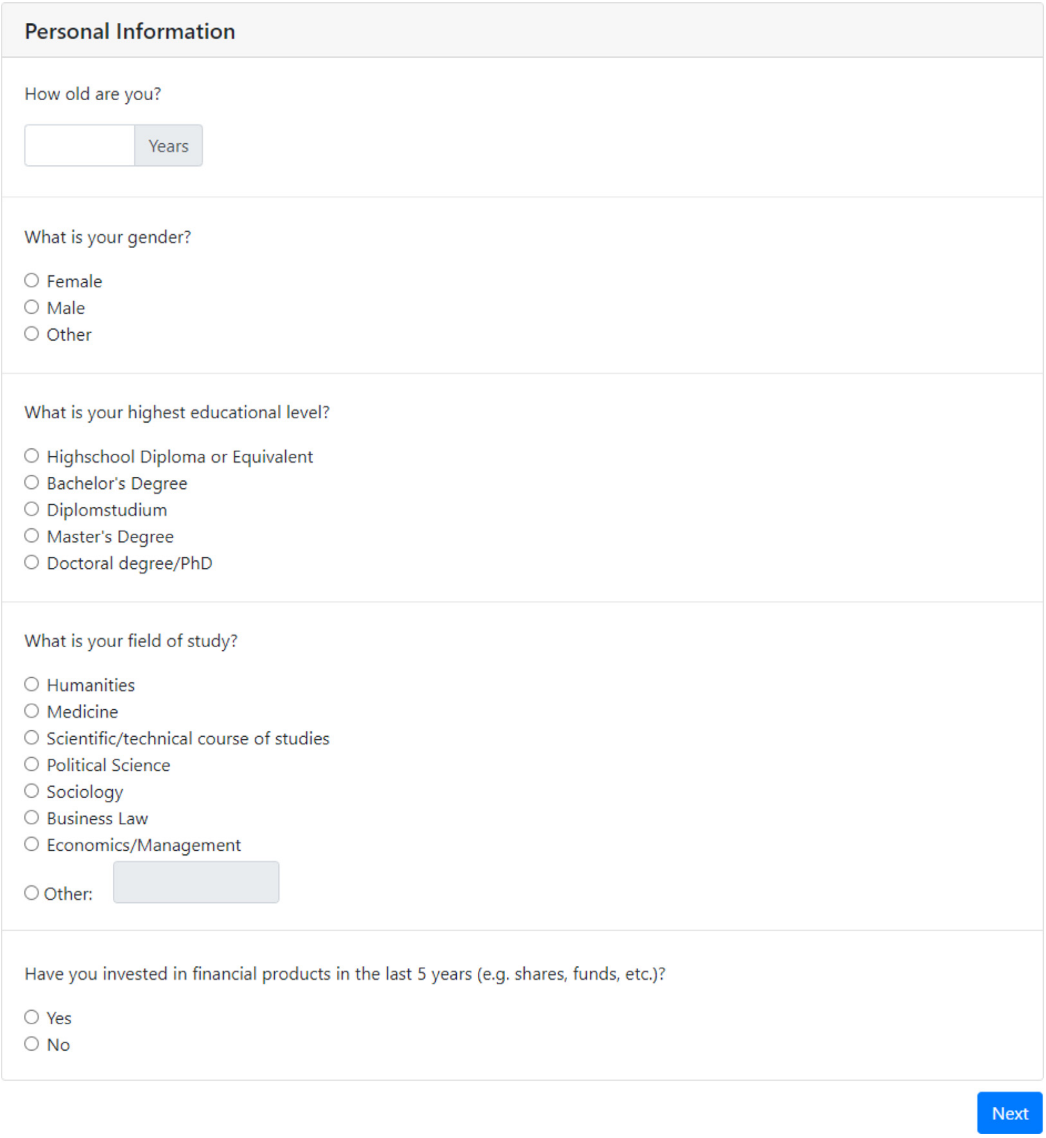


Fig. B.24. Risk Preferences.



Personal Information

How old are you?

Years

What is your gender?

- Female
- Male
- Other

What is your highest educational level?

- Highschool Diploma or Equivalent
- Bachelor's Degree
- Diplomstudium
- Master's Degree
- Doctoral degree/PhD

What is your field of study?

- Humanities
- Medicine
- Scientific/technical course of studies
- Political Science
- Sociology
- Business Law
- Economics/Management
- Other:

Have you invested in financial products in the last 5 years (e.g. shares, funds, etc.)?

- Yes
- No

Next

Fig. B.25. Personal Information.

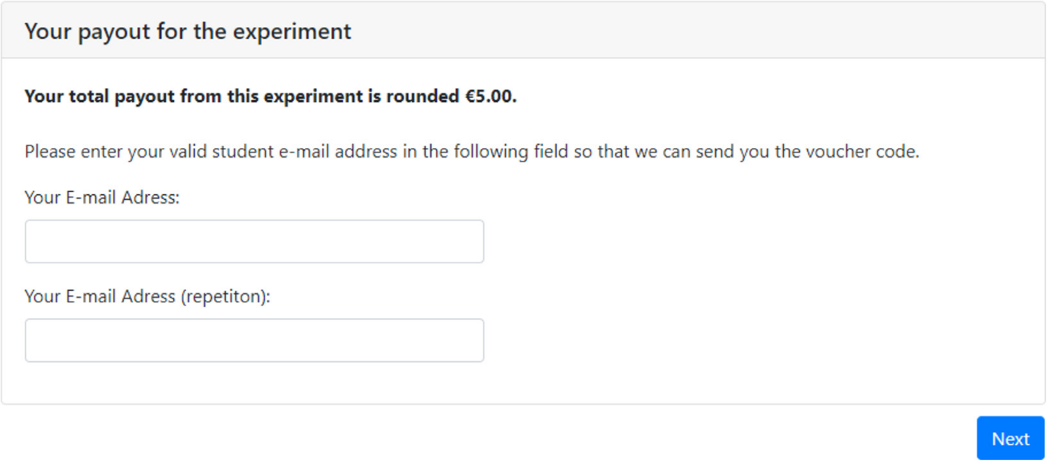


Fig. B.26. Example of Payoff Information.

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