Myopia and Randomness in Choice *

Piotr Evdokimov
Higher School of Economics

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Abstract

Subjects in laboratory experiments are more risk-averse when they make their decisions myopically (e.g., one versus several at a time). While this finding is typically explained using loss-averse preferences, it is also consistent with the predictions of random choice (e.g., risk neutrality with random errors). Because loss aversion and random choice make similar predictions, their effects are difficult to disentangle. This paper presents an experiment for which random choice predicts a *crossover pattern* of more risk taking with long evaluation periods if and only if a risk-neutral decision maker prefers the risky option, while loss aversion does not. The crossover pattern is observed in the data, which implies that loss aversion cannot explain the effect of evaluation periods on risk-taking in the experiment.

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1 Introduction

A number of experiments have studied the effect of choice bracketing on decisions and found that subjects are more risk-averse when they consider gambles one at a time than when they consider several gambles at once. This effect, typically referred to as myopic loss aversion, is typically interpreted through the less of loss-averse preferences (Kahneman and Tversky, 1979). As an illustration, consider the following pair of choice problems. In the first problem, the decision maker (DM) decides between a lottery with equal chances of winning \$200 and losing \$100 and zero, as in Samuelson (1963). In the second, the DM decides between two instances of the same lottery and zero. 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 $\lambda = 2.5$ as in Tversky and Kahneman, 1992, this functional form 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.[1] Thus, loss-averse preferences predict a greater willingness to take risks when the choice is broadly bracketed.

Blavatskyy and Pogrebna (2010) (BP2010) were the first to make the point that a stochastic choice model can predict the same aggregate choice pattern.[2] For simplicity, assume that the DM is risk-neutral, and that utility from a given prospect is given by the expected value plus a random error ϵ, which is independently drawn from a Gumbel distribution for every choice option. Thus, $U(\text{Lottery}) = 50 + \epsilon$, $U(\text{Two lotteries}) = 100 + \epsilon$, and $U(0) = \epsilon$.[3] It follows that the probability of choosing a single lottery over a sure amount of zero is given by $\frac{1}{1+\exp(-50)}$, while the probability of choosing two lotteries is given by $\frac{1}{1+\exp(-100)} > \frac{1}{1+\exp(-50)}$. Intuitively, the stakes are higher in the decision involving two lotteries, which amplifies utility differences and lessens the impact of ϵ on the DM's decision.

Because loss aversion and random choice make similar qualitative predictions in this pair of choice problems (i.e., greater willingness to take risks with two lotteries as opposed to one), their impacts are difficult to disentangle. In particular, it's pos-

[1] This argument is employed in both Gneezy and Potters (1997) and Thaler et al. (1997).

[2] That economic behavior contains an element of randomness has been known since at least the 1960s; see Wilcox (2008) for a survey of the stochastic choice literature and its applications to experiments.

[3] Risk-neutrality is not necessary for this argument, and a random parameter model produces similar qualitative conclusions.

sible that subjects have preferences that are both random and loss-averse: a greater willingness to take risks with multiple lotteries might be driven by both factors at the same time. Section 2 expands on this point in the context of existing experiments on risk-taking and evaluation periods, such as Benartzi and Thaler (1999) and Gneezy and Potters (1997), and shows how how the role of loss-averse preferences in generating the observed behavior cannot be ruled out in prior studies. To address this issue, this paper presents a new experiment for which the predictions of random choice differ from those of deterministic preferences of any form typically considered in the literature, including loss aversion.

The experiment is built around a choice between a sure amount s on the one hand, and a binary lottery L that pays an amount X with probability $1/2$ and zero with probability $1/2$, on the other. In treatment T1, the DM chooses between one instance of L and one instance of s in each decision. In treatment T3, the DM chooses between three instances of L and three instances of s. Random choice predicts a *crossover pattern*, where the probability of choosing L is higher in treatment T3 for low values of s and higher in treatment T1 for high values of s. This prediction holds for a wide class of random utility and random parameter models (RUMs and RPMs, respectively). Because subjects incur no losses in the experiment, loss aversion per se makes no prediction,[4] while risk aversion in the gain domain predicts greater risk-taking in T3 for low values of s and no difference between treatments for high values of s. No standard form of loss-averse preferences predicts the crossover pattern associated with random choice.

