Narrow Bracketing Your Way to Reinvestment Success

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Abstract (Max: 175 words; Currently 174 Words):

Market behavior suggests that investors dislike losses and often focus on short term outcomes. Prior work investigating these mechanisms used an environment where past outcomes did not change how much money could be invested in the current round. In contrast, we use a more realistic environment, in which the past does affect current investments. Contrary to prior work, we find that investors who make investments one at a time—narrow bracketing—perform better than participants who make investments all at once—broad bracketing. Our standard of good performance, the time-average growth rate, unlike expected-value, corresponds to what an individual will likely see. Further, participants prefer final outcome distributions that reflect a high time-average over those that correspond to a high expected-value. In addition, narrow bracket participants demonstrate a better understanding of the risk structure: narrow brackets demonstrate how wealth unfolds over time. In more realistic investment environments, narrow bracket participants, compared to broad bracket participants, better understand the environment and make investments closer to the time-average standard. Thus, broad brackets are not always better.

Keywords: Bracketing, normative standard, financial decision making
Introduction

In an attempt to protect investors from themselves, firms and financial advisors often recommend that investors ignore their day-to-day returns, and instead focus on long term returns. For example, one Israeli bank sends performance reports to investors less often in order to protect investors from seeing downswings (Gneezy, Kapteyn, & Potters, 2003). This approach is bolstered by research in which experimental participants take on more risk, leading to higher final wealth, when investment decisions are bracketed broadly—that is, when participants make multiple investments at once and only see their aggregated outcomes (U. Gneezy & Potters, 1997; Thaler, Tversky, Kahneman, & Schwartz, 1997). The combination of narrow bracketing—when participants make one choice at a time and receive immediate feedback—and loss aversion is a leading behavioral explanation for the equity premium puzzle: the pattern that, despite their higher long run rate of return, stocks are underpriced relative to risk-free government bonds (Benartzi & Thaler, 1995; Lynch, 2015).

However, the majority of experimental work investigating the effects of loss aversion and narrow bracketing differs from the reinvestment environment faced by investors. In the market, investors reinvest their previous returns, whereas, in repeated investment experiments, participants are externally given a new allotment on each round, making each round’s returns independent of prior returns. Non-reinvestment environments, where whatever happens in previous rounds does not affect how much the person has available to invest in the current round, are less realistic than reinvestment environments, where the outcomes from previous rounds determine the amount available for investment in the current round.

Reinvestment environments also have different structural properties than non-reinvestment environments, yielding different models of how an individual’s wealth evolves over time.
Different models of an individual’s wealth evolution lead to different normative standards, in which, behavior considered suboptimal in a non-reinvestment environment may be considered normative in a reinvestment environment. For instance, narrow brackets may be bad for investors in non-reinvestment environments, but, due to a different normative standard, good for investors in reinvestment environments.

In defining investment performance, we focus on two normative standards—expected-value and time-average—which have been confounded in previous work. In reinvestment environments, the expected-value does not correspond to what an individual experiences over time, but the time-average growth rate does correspond to what an individual experiences over time. We therefore argue that the time-average growth rates are more relevant to investors in a reinvestment environment than the expected-value of the growth rate.

In line with narrow brackets being good for investors, four studies demonstrate that, in a reinvestment environment, narrow bracket participants, compared to broad bracket participants, make investments with higher time-average growth rates. In the target task, participants in the narrow bracket condition invest less of their wealth than participants in the broad bracket condition do, yielding higher time-average growth rates. Consistent with a preference for a higher time-average growth rate, participants rank final outcome distributions—histograms displaying the probability of receiving an amount of money—according to the time-average not the expected-value. In other words, narrow brackets brought participants closer not only to the time-average maximizing strategy but also closer to the preferred final outcome distribution. Further, in an incentive-compatible task testing participants’ understanding of the reinvestment environment, narrow bracket participants outperform broad bracket participants. In addition, by changing how broad bracket participants view their results, we show that narrow brackets lead to
improved performance, in part, because participants see their wealth evolve over time. These findings suggest that, in reinvestment environments, narrow brackets can lead to investment decisions with better outcomes than broad brackets.

**Literature Review**

Myopic loss aversion is a combination of loss aversion—the idea that people hate seeing their money decrease in value more than they like seeing their money increase in value—and shortsightedness—the tendency to care more about what happens to wealth in the short term than in the long term. Myopic loss aversion is a leading behavioral explanation of the equity premium puzzle: the fact that people invest more in bonds, even though bonds have lower returns than stocks. Myopic loss aversion posits that, if investors check their stocks less often, they will experience fewer interim losses, increasing their preference for stocks (Benartzi & Thaler, 1995).

Initial empirical studies of myopic loss aversion followed a standard format: people made repeated risky investment decisions and were given a set amount of money each round, which they could decide how much of to invest. These were characteristic non-reinvestment environments, in that, outcomes from prior rounds did not affect how much people had available to invest in the current round (U. Gneezy & Potters, 1997; Thaler et al., 1997). Overall, this body of research found that broad bracket participants invested more than narrow brackets participants, yielding higher final wealth.

In a prototypic myopic loss aversion study, on each of nine rounds, participants were given 200¢ and asked to decide how much of that 200¢ to invest in the following lottery: 2/3 of the time losing the amount invested or 1/3 of the gaining 2.5 times the amount invested (U. Gneezy & Potters, 1997). This lottery has a positive expected-value: the greater the amount invested, the
higher the expected-value. Importantly, this study design reflects a non-reinvestment environment: the amount participants had available to invest in round 2 did not depend on the results of round 1. In this environment, participants experience more losses if outcomes are evaluated one round at a time—narrowly bracketed—compared to if outcomes are evaluated 3 rounds at a time—broadly bracketed. Assume that two participants, one in the narrow bracket condition and one in the broad bracket condition, both invest a constant 50¢ and lose two times and win one time. The narrow bracket participant experiences two losses of 50¢ and one gain of 175¢; the broad bracket participant only experiences a gain of 75¢. Consistent with an aversion to losses, participants invested a smaller percentage when investments were made one at a time—narrowly bracketed—as opposed to when investments were made three at a time—broadly bracketed. Because the risky investment has a positive expected-value, high investment percentages result in a larger expected final wealth. Consequently, participants experiencing broad brackets, relative to those experiencing narrow brackets, have a higher expected final wealth—consistent with myopic loss aversion.

Notably, in reviewing this body of research, it is unclear whether narrow bracket participants realize in advance that, relative to small investments, investing more yields bigger losses, or if they learn over time that investing more yields bigger losses leading them to invest less. That is, the effect of brackets may be due to feedforward reasoning (predicting future consequences of investments), feedback reasoning (changing investments based on prior results) (Simon, 1996). In the Gneezy and Potters (1997) paradigm, a narrow bracket participant whose decisions are based solely on feedforward reasoning, realizes, in the first round, that they will likely see a loss and therefore will invests a small amount. In contrast, a participant using feedback reasoning would, after experiencing a loss in the first round, decide to invest less in the second round. A
participant using feedforward reasoning, invests less because they know they will likely experience a loss, they are not learning about the environment; however, a participant using feedback reasoning is learning about the environment, they invest less because of experienced losses. If participants use only feedforward reasoning, narrow bracket participants would invest less than broad bracket participants at the outset of the task and this difference would be constant throughout the task. However, if participants use only feedback reasoning, narrow bracket participants would invest a similar amount as broad bracket participants initially but, after experiencing losses, would invest less than broad bracket participants.

