On Myopic Loss Aversion*

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January 21, 2020

Abstract

It has been widely documented in laboratory experiments that subjects act more risk-averse when they make their decisions frequently (e.g., one as opposed to several decisions at a time), a phenomenon dubbed "myopic loss aversion" by Benartzi and Thaler (1995). The present paper uses two new experiments to show that this pattern of behavior can be reversed by making risky choices less atrractive, for example by increasing the value of the safe option. The results cannot be explained by mental accounting or loss aversion but are consistent with the hypothesis that behavior is less random when the stakes are higher.

*The author thanks Simon Board, Gary Charness, David Cooper, Yoram Halevy, Joshua Miller, Pietro Ortoleva, Nat Wilcox, the brown bag participants at ITAM, the seminar participants at Chapman University, and the participants of the 2017 International ESA Meeting for helpful comments. The financial support of the Asociación Mexicana de Cultura A.C. is acknowledged.

1 Introduction

To understand the idea behind myopic loss aversion (MLA), consider the following anecdote, relayed in Samuelson (1963):

> [...] a few years ago I offered some lunch colleagues to bet each $200 to $100 that the side of a coin *they* specified would not appear at the first toss. One distinguished scholar - who lays no claim to advanced mathematical skills - gave me the following answer: "I won't bet because I would feel the $100 loss more than the $200 gain. But I'll take you on if you promise to let me make 100 such bets."

In the years following Samuelson (1963), several experiments (Gneezy and Potters 1997, Thaler et al. 1997, Benartzi and Thaler 1999, Haigh and List 2005, and Fellner and Sutter 2009) have shown that people are less willing to take frequent than infrequent risks. Prominently, this observation has been used by Benartzi and Thaler (1995) to explain the equity premium puzzle: the reduced willingness to take risks associated with evaluating an investment portfolio over relatively short time periods (e.g., years as opposed to decades) is consistent with a large equity premium.

The present paper shows experimentally that the conclusions of Gneezy and Potters (1997)-type studies can be reversed. To understand how, let Choice H[1] denote the choice between a risky option (e.g., a high mean, high variance lottery) and a safe option (e.g., a certain amount). Let Choice L[2] denote the choice between two instances of the risky option in Choice H and two instances of the safe option in Choice H. Note that every MLA experiment has this Choice H-Choice L structure, as does the thought experiment in Samuelson (1963). One feature shared by most prior studies of MLA is that the risky option is relatively attractive, i.e., has substantially higher expected returns than the safe one.[3] What the present paper shows is that subjects are more willing to take risks in Choice H than in Choice L, i.e., show myopic loss seeking, when the risky option is unattractive, i.e., has a substantially lower expected value than the safe option ($P < 0.001$ with $N = 187$).[4]

The accepted interpretation of prior studies of MLA, such as Gneezy and Potters (1997), is

[1] "H" for "high frequency."

[2] "L" for "low frequency."

[3] In Thaler et al. (1997), for instance, the subjects choose between simulated stocks and bonds.

[4] In the experiment, the risky option is a binary gamble, while the safe option is a sure amount that can be either high or low.

to assume that the DM has a utility function of the following form:

$$u(x) = \begin{cases} x & \text{if } x \geq 0 \\ \lambda x & \text{if } x < 0 \end{cases} \tag{1}$$

Letting $\lambda = 2.5$, this generates a negative expected utility for the gamble (\$200, 0.5; -\$100, 0.5) and a positive expected utility for the gamble (\$400, 0.25; \$100, 0.50; -\$200, 0.25) implied by accepting to play (\$200, 0.5; -\$100, 0.5) twice in Samuelson's thought experiment. Similar calculations are used in other experiments in the MLA literature to argue that a loss-averse decision maker is more willing to take risks in when the decisions are broadly framed. The behavioral literature refers to the question how decisions are framed (one vs. several at a time, for example) as mental accounting.