The main result of this paper is that the crossover pattern is observed in the data (Result 1). Moreover, it is shown that subjects whose behavior is inconsistent with stable, increasing preferences cannot account for the crossover pattern, while subjects showing evidence of randomness can (Result 2). This suggests that random choice provides a better explanation of choice bracketing than stable preferences of any form, including loss-averse ones.

2 Disentangling the Loss-averse Functional Form from Random Choice

BP2010 argue that random choice can sometimes predict the same aggregate pattern of behavior as the loss-averse functional form. While their argument is built around

[4]Reasonable assumptions on reference points reduce the predictions of loss aversion to those of risk aversion.

Gneezy and Potters (1997) (GP1997) and related studies,[5] it can be extended to other studies of myopic loss aversion, such as Thaler et al. (1997) and Benartzi and Thaler (1999), as explained in more detail below.

In GP1997, subjects decide how much to invest out of a 200 cent endowment. The investment is lost with probability 2/3 and otherwise returned with interest. Thus, given an investment about x, the DM faces a lottery that earns $200 - x$ with probability 2/3 and $200+2.5x$ with probability 1/3, with expected value $200+(1/6)x$.

In treatment H, subjects make such investment decisions one at a time, with feedback following every decision. In treatment L, they make these decisions three at a time, with the restriction that the investment is identical in each of the three decisions ($x_1 = x_2 = x_3$, where x_i is the investment in decision i). Thus, given an investment x, subjects face an investment that pays $600 - 3x$ with probability 8/27, $600 + 0.5x$ with probability 12/27, $600 + 4x$ with probability 6/27 and $600 + 7.5x$ with probability 1/27, with expected value $600 + (1/2)x$.

BP2010 focus on the following features of the GP1997 data: (1) the majority of subjects invests an intermediate amount of their endowment in both treatments; (2) the invested amount does not differ across the two treatments for these subjects; (3) few subjects make an investment of zero; (4) more subjects invest all of their endowment in treatment L than in treatment H. To explain these patters BP2010 assume a RUM where the DM's utility from bet x is given by the expected value of the bet plus a random error term ϵ:

$$U_H(x) = 200 + (1/6)x + \epsilon$$
$$U_L(x) = 600 + (1/2)x + \epsilon$$

They also assume that the DM chooses an investment amount according to the following algorithm. First, the DM compares $U_i(0)$ to $U_i(\Delta)$, where Δ is the smallest portion of the endowment the DM considers investing. If $U_i(0) > U_i(\Delta)$, the algorithm stops. Otherwise, the DM compares $U_i(\Delta)$ to $U_i(2\Delta)$, and so on.

This model explains the patterns (1)-(4) highlighted above. For instance, the probability that the DM abstains from betting is given by $1 - F(\Delta/6)$ in treatment H and $1-F(\Delta/2)$ in treatment L, where F is the c.d.f. of ϵ. Because F is increasing, the probability of abstaining from betting is greater in treatment L, as in GP1997.