While some research favors a feedforward account, other research favors the feedback account. In support of the feedforward account, multiple studies found that narrow bracket participants invested less than broad bracket participants in the initial rounds (Fellner & Sutter, 2009; U. Gneezy & Potters, 1997; Moher & Koehler, 2010). In these studies, average investment percentages were relatively stable throughout the task, suggesting that feedback did not greatly alter investment percentages. People may realize before experiencing the lottery that they are likely to lose and decide to invest less making feedback less important.

By contrast, other studies supported for the feedback account, in that participants allocations evolve over the course of the study (Langer & Weber, 2008; Thaler et al., 1997). Specifically, when funds were reinvested, participants increased their investment percentages the more rounds they participate in (Langer & Weber, 2008). And when participants learned probabilities and outcomes via experience (as opposed to being given objective probabilities and outcomes) the effect of brackets only materialized after a number of rounds; that is, narrow bracket participants “gravitated to a lower level of risk” (Thaler et al., 1997, p. 650). Also of note, participants who experienced narrow brackets invest less than those who had experience broad brackets in an
equivalent, broadly-bracketed test block (Thaler et al., 1997). The feedback participants get in the learning block affects future decisions.

A clearer picture emerges of the seemingly-conflicting findings for feedforward vs feedback accounts of myopic loss aversion emerges by investigating the underlying environments. When risks are easily understood—i.e., probabilities are given to participants and the environment is simple—the effect of brackets may be due to feedforward reasoning. However, when risks are not easily understood—i.e., probabilities are not given or the investment environment is difficult to learn—the effect of brackets may be due to feedback reasoning.

Given that bracketing effects may be driven by feedforward reasoning in non-reinvestment environments, but by feedback reasoning in non-reinvestment environments, it follows that the bracketing may not necessarily transfer from non-reinvestment environments to reinvestment environments. In line with these different drivers of bracketing effects, and contrary to prior work, a study which used a reinvestment environment design found that narrow bracket participants invested a similar amount as broad brackets participants (Beshears, Choi, Laibson, & Madrian, 2017). The effect of brackets on investment percentages depends on the underlying environment.

Similarly, another reinvestment study dissected broad brackets into two components: commitment—committing to the same investment percentage for three rounds—and feedback—getting feedback based on their wealth after three rounds, as opposed to after each round (Langer & Weber, 2008). This study found that, compared to the traditional broad bracket procedure—committing to an investment and getting only final wealth feedback—participants invested more when they committed to multiple rounds at a time, but saw feedback after each round. By contrast, in a study similar to the non-reinvestment design of Gneezy and Potters (1997),
participants who committed to three rounds and got round-by-round feedback invested the same amount as participants in a traditional broad bracket condition (Moher & Koehler, 2010). Considered together, these three studies demonstrate that the effects of feedback and commitment in reinvestment environments differ from the effects in non-reinvestment environments. Specifically, the results indicate that the effects of brackets on risk taking do not necessarily transfer from a non-reinvestment environment to a reinvestment environment. While the effects of brackets may differ based on the underlying environment, a number of studies suggested that investors should be kept in the dark about their investment outcomes in order to increase returns (Fellner & Sutter, 2009; U. Gneezy & Potters, 1997; Haigh & List, 2005; Thaler et al., 1997).

To summarize, our review of the existing research on myopic loss aversion underscores the fact that the investment environment matters. Thus, in order to understand real-world decision making, it is imperative to mirror key aspects of the real world in our experimental paradigms. To this end, it is necessary to clarify what standards are used to judge investments in different environments: a sensible investment strategy in non-reinvestment environments may be disastrous in reinvestment environments.

**Normative standards for judging investment behavior**

Important characteristics of non-reinvestment environments are distinct from those of reinvestment environments. In a non-reinvestment paradigm, an individual’s wealth trajectory through time—i.e., across repeated rounds of investment—follows what happens to the average of a large group of individuals on a single round—i.e., the expected-value. In contrast, in a reinvestment paradigm, an individual’s wealth trajectory through time almost always diverges from the expected-value (Peters & Gell-Mann, 2016). That is, under non-reinvestment, an
individual making repeated decisions will likely achieve final wealth that is close to the expected-value. But under reinvestment, an individual’s final wealth will often end up far from the expected-value. This is crucial because the aggregate outcomes of reinvestment environments, depending on the exact parameters, have high variability: there can be a large likelihood of ending up bankrupt but a remote possibility of becoming a millionaire, resulting in a net positive expected-value.

To demonstrate the difference between non-reinvestment and reinvestment environments, we simulated individual’s wealth trajectories. For a non-reinvestment environment, we simulated, based on the Gneezy and Potters’ lottery, investments of 50% of $200 in each round. The per-round lottery therefore was: win $450 with p = 1/3; win $100 with p = 2/3. For illustrative purposes, we repeated the lottery 1000 times. In Figure 1A, the expected-value is shown in red—expected-value after 1000 rounds is \( \left( \frac{1}{3} \cdot 450 + \frac{2}{3} \cdot 100 \right) \cdot 1000 = 216666.6 \). The simulated trajectories of 50 separate hypothetical participants—each trajectory had 1000 independent draws of the lottery—are shown in gray. Of primary interest, all of the trajectories have a slope similar to the slope of the expected-value line. In a non-reinvestment environment, wealth trajectories trend in the same direction as the expected-value.
Figure 1: Fifty simulated trajectories over 1000 rounds from a non-reinvestment environment (A) and from a reinvestment environment (B). The red lines indicate the expected-value, purple line in (B) indicates the time-average growth rate. (Code at: https://osf.io/6mjk7/)

For a reinvestment environment, however, expected-value and the path average can trend in different directions. Figure 1B shows the expected-value and 50 simulated participants for the following lottery: participants start with $200 and do not receive any additional injections of funds. Current wealth in each round is multiplied by 2.25 with \( p = 1/3 \) and by .5 with \( p = 2/3 \). Round 1 of the reinvestment lottery is the same as round 1 of the non-reinvestment lottery—$450 with \( p = 1/3 \); $100 with \( p = 2/3 \)—but subsequent rounds of the reinvestment lottery depend on prior round’s results. The reinvestment environment has, after 1000 rounds, a very large expected-value—\( 200 \left( \frac{1}{3} \times 2.25 + \frac{2}{3} \times .5 \right)^{1000} = 1.16 \times 10^{37} \). All 50 trajectories, however, end up at an extremely small final value. The expected-value is so large because it accounts for the extremely unlikely individual who wins every round, thus making an obscene amount of money. In a reinvestment environment, the expected-value does not correspond to what we anticipate an individual will experience.

Despite the divergence between the expected-value of final wealth and the wealth of each path, the trajectories are similar to one another, suggesting an underlying regularity. The trajectories do not trend with the expected-value but do trend with the purple line which represents the time-average.

*Two Normative Standards: Expected-value versus Time-average*

To explain the differences between Figure 1A and 1B, we focus on rates of changes in wealth—by how much, in one round, wealth increases or decreases (Peters & Gell-Mann, 2016). These
growth rates, unlike wealth, are independent of prior outcomes. In both the non-reinvestment and reinvestment examples, the change in each round is a draw from a random distribution; however, the structure of that change differs. For the non-reinvestment environment, the *per-round difference in wealth*—wealth in round t minus wealth in round t-1—is independent of prior outcomes. For the reinvestment environment, however, the *per-round multiplier of wealth*—wealth in round t divided by wealth in round t-1—is independent of prior outcomes.