The results reported in the present paper challenge this accepted interpretation. Greater willingness to take risks cannot be attributed to mental accounting (because more broadly framed decisions sometimes induce a smaller willingness to take risks) or loss-averse preferences (because no accepted form of loss-averse preferences will predict a greater willingness to take risks in Choice L *if and only if* the risky decision is attractive). On the other hand, the results are consistent with a wide class of stochastic choice models or the hypothesis that people sometimes make mistakes.[5] Intuitively, assume that the DM is risk-neutral on average but sometimes trembles. If the risky option is attractive, she is more likely to choose it than the safe option in both Choice H and Choice L. Notice, however, that the stakes are higher in Choice L, which in most models of stochastic choice will imply that the random element will have less of an impact on behavior. The probability of choosing the risky option will therefore be higher in Choice L. If the risky option is unattractive, the random element having less of an influence implies that the probability of choosing the safe option is higher in Choice L, as observed in the present experiment.

Section 4 provides a more detailed elaboration of this argument and argues that other potential explanations of the findings are inadequate. While the suggestion that prior experimental results in the MLA literature is consistent with some models of stochastic choice is not new (Blavatskyy and Pogrebna, 2010), this is not the main contribution of the present paper. The main, empirical, contribution is to present results that challenge the standard, behavioral model of myopically loss-averse behavior.

[5]The source of randomness in a stochastic choice model is not necessarily mistake-driven. For instance, the DM might randomize on purpose.

2 Experimental Design

This paper reports two studies, an initial between-subjects study conducted in September 2016 (N=87) and a within-subjects replication conducted in May 2018 (N=100). Both studies were designed to be as simple as possible, be relatable to existing MLA experiments in the literature, and provide reasonably high incentives to the subjects. Both studies are similar to Benartzi and Thaler (1999) in that they use simple binary gambles. They are similar to Gneezy and Potters (1997) in that subjects made nine decisions, one decision at a time, in the high frequency condition and three decisions at a time in the low frequency condition.

Each session of each study had the following procedural features in common. After handing in their consent forms, the subjects were handed out their instructions. The instructions were then read out loud to the subjects. At this point, the subjects were allowed an opportunity to ask questions. After all the questions were privately answered, the subjects made practice decisions (three practice decisions in Treatment H of Study 1, one practice decision in Treatment L of Study 1, one practice decision in both treatments of Study 2). It was understood that any decisions made at this point would not count for the subjects' earnings. Following the practice decisions, subjects made decisions for real money. After all the decisions were made, each subject was privately paid.

Aside from the obvious difference in designs (between vs. within), the main difference between the two studies is that the subjects were paid for every decision in the between-subject study, while a single payoff-relevant decision was drawn randomly for each subject in each treatment of the within-subject study. The subjects thus received no feedback about what their earnings would be until they received their earnings at the end of the experiment. Paying subjects for every decision is consistent with the design in Gneezy and Potters (1997) and other prior studies in the MLA literature, while selecting payoff-relevant decisions at random is consistent with modern experimental procedures as outlined in Azrieli et al. (2018). The payoffs in the two studies (i.e., the lotteries and sure amounts) differed slightly so as to make the overall earnings comparable. Unlike Study 1, Study 2 included a show up fee of 60 local currency units (LCUs).

2.1 Study 1 (Between-subject; N=87)

Each session in Study 1 was randomly assigned into either Treatment H1 (high decision frequency) or Treatment L1 (low decision frequency). In Treatment H1, each subject was randomly assigned a personal winning outcome (heads or tails) in the beginning of the session. The subjects were then told that they will make several decisions between a sure amount and a lottery that pays 30 LCUs with probability 50% and 0 LCUs with probability 50%. At the time of the experiment, a 15km Uber ride from the author's house to the airport cost around 80 LCUs.