This argument, however, does not rule out the role of loss aversion in generating the GP1997 data. For instance, consider an alternative explanation where utilities

[5]Several studies provide replications of GP1997 using the same parameters as GP1997 but different subject pools and, in the case of Fellner and Sutter (2009), additional experimental conditions. Examples of these include Fellner and Sutter (2009), Haigh and List (2005), and one of the treatments in Langer and Weber (2005).

are loss-averse expected utilities with errors:[6]

$$U_H(x) = (1/3) * (2.5x) - \lambda(2/3)x + \epsilon$$
$$U_L(x) = (12/27) * (0.5x) + (6/27) * (4x) + (1/27) * (7.5x) - \lambda(3x)(8/27) + \epsilon$$

If $\lambda > 1$, this version of random choice leads to a different interpretation, as the effect of decision frequency is in part driven by loss aversion. While λ could be estimated to test the hypothesis that $\lambda > 1$, the scope of such an exercise would be limited, as its conclusions would depend on ad hoc modelling choices, such as the proposed decision algorithm, the step size Δ, which could in principle differ across the two treatments, etc. Moreover, a different model of random choice that allows for loss aversion might in principle lead to different conclusions about the relative importance of randomness and loss aversion in generating the observed results. Thus, while the exercise in BP2010 is useful in pointing out an alternative explanation of the GP1997 data, a new experiment is necessary to isolating the impact of randomness in subjects' responses to changing evaluation periods.

The same holds for other experiments on myopic loss aversion. In Thaler et al. (1997), subjects choose how to allocate a portfolio of 100 shares between two investments. Fund A as mean return of 0.25 percent per period and a standard deviation of 0.177, while Fund B has a mean return of 1 percent per period with a standard deviation of 3.54 percent. The experiment was designed to simulate monthly and yearly investments, with monthly investments corresponding to a high frequency feedback condition in GP1997, and yearly ones corresponding to a low frequency of feedback one. Subjects made 200 decisions in the monthly condition and 25 decisions in the yearly one, with each decision binding for eight periods in the latter case.

As in the preceding discussion, assume that the utility associated with a prospect is given by the expected utility of a prospect plus a random error. I.e.,

$$U_{monthly}(A) = 0.25 + \epsilon, \quad U_{monthly}(B) = 0.177 + \epsilon,$$
$$U_{yearly}(A) = 2 + \epsilon, \quad U_{yearly}(B) = 1.416 + \epsilon$$

It follows that the probability of A being chosen in the monthly condition is given by $F(0.073)$, while that in the yearly condition is $F(0.584)$. Risk-neutral random choice predicts the same behavioral pattern of greater willingness to take risks as loss aversion.

To take another example, Benartzi and Thaler (1999) conduct several separate studies. Study 1 provides an experimental test of Samuelson's thought experiment

[6] A reference point of 200 is assumed.

described in the introduction and finds evidence of myopic loss aversion among MBA students. Study 2 tests the myopic loss aversion hypothesis using simple binary gambles and therefore is the closest in spirit to the experiment in this paper. It is unlike it, however, in that a risk-neutral DM would find the gambles in Study 2 of Benartzi and Thaler (1999) attractive. A risk-neutral RUM predicts greater risk-aversion in a high frequency condition *for any such gamble*. Studies 3 and 4 find evidence in favor of myopic loss aversion using investment tasks similar to that in Thaler et al. (1997), and a risk-neutral RUM can accommodate the pattern predicted by loss aversion for the same reason.

Thus, while random choice can accommodate the predicted effect of longer evaluation periods in a wide range of experiments, explanation that also rely on loss aversion cannot be ruled out. In particular, it's possible that the results of these experiments are driven by subjects with loss-averse preferences that are in part random. To disentangle the role of randomness from that of loss aversion, a new experiment is necessary.

3 Experimental Design

The experiment was designed around two treatments: T1 and T3. Each decision in T1 involved a choice between a sure amount $s \in \{20, 30, 40\}$ and a lottery $L = (60,\ 0.5;\ 0,\ 0.5)$ that paid 60 with probability 50% and zero with the remaining probability. For each decision in T1, the experiment contained a decision in T3 which involved a choice between a sure amount $3s$ and three instances of lottery L.[7] Risk-neutral random choice implies the following prediction for this experiment:

PREDICTION 1 (**Random choice**). *Under random preferences, subjects are* ***more*** *willing to take risks in T3 than in T1 when* $s = 20$ *and* ***less*** *willing to take risks in T3 than in T1 when* $s = 40$.