Both the *per-round difference in wealth* and the *per-round multiplier of wealth* constitute growth rates. Each growth rate can be averaged in two ways: by expected-value—taking the arithmetic mean across for many individuals for one round—or by time-average—starting with a model of an individual’s wealth through time and, across many rounds, taking the average change. The expected-value of a growth rate is the sum of each outcome multiplied by its corresponding probability. In contrast, the time-average of the growth rate first takes model of how an individual’s wealth changes through a long period of time and then takes the average of the rate over time. Thus, we can compute the expected-value and the time-average of both per-round differences and multipliers. Taken together there are four possible averages; however, not all of the averages are relevant to an individual’s evolution of wealth.

**Expected-value of per-round difference.** In non-reinvestment environments, the expected-value of the per-round difference in wealth, \( d \), is the same as and the time-average. The expected-value of the per-round difference in wealth is

\[
ev_d = p_1 * d_1 + p_2 * d_2
\]

where \( d_1 \) indexes the first difference in wealth, $100 in the example above, and \( p_1 \) is the probability of that difference, 2/3 in the example above. On each round, wealth either increases by \( d_1 = 100 \) or \( d_2 = 450 \), realized, respectively, with probabilities: \( p_1 = 2/3, p_2 = 1/3 \). The dollar value of the increase in wealth is independent of what happened previously. If we take a large number of
participants \((N \to \infty)\) and calculate the expected-value of their increase in wealth for, say round 2 of the investment, the average converges to— \(e_{v_d} = 100 \times 2/3 + 450 \times 1/3 = 216.67\).

**Time-average of per-round difference.** To calculate the time-average of individual’s wealth, we first need a model of how their wealth evolves through time. Final wealth is the sum of the starting wealth and the amount made on each round:

\[
1) \quad w_T = w_0 + \sum_{t=1}^{T} d(t),
\]

where \(w_T\) is final wealth, \(w_0\) is initial wealth, and \(\sum_{t=1}^{T} d(t)\) is the sum of the per-round differences in wealth experienced in each of the \(T\) rounds. In the limit as \(T \to \infty\), the time-average of the per-round difference in wealth is \(ta_d = p_1 \times d_1 + p_2 \times d_2\). As we can see, the time-average converges to the same number as the expected-value—\(ta_d = 100 \times 2/3 + 450 \times 1/3 = 216.67\). Thus, for non-reinvestment environments, the per-round rate of change in wealth for a single individual across multiple rounds—the time-average—is the same as the per-round rate of change in wealth for a single round across a large group of individuals—the expected-value.

**Expected-value of per-round multiplier.** In reinvestment environments, the per-round multiplier—\(r = \frac{w_t}{w_{t-1}}\), where wealth, \(w_t\), is wealth in round \(t\) — is a pull from a random distribution. In the reinvestment environment above, wealth is either multiplied by \(r_1 = 2.25\) or \(r_2 = .5\). Thus, the expected-value of the per-round multiplier is: \(e_{v_r} = 2.25(1/3) + .5(2/3) = 1.083\) per-round. On any given round the expected-value of wealth increases by 8% (as seen in the red line in Figure 1B). Because of the dynamics of reinvestment, almost no specific individual follows the trajectory of the expected-value. The expected-value is positive because it averages over the exceedingly rare but uber-rich trajectories in the ensemble who, by luck, won
most or all of the rounds. However, as seen in Figure 1B, the vast majority of individuals experience a decline in wealth over rounds, while a tiny fraction experiences a huge increase.

**Time-average of per-round multiplier.** The expected-value of the per-round multiplier, \( r \), does not correspond to how an individual’s wealth evolves over multiple rounds. An individual’s wealth evolves according to the product of the per-round multipliers they experience over the \( T \) rounds:

\[
2) \ w_T = w_0 \prod_{1}^{T} r(t).
\]

where \( r(t) \) indexes which value by which the participant had their wealth multiplied in round \( t \), and \( T \) is the total number of rounds played, \( w_0 \) is an individual participant’s starting wealth, \( w_T \) is an individual participant’s wealth after \( T \) rounds, and \( r(t) \) indexes the multiplier experienced in round \( t \). The right-hand side of 2) can be rewritten as: \( w_t * r_1^{n_{r_1}} * r_2^{n_{r_2}} \), where \( n_{r_1} \) indexes the number of times the trajectory experienced the \( r_1 \) outcome. The time-average of the per-round multiplier is \( r_1^{n_{r_1}/T} * r_2^{n_{r_2}/T} \). In the limit as \( \to \infty \), \( n_{r_1}/T = p_{r_1} \), yielding time-average per-round multiplier of \( r_1^{p_1} * r_2^{p_2} \).

The proportion of wins vs losses will of course vary across individuals; however, over many rounds we still would expect the time-average growth rate of any given individual to converge to \( r_1^{p_1} * r_2^{p_2} \). An individual’s time-average reflects the \( p_1 \) and \( p_2 \) that they experience (which could be different from the distribution parameters of 1/3 and 2/3). Say we take an extremely lucky, but unseen, trajectory from Figure 1B which won on each of the 1000 rounds and follow them for the next 1000 rounds. Over rounds 1001-2000, we would predict that their time-average per-round multiplier would be converge to \( r_1^{p_1} * r_2^{p_2} \).
The time-average per-round multiplier can be mapped onto per-round differences in the logarithm of wealth (Peters & Gell-Mann, 2016). Rearranging equation 2 yields: $ln(w_{t+1}) - ln(w_t) = ln(ta_r)$. A strategy for a reinvestment environment which maximizes differences in the logarithm of wealth is equivalent to maximizing the time-average growth rate. Empirically, there is evidence that in experimental scenarios, people value the money logarithmically in reinvestment environments (Rapoport, Funk, Levinsohn, & Jones, 1977). Moreover, Rapoport and colleagues used logarithmic wealth but, by adding a free parameter, accounted for individual differences in risk taking. Time-averages do not preclude individual differences in risk taking. In a reinvestment environment, consistent with people’s valuations of money, paying attention to differences in the logarithm of wealth is equivalent to paying attention to the time-average of the per-round multiplier of wealth.

**Normative Standard**

In order to investigate which bracket—narrow or broad—leads to better investment decisions, we must first define a normative model of investment decisions. The time-average makes the same normative claims as the expected-value in non-reinvestment environments; however, in reinvestment environments, the time-average is different than the expected-value (Peters & Gell-Mann, 2016). The time-average starts with a model of an individual’s wealth, making it the more attractive normative standard for both reinvestment and non-reinvestment environments.

While, in general, prior work has steered clear of making explicit normative claims, we can, based on the prescriptive claims to bracket broadly, infer that the underlying normative standard recommends larger investments (Gneezy & Potters, 1997; Kahneman & Lovallo, 1993; Thaler et al., 1997). Additionally, one paper that does take a more explicit stance about a normative standard states that: “a very simple heuristic—to always maximize expected return except on
huge gambles—would make people better off” (Read, Loewenstein, & Rabin, 1999, p. 193). This prescriptive recommendation, along with the relative obscurity of the time-average, suggests that the implicit the normative standard was the expected-value. In non-reinvestment environments, our normative model—time-average growth rate—is the same as the implicit normative model of prior studies—expected-value. In reinvestment environments, however, the normative standards can diverge. The time-average standard aligns with the prescriptive recommendations from prior work in non-reinvestment environments and, unlike the expected-value standard, makes sensible recommendations for reinvestment environments.