In any given round, after every subject in the session made his or her decision, the researcher flipped a coin. If any subject chose the lottery and the outcome of the coin flip matched his or her personal winning outcome, 30 LCUs were added to the subject's earnings. If any subject chose the lottery and the outcome of the coin flip did not match his or her personal winning outcome, nothing was added to the subject's earnings for the decision. If any subject chose the certain amount, the certain amount was added to the subject's earnings. Every subject made three practice decisions with a certain amount of 15 before making decisions for real money.

When making decisions for real money, each subject was randomly assigned an order of the following four certain amounts: 10, 13, 16, 19. The subjects did not know what certain amounts they will face before making their decisions. They also made three decisions for each certain amount. For example, a subject with the order (13, 16, 10, 19) first made three choices between the fixed lottery and a certain amount of 13, then three choices between the fixed lottery and a certain amount of 16, then three choices between the fixed lottery and a certain amount of 10, and then three choices between the fixed lottery and a certain amount of 19. This block structure was borrowed from Gneezy and Potters (1997) to make Treatment H1 and Treatment L1 as similar as possible. Following every decision, each subject waited for all other subjects' decisions to be made. The researcher then flipped a coin, announced the outcome out loud, asked one of the participants in the room to verify the outcome, and entered the outcome of the coin flip into his computer. The computer software then calculated each subject's earnings and displayed it on the subject's screen.

In Treatment L1, as in Treatment H1, each subject was randomly assigned a personal winning outcome (heads or tails) in the beginning of the session. They were then told that they will make several decisions between a sure amount and *three plays* of the lottery in Treatment H1. In any given round, after every subject in the session made his or her decision, the researcher flipped a coin *three times*. As in Gneezy and Potters (1997), the three outcomes were announced together after all three coin flips were made. This was done to facilitate the evaluation of the three lotteries in an aggregated way. If any subject chose the certain amount, the certain amount was added to the subject's earnings. If any subject chose the three lotteries, he or she was paid 30 LCUs for each instance of the researcher's coin flip agreeing with the subject's personal winning outcome. For example, if the outcome was "two heads, one tails" and the subject's personal winning outcome was heads, the subject was paid 60 LCUs. Each subject made one practice decision with a certain amount of 45 before making decisions for real money.

When making decisions for real money, each subject was randomly assigned an order of the following four certain amounts: 30, 39, 48, 57. Note that dividing these certain amounts by three we obtain the certain amounts in Treatment H1. The subjects did not know what certain amounts they will face before making their decisions. Each subject made one decision for each certain amount. Following each decision, each subject waited for all other subjects' decisions to be made. The researcher then flipped three coins, announced the outcomes out loud, asked one of the participants in the room to verify the outcomes, and entered them into his computer. The computer software then calculated each subject's earnings and displayed it on the subject's screen.

2.2 Study 2 (Within-subject; N=100)

Study 2 also had two treatments, Treatment H2 (high decision frequency) and Treatment L2 (low decision frequency). Every subject participated in one of the treatments in the first half of the experiment and in the remaining treatment in the second half of the experiment, without knowing what will happen in the second half of the experiment ahead of time. Thus, the instructions for the second half of the experiment were received only after the first half of the experiment was completed. Every session was randomly assigned to either begin with Treatment H2 or with Treatment L2, so that all subjects in a single session participated in the two treatments in the same order. As in Study 1, each subject was randomly assigned a personal winning outcome (heads or tails) in the beginning of the session.

Subjects in treatment H2 made decisions between a sure amount and a lottery that pays 60 LCUs with probability 50% and 0 LCUs with probability 50%. One practice decision was made with a sure amount of 30 LCUs, after which six decisions were made with real monetary incentives. Every subject made two incentivized decisions with each of the following sure amounts: 20, 30, and 40. The order was randomized between 20, 30, and 40 in the first three decisions and, likewise, between 20, 30, and 40 in the last three decisions. The subjects did not know what certain amounts they will face before making their decisions. The subjects were informed that only one of the decisions would count for their monetary earnings, and that they would not find out which decision counts until the end of the experiment.