The DM need not be risk-neutral on average for the prediction to hold. Thus, 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 a logistic distribution. It follows that:

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

[7]The design is similar to GP1997, where subjects choose how much of 200 cents to allocate to a risky investment. This choice essentially implies a decision between 200 lotteries. To reduce complexity and simplify the theoretical predictions, the present experiment is designed around binary gambles, as Benartzi and Thaler (1999).

and

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

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. 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 same prediction follows from a random parameter model. To see this, consider the choice between a single lottery L and a sure amount s. Assume that each subject has a CRRA utility function, $u(x) = \frac{x^{1-(\rho+\epsilon)}}{1-(\rho+\epsilon)}$, where ρ is fixed and ϵ follows a logistic distribution, as in Apesteguia and Ballester (2018). This implies that the probability that the lottery is chosen is given by:

$$P_H(L) = P(\rho + \epsilon \leq \rho_H(s)) = \frac{1}{1 + \exp(\rho - \rho_H(s))},$$

where $\rho_H(s) = 1 - \frac{log(2)}{log(60) - log(s)}$ is a threshold value for choosing the lottery.[8]

Now consider the aggregated choice between three lotteries and $3s$. Following similar logic, the probability that the three lotteries are chosen is given by:

$$P_L(L) = P(\rho + \epsilon \leq \rho_L(s)) = \frac{1}{1 + \exp(\rho - \rho_L(s))},$$

where $\rho_L(s)$ is a threshold value. Thus,

$$P_H(L) > P_L(L) \Leftrightarrow \rho_H(s) > \rho_L(s) \tag{2}$$

This captures the intuition that if $\rho_H(s) > \rho_L(s)$, there is a larger set of shocks inducing the subject to make the risky choice in the high frequency case. This holds if and only if the safe choice is favored under $\rho + \epsilon = \rho_H(s)$ in the low frequency decision, i.e. if and only if

$$\frac{(3s)^{1-\rho_H(s)}}{1 - \rho_H(s)} > (3/8) * \frac{60^{1-\rho_H(s)}}{1 - \rho_H(s)} + (3/8) * \frac{120^{1-\rho_H(s)}}{1 - \rho_H(s)} + (1/8) * \frac{180^{1-\rho_H(s)}}{1 - \rho_H(s)}$$

This makes it straightforward to verify that Prediction 1 holds. Intuitively, if more values of ϵ are associated with the risky choice in the high frequency condition, then

[8] This solves $\frac{1}{2} \cdot \frac{60^{1-\rho_H(s)}}{1-\rho_H(s)} = \frac{s^{1-\rho_H(s)}}{1-\rho_H(s)}$.

raising the stakes and moving to the low frequency makes even more values of ϵ associated with it. Note that the random parameter argument does not depend on expected risk preference of the individual. I.e. $E(\rho + \epsilon) = \rho$ could be less or greater than zero; the prediction holds in both cases.

Thus, in the context of the present experiment, the crossover pattern is predicted by a wide class of random choice models. A characterization of this class is beyond the scope of this paper, but presents a promising direction for future work. A theoretical exercise along these lines could be extended to arbitrary bundles of choices (i.e., more than three at a time) and arbitrary lotteries (i.e., more general choices than those between a binary lottery and a safe amount).

Because subjects incur no losses in the experiment, loss aversion per se makes no prediction. According to Kahneman and Tversky (1979), preferences are risk-averse in the domain of gains. If $u(x) = \frac{x^{1-(\rho+\epsilon)}}{1-(\rho+\epsilon)}$ with $\rho > 0$, the following prediction is implied:

PREDICTION 2 (**Risk aversion**). *Under risk-averse preferences, subjects are **more** willing to take risks in T3 than in T1.*

Another interpretation of the experimental design is that subjects are loss-averse, with the reference point equal to the sure amount (s for every decision in T1 and $3s$ for every decision in T3). In this case, the expected utility from picking the lottery in T1 is:

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

while the expected utility from picking the three lotteries in T3 is:

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

Notice that $EU(\text{Three lotteries}|3s) > 3EU(\text{Lottery}|s)$ if and only if $\lambda > 1$. Again, the model predicts the DM to be more risk-averse in T1 for any value of s. I.e., this formulation of loss aversion makes Prediction 2 unaffected.[9] This is true even if the

[9]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):

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

λ parameter is random, as long as it is always greater than one. No standard form of loss aversion predicts the crossover pattern associated with random choice.

Is the crossover pattern consistent with any form of deterministic preferences? One way to interpret the effect of randomness is that it enters at the level of individual subjects rather than individual choices. E.g.., one possibility is that every subject has preferences of the form $u(x) = \frac{x^{1-(\rho+\epsilon)}}{1-(\rho+\epsilon)}$ with a fixed ρ parameter that could be either positive or negative. In this case, Prediction 1 also follows, although crucially it is not driven by loss aversion. Because the experiment is implemented within-subjects, the design allows us to test whether the observed treatment effect is driven by randomness at the level of subjects with different fixed preferences or fluctuating preferences within subjects. As shown below, the results are consistent with the latter interpretation: subjects' preferences fluctuate, and this generates the observed aggregate patterns in the data.

3.1 Implementation Details

Every subject participated in one of two treatments (T1 or T3) in the first half of the experiment and in the remaining treatment in the second half, without knowing what will happen in the second half ahead of time. Every session was randomly assigned to either begin with T1 or T3, so that all subjects in a single session participated in the two treatments in the same order.

3.1.1 T1

Each subject was randomly assigned a personal winning outcome (heads or tails) in the beginning of the session. In any given round, after every subject in the session made his or her decision, the researcher flipped a coin, announced the outcome, asked one of the participants to verify it, and entered it into this computer. If any subject chose the lottery and the outcome of the coin flip matched his or her personal winning outcome, 60 pesos were added to the subject's earnings for the decision. If the subject chose the lottery and the outcome of the coin flip did not match his or her personal winning outcome, nothing was added. If the subject chose the certain amount, the certain amount was added.

One practice decision was made with a sure amount of 30 pesos, after which six decisions were made with real monetary incentives. Every subject made two

Then the risky option is chosen in T1 if and only if $\left(\frac{X-s}{s}\right)^{\alpha} > \lambda$, and in T3 if and only if $\frac{(3X-3s)^{\alpha}+3(2X-3s)^{\alpha}}{(3s)^{\alpha}+3(3s-X)^{\alpha}} > \lambda$. For any $\sigma \in (0,1]$, the threshold remains greater in T3 than in T1 when $s = 20$ and below one in both treatments when $s = 40$.

incentivized decisions with each of the following sure amounts: 20, 30, and 40.[10] The subjects did not know what certain amounts they will face before making their decisions. They were informed that only one of the decisions in T1 will count for their take-home earnings, and that they would not find out which decision counts until the end of the experiment.

3.1.2 T3

In any round, after every subject made their decision, the researcher flipped three coins, announced and verified the outcomes, and entered them into his computer.[11] If a subject chose the certain amount, the certain amount was added to the subject's earnings. If a subject chose the three lotteries, he or she was paid 60 pesos 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 120 pesos.

After making one practice decision with a sure amount of 90 pesos, every subject made two incentivized decisions with each of the following sure amounts: 60, 90, and 120. The subjects did not know what certain amounts they will face before making their decisions and were informed that only one of the decisions in T3 will count for their earnings.

Overall, each subject made twelve decisions across the two treatments.

4 Results

Data was collected from 100 subjects in May 2018 at Instituto Tecnológico Autónomo de México (ITAM) in Mexico City in four sessions. Average earnings were approximately 206.7 (including the 60 peso show-up fee), and each session lasted around 45 minutes.