**Summary**

We argue that the normative standard we use to judge an investor’s behavior should match the environment—non-reinvestment or reinvestment—the investor sees. In the non-reinvestment environments used in prior work, the relevant growth rate is the per-round difference in wealth; in reinvestment environments the relevant growth rate is the per-round multiplier of wealth. In non-reinvestment environments, the per-round difference in wealth has equivalent time-averages and expected-values; in reinvestment environments, the per-round multiplier of wealth has different time-averages than expected-values. Given the structural differences between reinvestment and non-reinvestment environments, bracketing effects that are seen as normatively poor in one environment, may be normatively optimal in another. While broad brackets lead participants to higher expected-values and time-averages in non-reinvestment environments, this may not be the case in reinvestment environments. For reinvestment paradigms, we propose maximizing the time-average per-round multiplier, rather than the expected-value of the per-round multiplier, as the normative standard. Relatedly, under reinvestment, we predict that people will not want to maximize expected-value but instead will prefer outcome distributions
corresponding to a high time-average per-round multiplier. Given that, in our paradigm, investing a smaller percentage increases growth rate but decreases expected-value, we expect narrow brackets participants to have higher time-average per-round multipliers, compared to broad bracket participants.

We test these hypotheses in four studies. In study 1, according to the time-average standard, narrow bracket participants make better decisions than broad bracket participants. Further, in an initial learning block, narrow bracket participants chase their losses: participants invest more if they lost on the previous round and invest more the further they are below their starting wealth. Loss chasing in the learning block may obscure the effect of brackets on risk taking. In study 2, when ranking final outcome distributions, participants prefer time-average maximizing strategies to expected-value maximizing strategies. In study 3, narrow bracket participants perform better than broad bracket participants on an incentive compatible task with an objectively correct answer. In study 4, broad bracket participants who, after making their initial learning block allocations, see the evolution of their wealth invest less than participants who did not see the evolution of their wealth. Seeing the evolution of their wealth is part of what makes narrow bracket participants invest less in the test block. Taken together, our results show that the prescriptive recommendation to bracket risks broadly may not apply in all environments.

Studies

Study 1: Narrow versus broad brackets with reinvestment

In Study 1 we empirically tested the prediction that narrow brackets lead to smaller investments than broad brackets in a reinvestment environment. This prediction is in contrast to prior empirical work which found no difference between participants’ investment percentages in
narrow and broad brackets in a reinvestment environment (Beshears et al., 2017); however, the research design in that previous study only investigated the effects of brackets in an initial, learning block. Our design used an additional test block that provides an identical testing procedure for both the narrow and broad bracket conditions. Specifically, in our studies, participants were randomly assigned to make investment decisions under either a narrow or broad bracket condition in an initial learning block; participants from both conditions then made an additional, identical investment decisions in the test block.

We argue that the test block comparison provides a cleaner test of the bracketing effects; in the learning block the effect of bracket can be obscured by multiple factors. For instance, narrow bracket participants may chase their losses (Imas, 2016)—that is, they may see their wealth decrease and decide to invest more on subsequent rounds. Broad bracket participants, in contrast, are not given feedback about their gain and loss outcomes until all rounds have completed; consequently, broad bracket participants cannot chase losses. Thus, in the learning block the effects of bracket can be obscured by factors other than what participants learn about the risk structure, necessitating a test block. For similar reasons as above, the test block should be broadly bracketed.

**Method**

*Open practices statement*

For each study, sample size was set prior to data collection and, where applicable, was based on power analyses. All materials, data and code, and links to preregistrations are online at:


*Participants*
We recruited 500 participants (501 completed the survey) on Amazon Mechanical Turk who were paid $2 to complete a 15-minute survey. Participants were randomly assigned to one of two learning block conditions: narrow bracket or broad bracket. The sample size was based on a power analysis assuming an effect size of 0.2. In our preregistration we said that we would remove no participants; however, in the intervening months there has been growing concerns about a few bad participants on Mechanical Turk. To ensure data quality we removed participants whose IP addresses were identified as suspicious on 
https://itaysisso.shinyapps.io/Bots/. There were 17 suspicious participants who were removed from the study, yielding 484 usable participants.

**Procedure**

Participants were first given instructions that explained the reinvestment task and were explicit about how results of prior rounds affected investments on the current round. To ensure participant understanding, we included a quiz which did not allow participants to proceed without answering the questions correctly.

The instructions explained to the participants that they would start with $200 hypothetical dollars to invest in the following lottery: 2/3 of the time they would lose the amount invested, and 1/3 of the time they would win 2.5 times the amount invested.

There are a number of notable properties of the lottery, all of which participants were not explicitly told. If an individual invested 100% on the first round and lost, they would then have $0 and be unable to continue. While investing 100% over all 9 rounds maximizes the expected-value, it would also lead to the participant’s final wealth being zero 99.999% of the time. The
time-average per-round multiplier maximizing strategy is investing ~6% in each round with a modal final wealth of $209.90.

Participants decided what percentage of their assets to invest on each of 9 rounds. A similar design has been used in other reinvestment tasks (Langer & Weber, 2008; Lejarraga, Woike, & Hertwig, 2016). Participants were, in each round, able to invest between 0 and 99% of their assets; the upper cap was implemented to decrease the number of participants ending with $0 wealth.

Participants completed two blocks. The learning block manipulated how participants made investment decisions and saw feedback on their results. In the narrow bracket condition participants made one choice at a time and were given immediate feedback consisting of the percentage they had invested in the previous round, their wealth at the start of that round, whether they won or lost that round, and their new wealth at the end of the round. In contrast, in the broad bracket condition participants made all nine choices at once; after all 9 rounds were played out they were given feedback on which the rounds they won and their final wealth.

Following the learning block, participants completed a test block that was equivalent for the narrow and broad bracket conditions. That is, after experiencing either a broad bracket or a narrow bracket in the learning block, participant’s wealth was reset at $200 and were asked to make another 9 investment decisions. To ensure that intermediate outcomes did not influence investment percentages, the test block was identical to the broad bracket condition used in the learning block: participants were given $200 and decided on a percentage of wealth to invest in each of nine rounds, with no outcome feedback.

Results
We first compared the participant mean test block investment across conditions. Participants invested less in the test block if, in the learning block, they were in the narrow ($M = 18.5$), rather than broad ($M = 24.5$) ($t(478.67) = 3.44, p < .001, \text{Cohen’s } D = .31$). Note we pre-registered a number of statistical models to test for the difference between narrow and broad bracket investment, which are presented at https://osf.io/pt4a6. Because narrow bracket participants invested a smaller percentage in the test block, they obtained a lower expected-value of final wealth.

However narrow bracket participants ($M = -0.09$) achieved a higher log time-average per-round multiplier than broad bracket participants ($M = -0.13$) ($\text{Wilcoxon } W = 24438, p = .002$). As previously mentioned, we consider maximizing the time-average growth rate to be the normative standard by which to judge decisions.

While we show that narrow bracket participants invested less than broad bracket participants, other work has found no difference between investments (Beshears et al., 2017). However, our focus was on the test block and Beshears and colleagues was on the learning block. We replicated the results of Beshears et al. in the learning block: narrow bracket participants ($M = 28.39$) invested approximately the same amount as broad bracket participants ($M = 27.33$) ($t(476.39) = -0.52, p = .60$, Cohen’s $D = 0.05$). However, in the learning block narrow bracket participants ($M = -0.29$) had a marginally lower log time-average per-round multiplier than broad bracket participants ($M = -0.16$) ($\text{Wilcoxon } W = 32233, p = .055$). The time-average growth rate results do not comport with the investment percentage results because growth rates are sensitive to fluctuations in investment percentages.

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1 We use the Wilcoxon test because per-round multipliers are highly non-normal
The divergence between the effect of bracket in the learning block and the effect of bracket in the test block illustrated the important of inclusion of a test block, but it also raises questions. Why did narrow brackets only invest less in the test block? Did narrow brackets encourage something other than less risk taking?