After completing all of the decisions in Treatment H2, the subjects that started with Treatment H2 received the instructions for Treatment L2. In Treatment L2, the subjects made decisions between a sure amount and *three plays* of the lottery in Treatment H2. After making one practice decision with a sure amount of 90 LCUs, every subject made two incentivized decisions with each of the following sure amounts: 60, 90, and 120. Note that dividing these certain amounts by three we obtain the certain amounts in Treatment H2. The subjects did not know what certain amounts they will face before making their decisions and were informed that only one of the incentivized decisions will count for their earnings. After completing all of the decisions in Treatment L2, the subjects that started with Treatment L2 received the instructions for Treatment H2.

The coin flip announcements in Study 2 were handled in the same was as those in Study 1. After all decisions in both of the treatments were made, the subjects received their earnings and feedback about which decision rounds were selected to be payoff-relevant.

3 Results

Data for Study 1 was collected in September 2016 at a well-known university over the course of six sessions (three each with Treatment H1 and Treatment L1) from 87 subjects (46 in Treatment H and 41 in Treatment L). Average earnings were approximately 188 LCUs, and each session lasted close to 30 minutes on average.

The results are shown in Table 1 (a).[6] The variable s represents the safe amount in each decision in Treatment H1 and the safe amount divided by three in Treatment L1. We find that safe decisions were more likely in Treatment H1 when the lottery was attractive, which mirrors the findings of previous MLA experiments, and more likely in Treatment L1 when the lottery was unattractive. As discussed in more detail below, this pattern of results is inconsistent with deterministic loss-averse preferences.

To study the significance of these findings, we can compare the distributions of making the safe choice in Treatment H1 and Treatment L1 for each value of s. The difference in distributions is significant at a 5% level both when $s = 13$ and when $s = 19$ according to logit regressions (one regressions for each value of s) of a dummy variable for choosing the safe option against a dummy variable for being in Treatment L1 with standard errors clustered at the level of the subject.[7]

Data for Study 2 was collected from 100 subjects on May 2, 2018 at the same well-known university in four experimental sessions. Average earnings were approximately 206.7 (including the 60 LCU show-up fee), and each session lasted around 45 minutes on average. The results are shown in Table 1 (b).[8] As in Study 1, safe decisions were more likely in Treatment H2 when the lottery was attractive and more likely in Treatment L2 when the lottery was unattractive.

[6] Only the incentivized decisions are included in the analysis.

[7] Logit regressions with subject-clustered variables and a treatment dummy are used for all statistical comparisons reported in the paper.

[8] As in Table 1 (a), the variable s represents the safe amount in each decision in Treatment H2 and the safe amount divided by three in Treatment L2.

(a) Study 1 (E.V. of lottery = 15 LCUs):

s	10	13	16	19
Treatment H1	**17%**	**24%**	45%	60%
	(23/138)	**(33/138)**	(62/138)	(83/138)
		$\vee^{**}$		$\wedge^{**}$
Treatment L1	7%	7%	**49%**	**78%**
	(3/41)	(3/41)	**(20/41)**	**(32/41)**

(b) Study 2 (E.V. of lottery = 30 LCUs):

s	20	30	40
Treatment H2	**18%**	47%	79%
	(35/200)	(93/200)	(157/200)
	$\vee^{***}$		$\wedge^{**}$
Treatment L2	7%	43%	**87%**
	(14/200)	(85/200)	**(173/200)**

(c) Both studies:

	Attractive lottery	Unattractive lottery
Treatments H1 and H2	**19%**	63%
	(91/476)	(302/476)
	$\vee^{****}$	$\wedge^{****}$
Treatments L1 and L2	7%	**80%**
	(20/282)	**(225/282)**

Table 1: **The probabilities of making the safe choice in the experiment.** When the lottery is attractive, subjects were more risk-averse in the high frequency treatments, but when the lottery is unattractive the result was reversed. **: $P < 0.05$, ***: $P < 0.01$, ****: $P < 0.001$ according to a logit regression with subject-clustered standard errors.