Figure 1 shows the probability of making the safe choice for each value of s and for each treatment. The observed pattern of results is consistent with Prediction 1: safe decisions were more likely in T1 when $s = 20$ and more likely in T3 when $s = 40$. A logit regression with subject fixed effects shows that both effects are significant ($P = 0.001$ and $P < 0.05$, respectively; see Table 1). This result is highlighted below.

[10]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.

[11]The three outcomes were announced together after all three coin flips were made, as in GP1997. This was done to facilitate the evaluation of the three lotteries in an aggregated way.

Result 1 (**Crossover pattern**). *Consistent with random preferences, subjects are* ***more*** *willing to take risks in T3 than in T1 when* $s = 20$ *and* ***less*** *willing to take risks in T3 than in T1 when* $s = 40$.

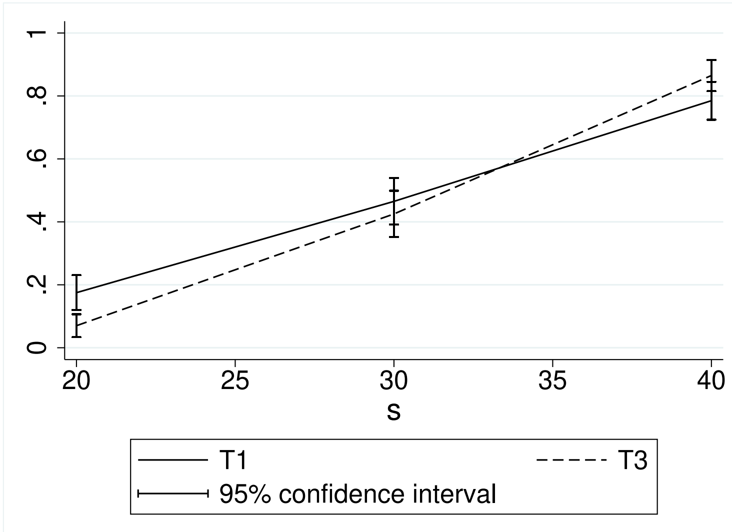

Figure 1: **The probability of making the safe choice in treatments T1 and T3.** The variable s represents the safe amount in each decision in T1 and the safe amount divided by three in T3. When $s = 20$, subjects were more risk-averse in T1, but when $s = 40$ the result was reversed.

Let $N_{Ti}(s)$ denote the number of safe choices in treatment Ti for a given value of s. For each Ti, the upper bound on the percentage of subjects with stable, increasing preferences can be obtained as the number of subjects for which $N_{Ti}(20) \leq N_{Ti}(30) \leq N_{Ti}(40)$ and $N_{Ti}(s) = 1$ for at most one value of s. Note that this definition of stability in preferences is quite liberal, in that it allows for choice inconstencies. This is done because, at least in principle, a single choice inconsistency within a treatment might be driven by indifference between the two options. In practice, the proportion of subjects with stable preferences is likely to be well below the upper bound.

Using the definition above, 71% of the subjects in T1 and 88% of the subjects in T3 exhibit stable choices, while 65% show stable choices in both treatments. The second column of Table 1 repeats the analysis in the first column focusing on subjects whose behavior is consistent with stable preferences throughout the experiment ($N = 65$). The observed pattern differs from that in the first column. First, no significant treatment effect is observed when $s = 40$ ($P = 0.539$), and the difference between the two probabilities is close to zero in magnitude. Moreover the probabilities of making the safe choice in both treatments are closer to zero when $s = 20$ (9% in T1 and 1% in T3) and closer to one when $s = 40$ (92% in T1 and 94% in T3). The overall pattern suggests approximate risk-neutrality.

The third column of Table 1 repeats the same analysis focusing on subjects whose behavior is *not* consistent with stable preferences. The overall pattern is similar to that in Table 1 (a). Thus, despite the small sample size ($N = 35$), more risk-taking is observed in T3 if $s = 20$ and in T1 if $s = 40$ (both $P < 0.05$).