**Loss Chasing Analyses**

Based on prior work, we posited that, narrow bracket participants would chase their losses during the learning block (Imas, 2016). That is, a narrow bracket participant who sees their wealth go down in the learning block is motivated to recoup that loss by investing a greater amount than they had invested in the prior round. While loss chasing may alter the effect of narrow brackets, in our paradigm, it is impossible for broad brackets to elicit loss chasing in the learning block: broad bracket participants make all 9 investment decisions at once and only receive feedback after the ninth and final round.

To understand loss chasing we must first understand what gets encoded as a loss, which, by extension, necessitates an understanding of the reference point. In reinvestment environments, reference points are a combination of the starting wealth and the most recent wealth (Baucells, Weber, & Welfens, 2011). In the current experiment, the reference point should be a combination of the starting wealth—$200—and the wealth from the prior round. Given that losses are encoded relative to the reference point, we should expect to see an increase in investment if the prior round was a loss and if current wealth is below the starting point. As seen in the appendix, participants invested more if they lost on the previous round than if they won. Further, initial wealth was salient: participants invested a higher percentage the further they were below $200. These results suggest that loss chasing competes with the effect of brackets: narrow
brackets may both decrease participant’s risk taking as a result of their increased understanding the reinvestment risk structure and increase their risk taking because they chase their losses.

While the above analysis showed that narrow bracket participants chased their losses in the learning block, it did not show whether their loss chasing transferred to the test block. Loss chasing staying in the test block is an important for the validity of our design. If narrow bracket participants continued chasing learning block losses into the test block, then the test block was contaminated and no longer provided a clean comparison between conditions. Specifically, we looked at how prior wealth affects risk taking in the last round of the learning block and the first round of the test block. ² This comparison can be thought of as risk taking after gains and losses are on paper—on round 9 of the learning block funds have not been transferred—versus when gains and losses are realized—on round 1 of the test block funds have been transferred. As seen in the appendix, loss chasing does not transfer from the learning block to the test block. Loss chasing does not carry over from the learning block to the test block.

**Study 2: Distribution Rankings**

Study 1 showed that, compared to broad brackets, narrow brackets lead people to make smaller investments which in turn result in higher time-average growth rates but lower expected-values in the test block. However, it did not show which standard people prefer. Do people prefer the results of an EV-maximizing strategy or the result of a time-average-maximizing strategy? Study 2 measured which standard people prefer by having participants rank outcome distributions based on outcomes from various investment percentages in the paradigm from study 1. If people prefer growth rate then they should rank the time-average growth rate maximizing strategies

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² We thank Alex Imas for suggesting this analysis.
higher, and similarly if they prefer the expected-value maximizing strategies they should rank them higher. We predicted that people will rank time-average growth rate maximizing strategies higher.

**Method**

**Participants**

We recruited 200 participants on Amazon Mechanical Turk who were paid $1.33 to complete a 10-minute survey. All participants were assigned to a single condition. The sample size was based on a pilot study.

**Procedure**

Participants ranked 5 different outcome distributions that were created by playing out the lottery used in Study 1 based on the following investment percentages: 50%, 25%, 12.5%, 6.25%, and 0%. An investment percentage of 50% had the highest expected-value but the lowest time-average growth rate; an investment percentage of 6.25% had the highest time-average growth rate.

Participants made binary comparisons between all possibly pairs of the distributions. Distribution pairs were presented in a random order. Participants’ relative rankings were turned into a

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3 We calculated the probability of each number of wins, zero to nine, via the binomial distribution. The probability of the outcomes was, for zero to six wins, rounded to the nearest tenth of a percent. Because the probabilities of winning 7, 8, and 9 times were small, we combined these into a single row in our stimuli. To combine these three probabilities into a single probability with associated final wealth outcome, we first summed the probabilities and took the arithmetic mean of the three final wealth outcomes. That is, we kept the combined expected value of the three outcomes constant. Because the total probability of the rounded values summed to .99, we added .01 to the probability of the 7-8-9 win bin. We did this to increase the expected value of the higher investment percentage distributions more than the expected value of the lower investment percentage distributions. That is, if people cared about expected value, they should prefer the 50% distribution stimulus we used over the actual 50% distribution before this adjustment. This adjustment should bias people towards selecting the higher percentage distributions, making our test conservative. See code at XXX.
unidimensional scale via Thurstone scaling. The differences on the scale are assumed to correspond to standard normal distributions. Therefore, the difference in scale values for any two stimuli is like the Cohen’s D effect size.

Results

Participants preferred outcome distributions from small investment percentages to high investment percentages. The distribution based off of an investment percentage of 12.5%—the highest rated investment percentage—is 1.14 standard deviations away from the lowest ranked investment of 50%. The other investment percentages, measured in SD from the 50% distribution, were: 6.25%, .9SD from 50; 0% .6 SD from 50; 25% .6 SD from 50%. The highest rated distributions had high time-average growth rates and the lowest rated distributions had high expected-values.

Figure 2 shows how well the expected-value and time-average predict participants distribution preferences. We used ranks of the Thurstone scale and normative standards to make comparisons easier: the normative standards are both highly non-normal. If the distributions are ranked according to the normative standard, then the points in the figure should line up on the diagonal. For expected-value, rankings of distributions do not fall on the diagonal. However, for the time-average growth rate rankings the points fall almost directly on the line. From this we conclude that people prefer time-average growth rate maximizing strategies to expected-value strategies.
Figure 2: Rankings of expected-value and time-average standards predicting participant rankings of distributions. If points lie on the 45-degree line then the standard aligns with participants’ rankings.

Study 3: Best Investment Percentage

While studies 1 and 2 suggested that narrow brackets yielded investment percentages closer to the standard people prefer, they are not incentive compatible. It is difficult to create a straightforward incentive compatible version of the task used in study 1 because of the highly skewed outcome distribution. Therefore, in study 3 we adapted the study 1 procedure to have, after the learning block, an incentive compatible question about the reinvestment environment with an objectively correct answer. This design allowed us to measure the effects of brackets on understanding of the risk structure rather than the effect of brackets on how much risk participants are willing to take.

Method
**Participants**

We recruited 500 participants from Amazon Mechanical Turk. Participants were randomly assigned to one of two learning block conditions from Study 1: narrow bracket or broad bracket.

**Materials**

Participants experienced the same learning block conditions as study 1; however, instead of seeing a test block afterwards they were presented with the following scenario:

Your friend, Marty McFly, needs money to help save the clock tower. He is given the same investment opportunity you just had - there are 9 rounds and he starts with $200. However, he has to invest the same percentage each round. Since he has a time machine, he already knows that he will lose the lottery 6 times and win 3 times. However, Biff punched Marty making him forget the order of the wins and losses.

How much do you think Marty should invest to make the most money possible?

Remember: When Marty loses, he loses the whole amount he invested

When Marty wins, he wins 2½ times the amount he invested, e.g. he gets to keep the amount he invested + he gains an amount that is 2½ times the amount he invested.

If you get within 3 percentage points, in either direction, of the right answer -- the investment percentage that gives Marty the most money -- you will receive a bonus of 25 cents.