Comparing the empirical distributions of making the safe choice in Treatment H2 and Treatment L2 for each value of s, we find a significant difference at a 1% level when $s = 20$ and a significant difference at a 5% level when $s = 40$. Because Study 2 was implemented within subjects, we can also evaluate the significance of the effects using regressions with subject fixed effects. This produces the same levels of significance ($P < 0.01$ when $s = 20$ and $P < 0.05$ when $s = 40$) whether or not the standard errors are clustered at the level of the subject. Overall, the results of Study 2 are qualitatively similar to those of Study 1.

We can also analyze the results of Study 1 and Study 2 together. To this end, the observations with $s = 10$ and $s = 13$ in Study 1 and $s = 20$ in Study 2 can be pooled together as observations where the lottery was attractive. Similarly, the observations with $s = 16$ and $s = 19$ in Study 1 and $s = 40$ in Study 2 can be pooled as those where the lottery was unattractive. The pooled data is reported in Table 1 (c). In the pooled data, the effect of being in the L treatments is significant at a $P < 0.001$ level both for attractive and unattractive lotteries. The main result can be summarized as follows:

Main Result. *Narrow framing leads to a smaller willingness to take risks if the lottery is attractive and a greater willingness to take risks if the lottery is unattractive.*

Because this result holds in Study 2, it is not driven by differences between subjects. Because it holds in Study 1, it is not driven by experimenter demand effects or order effects in how the treatments were presented. Because of the differences in how the two studies were implemented, the result is robust to paying subjects for every decision or having one payoff-relevant decision selected at random, and it is robust to subtle changes in payment amounts or the presence of a show-up fee.

4 Discussion

The main result is consistent with a wide class of stochastic choice models. To see how a random parameter model can predict the observed pattern of behavior,[9] assume that each subject has a CRRA utility function, $u(x) = \frac{x^{1-\rho}}{1-\rho}$, with the caveat that the ρ parameter is subject to shocks. Assume for simplicity that the shocks follow the logistic distribution. This implies that the probability that the lottery is chosen in Treatment H is given by:

$$P(\text{Lottery}) = P(\rho + \epsilon < \rho_H(s)) = \frac{1}{1 + \exp(\rho - \rho_H(s))},$$

[9]It has been argued that random utility models lead to biased estimates of preference parameters, and that random parameter models provide a better alternative (Apesteguia and Ballester, 2018).

where $\rho_H(s)$ is a threshold value that depends on s, the sure amount being offered. In Treatment L, the probability that three lotteries are chosen over $3s$ is given by:

$$P(\text{Three lotteries}) = P(\rho + \epsilon < \rho_L(3s)) = \frac{1}{1 + \exp(\rho - \rho_L(3s))}.$$

It follows that, for a given s, $P(\text{Lottery}) > P(\text{Three lotteries})$ if and only if $\rho_H(s) > \rho_L(3s)$. Intuitively, if $\rho_H(s) > \rho_L(3s)$, there are less shocks to ρ that can switch the decision to the safe option in Treatment H than in Treatment L. The threshold values of ρ in both treatments of Study 1 are as follows:

	$s = 10$	$s = 13$	$s = 16$	$s = 19$
$\rho_H(s)$	0.37	0.17	-0.10	-0.52
	$\wedge$	$\wedge$	$\vee$	$\vee$
$\rho_L(3s)$	0.72	0.44	-0.36	-2.07

Table 2: CRRA thresholds for choosing the risky option in Study 1.

A quick inspection of Table 2 shows that the condition $\rho_H(s) > \rho_L(3s)$ is satisfied if and only if the risky option is unattractive ($s = 16$, $s = 19$), consistent with the results of the experiment. The explanation for Study 2 is analogous.