The correct answer was investing 6.66% on each round. For a constant investment percentage over all 9 rounds in this lottery, the final value depends only on the number of wins and the investment percentage. $v = 200 \times \left[ (1 + 2.5i)^{n_{\text{win}}} \times (1 + (-1 \times i))^{n_{\text{loss}}} \right]$; where $i$ denotes the
investment proportion; \(n_{\text{win}}\) and \(n_{\text{loss}}\) index the number of wins and losses. Given that the number of wins is set at 3 and the number of losses is set at 6, the function reduces to \(\max_{0<i<1} (1 + 2.5i)^3 \ast (1 - i)^6\). The maximum \(m\) occurs when \(i = .06\) or investing 6.66%. This maximum equals the time average growth rate.

**Results**

Participants in the narrow bracket condition allocated a smaller percentage (\(M = 27.5\)) than participants in the broad bracket condition (\(M = 34.0\)) \(t(485.7) = 3.19, p = .002, \text{Cohen’s } D = 0.29\). Narrow bracket participants had higher log time-average growth rates (\(M = -0.13\)) than bracket participants (\(M = -0.24\)) \(\text{Wilcox } W = 25960, p = .001\).

Taken together these results suggest that narrow brackets lead to improved performance on an incentive compatible task that eliminates the role of risk perception. That is, narrow brackets led to a better understanding of the task in a riskless environment rather than simply changing the participants’ preferences for more or less risky strategies.

**Study 4: Replay**

Studies 1-3 demonstrated that narrow bracket participants, compared to broad bracket participants, made investments closer to the time-average standard. The studies did not, however, reveal what about the narrow bracket condition that enables participants to better understand the risk structure. In study 4, we included a third experimental condition which changed how broad bracket participants saw their learning block results. In this replay condition, participants made learning block decisions in the exact same way as broad bracket participants, but they saw the outcomes of their results in the same way as narrow bracket participants do.
The replay condition is similar to prior studies on repeated reinvestment. Specifically, in Langer and Weber (2008) the long commitment plus frequent feedback condition—where participants committed to three decisions in a row but receive round by round feedback. The long commitment plus frequent feedback led to increased investment relative to the traditional broad bracket—long commitment and infrequent feedback. In Langer and Weber (2008), increasing investment increased both expected-value and expected growth rate; however, in our study increasing investment increases expected-value but generally decreases the expected growth rate.

Method

Participants:

We recruited 1200 participants from Amazon Mechanical Turk. Sample size was based on an a priori power analysis. Participants were randomly assigned to one of three learning block conditions: broad, narrow, or replay.

Materials

In addition to the narrow and broad bracket learning block conditions from study 1, we included a replay condition. The replay condition mimicked the broad bracket condition in the learning block, but after participants made all nine investment decisions, they received round-by-round feedback on their outcomes. For example, if a replay participant invested 10% in the first round and lost they saw the following:

You invested 10 Percent of $200 and lost. Thus, you ended round 1 with $180. That's what you had available for round 2.

Results
The result from study 1 replicated: a linear regression predicting participant mean percent invested in the test block showed that narrow bracket participants (M = 18.39) invested less than broad brackets participants (M = 23.75) ($\beta = -5.36, SE = 1.41, p < .001$). Further, compared to broad bracket participants, replay participants (M = 20.9) invested less in the test block than ($\beta = -2.84, SE = 1.41, p = .043$). However, there is no significant difference between replay participants’ investments and narrow bracket participants’ investments ($\beta = -2.51, SE = 1.40, p = .073$). When using different distributional assumptions, as seen in the online Appendix, similar results emerge.

Compared to the percent invested analyses, the time-average growth rate analyses were less decisive. Because growth rates are highly skewed, we transformed test block growth rates via the rank-z transformation (Gelman et al., 2014). Narrow bracket participants had significantly higher time-average growth rates than broad bracket participants ($\beta = 0.23, SE = 0.073, p = .002$). However, there was no difference between the time-average growth rates of broad bracket participants and replay participants ($\beta = 0.08, SE = 0.073, p = .25$). We ran a model comparing just replay participants with broad bracket participants while adjusting for their learning block experiences. When adjusting for learning block time-average growth rate ($\beta = 0.79, SE = 0.031, p < .001$) and learning block log final wealth ($\beta = -0.09, SE = 0.02, p < .001$) the effect of replay is significant ($\beta = 0.11, SE = 0.05, p = .035$). The model comparing the effects of replay to broad brackets while adjusting for what happened to participants provides a fair comparison.

In order to assuage our doubts about p-values close to .05, we ran a replication study (N = 800) that included solely broad bracket and replay conditions. Predicting test block investment percentage, when adjusting for learning block mean investment percentage ($\beta = 0.72, SE = 0.07$).
0.032, p < .001) and learning block log final wealth (β = 1.44, SE = 0.35, p < .001), replay participants invest less than broad bracket participants (β = −2.13, SE = 0.91, p = 0.029). Predicting test block time-average growth rate, when adjusting for learning block time-average growth rate (β = 0.76, SE = 0.002, p < .001) and learning block log final wealth (β = −0.08, SE = 0.01, p < .001), replay participants have a higher time-average growth rate than broad bracket participants (β = 0.09, SE = 0.04, p = 0.02). In the test block, replay participants invest less and have higher time-average growth rates than broad bracket participants.

**Discussion**

Prior studies of myopic loss aversion typically used non-reinvestment environments, which are fundamentally different than the reinvestment environments that investors usually confront. In non-reinvestment environments, the expected-value of the per-round difference in wealth equals the time-average, whereas, in reinvestment environments, the expected-value of the per-round multiplier of wealth often does not equal the time-average. In both environments, the time-average of the growth rate corresponds to an individual’s wealth evolution, making it a compelling normative standard.

In prior work, maximizing the time-average and expected-value yielded equivalent investment recommendations: invest 100% of assets. In these previous studies, narrow bracket participants generally invested less than broad bracket participants, leading to both smaller expected-values and smaller time-averages of growth rates. In our lottery, however, the investment percentage that maximized expected-value of the growth rate—investing 100%—diverged from the strategy for maximizing time-average—investing ~6.6%. Narrow bracket participants, compared to broad bracket participants, invested closer to 6.6%, yielding a higher time-average growth rate. While
we consider the time-average of the growth rate to be the appropriate normative quantity to maximize, participants’ preferences may have differed from our normative analysis. When ranking outcome distributions, participants endorsed the time-average growth rate standard and rejected the expected-value standard. Overall, our normative analysis and distribution ranking results imply that narrow bracket participants make better decisions than broad bracket participants.

While the above results suggest that narrow bracket participants make better decisions, they do not explain what, specifically, about narrow brackets led to higher time-average growth rates. To determine if narrow brackets led participants to an increased understanding of the task, we ran an incentive compatible study with an objectively correct answer. The narrow bracket participants made better decisions than broad bracket participants, indicating that narrow bracket participants understood the reinvestment structure better than broad bracket participants. In order to determine why narrow bracket participants had superior understanding, we added a third condition where participants made learning block decisions like the broad bracket participants did, but also observed the evolution of their learning block wealth—i.e., the replay condition. The replay participants invested a smaller percentage in the test block than regular broad bracket participants. Effectively, our results indicate that narrow bracket participants gained a superior understanding of the risk structure by seeing their wealth evolve over time.

While narrow bracket participants seemed to gain a superior understanding of the risk structure, in the learning block, both groups of participants invested a similar percentage. This was, in part, because narrow bracket participants chased their losses—meaning, they invested a higher percent if they lost on the prior round than if they won and, when they were below the starting wealth of $200, there was a negative relationship between the prior round’s wealth and the percent they
invested. While participants chased their losses in the learning block, they did not in the test block. Thus, these results point to the importance of the test block for understanding the effects of brackets. In particular, narrow brackets may have multiple, competing influences on choice.