The results can also be accommodated by a random utility model. Assume that the DM's utility is given by $U = EU + \epsilon$, where EU is the expected utility of the prospect being evaluated and ϵ is an i.i.d. error term with an extreme value distribution. It follows that:

$$P(\text{Lottery}) = \frac{1}{1 + \exp(EU(s) - EU(\text{Lottery}))}$$

and

$$P(\text{Three lotteries}) = \frac{1}{1 + \exp(EU(3s) - EU(\text{Three lotteries}))}$$

Assume that $EU(3s) - EU(\text{Three lotteries}) < EU(s) - EU(\text{Lottery})$ for low values of s and $EU(3s) - EU(\text{Three lotteries}) > EU(s) - EU(\text{Lottery})$ for high values of s, which holds for a wide class of utility functions. It holds, for example, if the decision maker is risk-neutral. Then, the probability of choosing the lottery is smaller in Treatment H for low values of s and smaller in Treatment L for high values of s.

The argument above raises an additional issue: can the results can be explained by a population of risk-averse and risk-seeking subjects, for example with $u(x) = \frac{x^{1-\rho}}{1-\rho}$, where each subject has a fixed, individual-specific value of ρ? Consistent with the results of the paper, a risk-averse subject with $\rho > 0$ will choose the safe option when $s > 15$ in both treatments and be more likely to choose the risky option in Treatment L when $s < 15$. A risk-seeking subject will choose the risky option when $s < 15$ and be more likely to choose the risky option in Treatment H when $s > 15$. Is this an adequate explanation of the data?

	Treatment H1	Treatment L1	Treatment H2	Treatment L2
Inconsistent	82.61%	-	59%	51%
Non-monotonic	-	17.07%	-	-
Decreasing	-	2.44%	3%	-
Increasing	17.39%	80.49%	38%	49%

Table 3: Categories of behavior.

To argue that this explanation falls short, we first classify subjects in each treatment into four categories: (1) inconsistent, (2) non-monotonic, (3) decreasing, and (4) increasing.

- Inconsistent subjects are those that make different choices when presented with the same question several times, as in Agranov and Ortoleva (2017).[10] Agranov and Ortoleva (2017) interpret such behavior as arising from a preference for randomization.

- Non-monotonic subjects are those for whom the probability of choosing the sure amount is non-monotonic in the sure amount. We only find such subjects in Treatment L1 and their behavior is consistent with stochastic choice and particular draws of ϵ.

- The increasing subjects are those for whom the probability of choosing the sure amount is decreasing in the sure amount, with a strict inequality for at least one comparison. Such subjects appear to have deterministic but non-standard (decreasing) utility functions.

- The increasing subjects are those for whom the probability of choosing the sure amount is weakly increasing in the sure amount. Such subjects act in line with standard deterministic preferences, such as CRRA.

In Treatment H1, behavior of only 17.39% of the subjects is consistent with CRRA preferences. While this number is larger in Treatment L1, recall that this treatment did not give

[10] Recall that subjects made three choices for each sure amount in Treatment H1, and two choices for each sure amount in Treatments H2 and L2. Treatment L1 did not give subjects an opportunity to be inconsistent.

subjects an opportunity to be inconsistent since each subject faced each particular choice problem only once. For a more powerful test, consider Treatments H2 and L2, where every subject faced every choice problem two times. We find that behavior of 38% of the subjects in Treatment H2 and 49% of the subjects in Treatment L2 is consistent with CRRA.

Since Experiment 2 was implemented within subjects, we can also compare behavior of subjects across treatments. We find that only 52% of subjects fell into the same category in both treatments of Experiment 2, further providing evidence in favor of a stochastic model. Moreover, of the subjects whose behavior is consistent with a deterministic model in Treatment H2, 47.37% show inconsistent behavior in Treatment L2. Of the subjects whose behavior is consistent with a deterministic model in Treatment L2, 55.1% show inconsistent behavior in Treatment H2. This provides clear evidence that behavior in the experiment was to a large extent driven by randomness.

s	20	30	40
Treatment H2	**18%**	46%	76%
	(29/160)	(73/160)	(121/160)
	$\vee^{**}$		$\wedge^{**}$
Treatment L2	9%	39%	**84%**
	(14/160)	(63/160)	**(135/160)**

Table 4: **The probabilities of making the safe choice in Study 2 for subjects other than the monotonically increasing ones.** **: $P < 0.05$ according to a logit regression with subject-clustered standard errors.

We can also reassess the main result of the paper excluding subjects with deterministic CRRA-type preferences from the sample. Consider Study 2, where each subject participated in both Treatment H2 and Treatment L2 with every value of the sure amount.[11] 20 out of 100 subjects in this study showed preferences consistent with CRRA in *both* treatments, and Table 4 shows the proportions of safe choices in Study 2 when these subjects are excluded from the analysis. The main result remains significant and qualitatively similar to that observed in the pooled data, suggesting that it is not generated by the excluded subjects.

We now show that the results are not consistent with deterministic models of loss aversion. The argument considers both deterministic and stochastic reference points, beginning with the former case. Thus, assume that the reference point is given by s for every decision in Treatment

[11] As discussed previously, many subjects in Treatment L of Study 1 likely appear deterministic only because they made very few choices. We avoid an asymmetric analysis where more subjects are excluded from Treatment L than Treatment H for artificial reasons.

H1 and Treatment H2 and $3s$ for every decision in Treatment L1 and Treatment L2. Let the prize amount from the lottery (30 in Study 1, 60 in Study 2) be denoted by P, and let subjects' reference-dependent utility be defined as follows:

$$u(x|r) = \begin{cases} x - r & \text{if } x - r \geq 0 \\ \lambda(x - r) & \text{if } x - r < 0 \end{cases} \tag{2}$$

It follows that the expected utility from picking the lottery in Treatment H1 and Treatment H2 is:

$$EU(\text{Lottery}|s) = \frac{P - s}{2} - \frac{\lambda s}{2} = \frac{P - s(1 + \lambda)}{2}, \tag{3}$$

while the expected utility from picking the three lotteries in Treatment L is:

$$\begin{aligned} EU(\text{Three lotteries}|3s) &= \frac{3(P - s)}{8} + \frac{3(2P - 3s)}{8} + \frac{3\lambda(P - 3s)}{8} - \frac{\lambda(3s)}{8} = \\ &= \frac{9P - 12s + \lambda(3P - 12s)}{8}. \end{aligned} \tag{4}$$

Notice that $EU(\text{Three lotteries}|3s) > 3EU(\text{Lottery}|s)$ if and only if $\lambda > 1$. Thus, loss aversion with a deterministic reference point–which is assumed in all prior studies of MLA–predicts the DM to be more risk-averse in the H treatments for any value of s.[12] The same conclusion is obtained if we assume that that the reference point is given by the expectation of the lottery in each decision.

Another possibility is that the lottery itself served as a reference point, as in Kőszegi and Rabin (2006). In this case, we may assume that the utility of a gamble F given a referent lottery G is given by:

$$U(F|G) = \int \int u(x|r) dF(x) dG(r) \tag{5}$$

[12] It's worth noting that the linearity assumption is unnecessary for this qualitative prediction. Assume, for example, that the utility function is concave for gains and convex for losses (Tversky and Kahneman, 1992):

$$u(x|r) = \begin{cases} (x - r)^\alpha & \text{if } x - r \geq 0 \\ -\lambda\big(-(x - r)\big)^\alpha & \text{if } x - r < 0 \end{cases}.$$

Then the risky option is chosen in Treatment H1 or Treatment H2 if and only if $\big(\frac{P-s}{s}\big)^\alpha > \lambda$, and in Treatment L1 or Treatment L2 if and only if $\frac{(3P-3s)^\alpha + 3(2P-3s)^\alpha}{(3s)^\alpha + 3(3s-P)^\alpha} > \lambda$. For any $\sigma \in (0, 1]$, the threshold remains greater in Treatment L1 than in Treatment H1 when $s \in \{10, 13\}$, equal to one in both treatments when $s = 15$, and below one in both treatments when $s \in \{16, 19\}$. Similarly, the threshold is greater in Treatment L2 than in Treatment H2 when $s = 20$ and below one in both treatments when $s = 40$.