While it may seem that chasing losses forced narrow bracket participants to confront their poor decisions making, the effect of replays suggest caution in this interpretation. Replay participants could not chase their losses but still invested a smaller percentage in the test block than broad bracket participants. Thus, loss chasing may not be integral to learning the risk structure of reinvestment environments.

*Links to prior literature*

At first glance, it appears difficult to reconcile our findings with prior studies of brackets and risk taking (Kahneman & Lovallo, 1993; Read et al., 1999). However, we can reconcile many of the apparent contradictions by reconsidering the divergence between non-reinvestment and reinvestment environments and their corresponding normative standards. That is, by considering the time-average growth rate, many of the contradictions between prior work and our results melt away. We also place our results within the context of former mechanistic accounts of myopic loss aversion and argue for the importance of including a test block in study designs, especially under reinvestment environments. Our results further add to the understanding of how investors react to losses in reinvestment environments.

*Investment Environments and Normative Standards*

Prior studies on bracketing and risk taking conflate the normative standards of expected-value and the time-average of growth rates (Beshears et al., 2017; U. Gneezy & Potters, 1997; Haigh & List, 2005; Langer & Weber, 2008; Thaler et al., 1997). In non-reinvestment environments,
interchanging these two standards is not important; the two averages are necessarily equivalent to each other. By contrast, in reinvestment environments, the two averages do not necessarily equal each other. In previous reinvestment studies, the time-average and expected-value of growth rates were both maximized by equivalent strategies: investing 100% of assets (Beshears et al., 2017; Langer & Weber, 2008). However, when the two averages make the same prescription, it is not possible to determine which average investors actually care about. Because time-averages correspond to an individual’s wealth evolution, we argue that time-averages are the appropriate normative standard. In support of this argument, we found that, when the two averages were not equal, participants ranked distributions according to the time-average growth rate, not the expected-value. In other words, participants preferred the time-average standard to the expected-value standard.

While our results show that participants prefer the time-average standard, in prior work participants who saw outcome distributions made choices with higher expected values (Webb & Shu, 2017). However, these seemingly contradictory results can be reconciled by looking at the underlying investment environment and its time average of final wealth\(^4\). In a non-reinvestment environment, the time average of final wealth equals the expected value of final wealth\(^5\); however, in a reinvestment environment, the time average of final wealth can be very different.

\(^4\) The time average of final wealth and expected value of total wealth can be calculated by treating the series of lotteries as a single round. That is, taking the probabilities and outcomes after 9 rounds at a certain investment percentage and applying the appropriate formula.

\(^5\) In Webb and Shu Figure 1 top panel, the gamble is 90 rounds of winning $.75 with \(p = .1\) and losing $.01 with \(p=.9\). The expected value of the gamble is $6. The time average of the final wealth for individual experiencing the gamble is also 6: \(.75(p_1 \times n) - .01(p_2 \times n)\). In contrast, for our study the time average of final wealth for a 50% investment is 200 * (.5^6 * 2.25^3 = $35.6, while the expected value is 200 * (.5*6 + 2.25*3) = $1950.
than the expected value of final wealth. Specifically, when time-averages diverge from expected-values, investors prefer final outcome distributions that reflect high time-average final wealth.

Additionally, investors’ preference for time-averages also reconciles our replay results, in which, replays led to smaller investments, with prior work in which replays led to larger investments (Langer & Weber, 2008). In the Langer and Weber paradigm, investing 100% of assets maximized both the expected-value of the growth rate and the time-average of the growth rate. In our paradigm, investing 100% maximized the expected-value of the growth rate but investing ~6.6% maximized the time-average growth rate. Replay participants’ investment percentages moved down in our case, but up in the Langer and Weber’s. However, in both paradigms, replay participants had higher time-average growth rates than broad bracket participants. In sum, replaying results may move participant’s investments in the direction of higher time-average growth rates, regardless of whether this means increasing investments or decreasing investments.

*Measuring and Contextualizing Bracketing Effects*

While we argue that a broadly bracketed test block is necessary to understand the effects of brackets, a number of prior studies did not employ this method (Beshears et al., 2017; Haigh & List, 2005; Moher & Koehler, 2010). In general, these studies found, in the learning block, that narrow bracket participants invested less than broad bracket participants. One study that had both a learning block and a broadly bracketed test block, found that the effects of brackets in the learning block—narrow bracket participants invested less than broad bracket participants—transferred to the test block (Thaler et al., 1997). This result suggests that, in non-reinvestment environments, the learning/test block design is unnecessary. However, our results show no significant difference between narrow and broad brackets in the learning block, but a significant
difference in the test block. Therefore, the test block may be more important in reinvestment environments than in non-reinvestment environments.

Furthermore, test blocks may be especially important in reinvestment environments for two reasons: 1) the reinvestment environments have a complicated risk structure, making feedback especially important; 2) however, this feedback can also lead narrow bracket participants to chase their losses. Narrow bracket participants may, as corroborated by the replay and best investment percentage results, have learned an important emergent feature of the risk structure: if they invested too much, their losses were not recouped over time. While prior work suggests that the overall properties of options are easier to recognize when choices are bracketed broadly, we argue that the overall properties of a reinvestment environment are difficult to understand with the sparse feedback of broad brackets (Read et al., 1999). If participants are like the authors, they find it easier to understand the emergent properties of non-reinvestment environments without feedback—losses will be offset by gains over the long haul—than to understand the emergent properties of reinvestment environments without feedback—losses may or may not be offset over the long haul, depending on the percent invested.

In addition to illuminating the risk structure, the feedback that narrow bracket participants received led them to chase losses in the learning block. However, their loss chasing did not transfer to the test block. That is, there were short-term effects of feedback that did not transfer to the test block—i.e., loss chasing—and longer-term effects of feedback that did transfer to test block—i.e., investing less in the test block.

These loss chasing results extend prior work in two ways. First, they demonstrate that loss chasing happens, not only in non-reinvestment environments, but also in more realistic reinvestment environments (Imas, 2016). Second, they hint at investors’ reference point.
Specifically, by observing the types of situations in which people chase losses, we may be able to infer their reference point. The structure of participant’s loss chasing—participant’s invested more if they lost on the previous round and more the further below the starting wealth of $200 their prior wealth was—suggests, consistent with prior work (Baucells et al., 2011), that a participant’s reference point is a combination of starting wealth and prior round’s wealth.

Effectively, when people chase losses in reinvestment environments, they seem to do so based on their starting wealth and their most recent wealth.

While participants in our study chased their losses, participants in other reinvestment environments have used momentum strategies—e.g., investing less after a loss and more after a win (Lejarraga et al., 2016). Whereas participants in our study were given a lottery with explicit probabilities and outcomes, participants in Lejarraga et al. (2016) were given a lottery with implicit outcomes and probabilities. Specifically, their participants invested in the stock market.

As a consequence, Lejarraga and colleagues’ participants were likely updating their estimate of how good their investment prospects were. If they had just lost, participants might assume that the market was going down and believe that they should invest less. On the other hand, if they had just won, they might assume that the market was going up, and believe that they should invest more. Consequently, these updated beliefs pull participant’s investment percentages in the opposite direction than loss chasing. And if this tension is true, then the estimated size of momentum strategies, especially those for losses, were actually underestimates. It is therefore essential to know, not only investors’ reference points’—and therefore how likely they are to chase losses—but also, how their beliefs about the market evolve.