with $u(x|r)$ determined as in Equation 2. Let G_1 denote the lottery with a 50% chance of earning P LCUs, and assume that G_1 served as a stochastic referent.[13] It's easy to check that $U(G_1|G_1) = U(0.5P|G_1)$ for any $\lambda > 1$.[14] Thus, the certainty equivalent of the referent lottery is $0.5P$. I.e., a loss averse DM is predicted to appear risk-neutral in Treatment H1 and Treatment H2. Now consider Treatment L, and denote by G_2 the lottery which pays $3P$ with probability 1/8, $2P$ with probability 3/8, P with probability 3/8, and 0 with probability 1/8. If we assume that the DM uses G_2 as an expectations-based reference point, it can be shown that for any $\lambda > 1$,

$$U(G_2|G_2) < U(3P|G_2)$$

Thus, a loss-averse DM is predicted to appear more risk-averse in the L treatments than in the H treatments for any $\lambda > 1$. While the prediction is qualitatively the opposite to that suggested by deterministic reference points, note that neither stochastic nor deterministic reference points can accommodate a result where loss-averse subjects appear more risk-averse in Treatment L for low values of s and more risk-averse in Treatment H for high values of s.

Finally, one might argue that subjects incur no losses in the experiment and a discussion of loss aversion is misplaced. Our response to this objection is twofold. First, subjects incur no losses in many prominent studies of myopic loss aversion, such as Gneezy and Potters 1997. Second, that explanations based on myopic loss aversion do not apply to the present results a priori can be seen as a strength of the experimental design. Consistent with prior studies, we find that segregating risky decisions leads to reduced risk-taking when risky decisions are attractive. If the findings in this paper cannot be explained by loss aversion, the accepted interpretation of the effect of segregating lottery decisions should also be reconsidered.

While this paper focuses on the evaluation period effect in MLA experiments, there are several promising avenues for future work. Other well-established behavioral regularities that have been given a deterministic explanation may possibly be reinterpreted through the lens of stochastic choice. Consider, for example, the following two problems from Kahneman and Tversky (1979):

Problem 7:

Option A: A payoff of 6000 with probability 45%, Option B: A payoff of 3000 with probability 90%.

Problem 8:

Option A: A payoff of 6000 with probability 0.1%, Option B: A payoff of 3000 with probability 0.2%.

Kahneman and Tversky (1979) find that subjects are more likely to choose B in Problem 7 and

[13]This assumption is reasonable, as the lottery was fixed in every decision of every treatment.

[14]See Sprenger (2015) for the general argument using binary gambles.

A in problem 8. This is inconsistent with expected utility because if $0.45u(6000) > 0.90u(3000)$, then $0.001u(6000) > 0.002u(3000)$. Because the stakes in Problem 7 are substantially higher than in Problem 8, a RUM can provide at least a partial account of these results. Thus, if there is a random component to the DM's utility function, this random component will have more of an influence in the latter problem. A risk-averse DM will therefore be more likely to choose Option B in Problem 7 than in Problem 8. The same intuition applies to Problems 3, 4, 5, and 6 in Kahneman and Tversky (1979). Future research should explore the extent to which stochastic choice can account for these and similar patterns of behavior in the judgment and decision making literature.

In Regenwetter et al. (2011), the authors state that Luce's *twofold challenge* (Luce, 1995) is to "(a) recast a deterministic theory as a probabilistic model (or a hypothesis) and (b) properly test that probabilistic model of the theory (or the hypothesis) on available data." An open question for future work is to determine how much of subjects' behavior is driven by the assumptions made in Kahneman and Tversky (1979) when prospect theory and expected utility are recast as probabilistic models.

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