Finally, our results suggest that feedback may be especially important in reinvestment environments. Prior work using the same gamble parameters as our study, but within a non-
reinvestment environment, found a feedforward effect of brackets, such that brackets had an initial and consistent effect throughout the study (U. Gneezy & Potters, 1997). However, in our reinvestment environment, brackets seemed to operate based on feedback, in that brackets had inconsistent effects in the learning and test block effects. One explanation for this divergence is that non-reinvestment environments have properties that are inherently easier to predict than reinvestment environments. In non-reinvestment environments initial allocations and results have no impact on the structure of future lotteries. In contrast, in reinvestment environments, lotteries have a serial dependency. If you invest a lot in the first round and win, your second is different. Non-reinvestment environments have risk structures that are easy to understand, reinvestment environments have risk structures that are hard to understand. Taken together, this suggests that, when environments are hard to understand, the effect of brackets may be due to feedback.

Marketing Implications

Our research highlights the need for marketers and financial advisors to appreciate the structure of the investment environment and the feedback that their investors receive. When communicating risk to investors, it is important to know which average to communicate: the expected-value or the time-average. Moreover, before deciding how to present investments, marketers must first understand the environment the investor is experiencing and what they want in that environment.

Instrumentally, proper communication requires not only practical knowledge, but also an understanding of what terms mean to investors. For instance, in reinvestment environments the time-average is likely to occur but the expected-value can be extremely unlikely to occur. However, the term “expected,” in common parlance, conveys that something is like to occur. The
average investor, might, understandably, be confused by being told they cannot expect to see the expected value.

Marketers need to understand not only an investors’ lexicon, but also their preferences. In order to help investors make more informed decisions, both lawmakers and investment firms are interested in measuring investor’s risk tolerance (Davies, 2008). A component of risk tolerance has been measured via psychological models like cumulative prospect theory (Murphy, 2017). Prospect theory, however, was designed to predict choice in non-dynamic non-reinvestment environments. In line with the expected-value standard in non-reinvestment environments “Prospect theory accepts utility theory’s cognitively implausible calculation of expected-values.” (Fischhoff, 2014, p. 730). We agree that the calculation of expected values is cognitively implausible, but under reinvestment we argue that expected value is not what investors should focus on. Psychological models of investor behavior need to focus on the environment in which people find themselves and how their wealth evolves in that environment. Extrapolating risk preferences assessed in non-reinvestment environments to reinvestment environments glosses over important structural differences.

In sum, our findings demonstrate that, in order to communicate effectively with investors, advisors need to understand the environment their investor are in—e.g., whether is it non-reinvestment or (more likely) reinvestment. Advisors should also be able to anticipate how their clients react to those environments—e.g., will they chase losses or follow a momentum strategy. Additionally, advisors need to know what kind of feedback their clients get—e.g., infrequent and sparse or frequent and rich. Furthermore, advisors need to know what investors want from their situation—maximizing expected-value or time-average growth rate.
References


Appendix: Loss chasing

Regression Modeling Framework

In order to investigate how participants chased losses, we ran a hierarchical generalized additive model predicting investment percentage in rounds 2 to 9. Generalized additive models are generalized linear models with a smooth, nonlinear, function of a linear predictor (Wood, 2017). We included a nonlinear effect of prior rounds wealth. We also included the prior rounds result as a predictor. While this precise analysis was not preregistered for study 1 data, we did preregister this analysis for the study 4 data. The results were nearly identical. To avoid the optimization issues which plague frequentist hierarchical generalized additive models and better estimate parameter uncertainty, we used a Bayesian modeling framework (Goodrich, Gabry, Imad, & Brilleman, 2018).

There were a few extremely high values of total wealth, therefore, we removed the highest 1% of values of total wealth from our final analysis. This 99% analysis allowed us to use untransformed wealth as an independent variable. The results of the 99% analysis hold for a number of different assumptions (https://osf.io/pt4a6/).

We predicted the current round’s investment by 1) the result of the prior round (win or loss); 2) an additive spline which allowed for non-linear effects wealth from the prior round; 3) the percent invested in the prior round. The percent invested in the prior round was included as an adjustment variable to ensure that people were not experiencing some sort of regime change in their risk attitudes: a participant may increase or decrease their investment percentage as the task progresses making the raw percent invested a biased estimate. We also included varying
intercepts for participant and round. The hierarchical Bayesian model was fit in Stan via the RStanArm package.  

How much a participant invested in the prior round was related to how much they invested in the current round (Posterior Median = 0.24; 95% Credible Interval [0.17, 0.32]). In line with loss chasing, participants invest less after win than after a loss (Posterior Median = -3.46; 95% Credible Interval [-5.40, -1.58]).

Figure 1A shows the spline for lagged wealth. For wealth less than $200, the line has a negative slope. The further below $200 a participant’s wealth was, the more they invested. For wealth levels above $200, the line is relatively flat. It is worth noting that the regression model did not contain any prior information about the starting wealth, it found the inflection point solely from the data. This result suggests that participants chase losses based on their starting wealth and the previous round’s result.

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6 For more information on splines see Wood (2017) specifically section 5.2.4.
Figure 1A: Nonlinear spline for wealth on the previous round predicting investment in the current round. Regression includes lagged percent invested and result of the prior round, hence the predicted percent invested can be negative. Vertical line indicates starting wealth in the task.

**Paper Versus Realized Losses Modeling Framework**

To test the realization effect, we ran a hierarchical regression predicting the rank-z transformed percent invested on the target round by block—either the 9th round of the learning block or the first round of the test block—lagged wealth—wealth after the 8th round of the learning block and 9th round of the learning block—and the interaction between block and lagged wealth. We included a varying intercept for each subject to capture individual differences in investment percentages. We did not include a spline for wealth because there was not enough data to reliably

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7 Models with a dummy variable for the prior rounds result—win or loss—had lower (better) AIC’s than the simpler model. For ease of exposition, we only present the wealth models here.
estimate one. To address the non-linear effects of wealth we fit models on subsets of the data. We, once again, subsetted the data to remove participants in the top 1% of wealth.

**Results**

In the first round of the test block participants invested significantly less than in the last round of the learning block ($\beta = -22.51, SE = 2.80, p < .001$). Wealth on the prior round was negatively associated with investment ($\beta = -0.05, SE = .007, p < .001$). More importantly, there was an interaction between block and wealth on the prior round ($\beta = 0.04, SE = 0.01, p < .001$). As seen in figure 2A, the effect of lagged wealth was smaller in the test block than in the learning block.

![Figure 2A: Interaction between block (9th round of the learning block or 1st round of the test block) and wealth from the previous round.](image)

To deal with the non-linearity of the effect of lagged wealth, we ran a model based on a subset of participants who had less than $200 after the 8th and 9th rounds of the learning block. That is,
their lagged wealth for both rounds used in the previous model are below $200—where lagged wealth had a steep negative slope in figure 1A. There was a main effect of block, participants invested less in the test block than in the learning block ($\beta = -42.00, SE = 4.21, p < .001$). There also was a main effect of lagged wealth ($\beta = -0.38, SE = 0.03, p < .001$). As seen in Figure 3A, the effect of lagged wealth was smaller in the first round of test block than in the last round of learning block. ($\beta = 0.25, SE = .04, p < .001$).

However, for participants who had more than $200 on both rounds, but were still in the 99%, there was a marginally positive effect of wealth ($\beta = 0.01, SE = 0.006, p = .069$). There was no main effect of block ($\beta = 0.16, SE = 3.65, p = .96$). There was no interaction between block and wealth ($\beta = 0.005, SE = 0.008, p = .52$).
Figure 3A: Interaction between block (9th round of the learning block or 1st round of the test block) and wealth from the previous round for participants who had less than $200 in wealth.