	All subjects $N = 100$	Stable, def. 1 $N = 65$	Unstable, def. 1 $N = 35$	Stable, def. 2 $N = 20$	Unstable, def. 2 $N = 80$
$s = 20$	-0.105****	-0.0791***	-0.157**	-	-0.0938**
	(0.0315)	(0.0285)	(0.0718)	-	(0.0372)
$s = 30$	-0.0399	-0.0576	0	0.00812	-0.0625
	(0.0458)	(0.0443)	(0.0834)	(0.0138)	(0.0529)
$s = 40$	0.0801**	0.0165	0.200**	0.0994	0.0875**
	(0.0360)	(0.0268)	(0.0797)	(0.0978)	(0.0433)
Observations	1200	780	420	200	960

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, **** $p < 0.001$

Table 1: **The marginal effect of being in T3 as opposed to T1 on making the safe choice.** The variable s represents the safe amount in each decision in T1 and the safe amount divided by three in T3. **: $P < 0.05$, ***: $P < 0.01$, ****: $P < 0.001$ according to a fixed effects logit model.

It is unlikely that every subject who made one safe choice and one risky choice for a given treatment and value of s has stable preferences with indifference exactly at the specified value of s. For this reason, the last two columns of Table 1 repeat the exercise of separating subjects into those with stable and unstable preferences using a more conservative definition of stability, where $N_{Ti}(20) \leq N_{Ti}(30) \leq N_{Ti}(40)$ and $N_{Ti}(s) \neq 1$ for any s. With this definition, the proportion of subjects exhibiting stable behavior across the two treatments is low (20%). As shown in the last column of Table 1, the subjects with unstable preferences exhibit the same pattern of risk-taking as all subjects considered together, which implies the following result.

Result 2 (**The crossover pattern and randomness**). *The crossover pattern is driven by subjects whose behavior is not consistent with stable preferences.*

Result 2 is stronger than the claim that Result 1 is not driven by loss or risk aversion. The definition of stable preferences above allows for risk aversion as well as risk-seeking, deterministic or stochastic reference points, etc. The data suggest that the crossover pattern observed in the data is not driven by increasing, deterministic preferences *of any form.* Far from showing the crossover pattern, behavior of subjects with deterministic preferences is close to risk-neutral.

To explore this further, note that risk neutrality predicts $N_{Ti}(20) = 0$, $N_{Ti}(30) \in \{0, 1, 2\}$, and $N_{Ti}(40) = 2$ for both Ti. The choices of 54% in T1 and 73% of subjects in T3 are consistent with risk neutrality. Overall, the results are consistent with preferences that are risk-neutral on average but subject to random error, which as predicted has less of an infuence in T3 than in T1. Such behavior can be modeled using both a random utility and a random parameter model.

5 Discussion

Typically, economists study lotteries that a risk-neutral DM would find attractive in order to estimate the extent to which the DM is willing to be compensated for risk. For the purposes of this experiment, however, lotteries that a risk-neutral DM would find unattractive are necessary to identify the effect of randomness. If only "attractive" lotteries were used, random choice would make the same predictions as risk-averse preferences, making the theoretical predictions of the two theories difficult to disentangle.

Moreover, gambling behavior is commonly observed in real life, and studying the forces behind it has more than just academic interest. Haisley et al. (2008) study the effect of choice bracketing on real-life lotteries and find an effect similar to that reported for high-s lotteries in the present paper. That paper, however, does not make a connection between its observed results and random choice, while this paper provides a unified argument for the effect observed in the literature. Moreover, while a risk-neutral decision maker would choose an unattractive lottery with probability zero, which largely happens in the experiment, attractive lotteries are chosen in the experiment with probability close to one. Attractive and unattractive lotteries are treated symmetrically by the experimental design.

Several papers in the literature on elicitation of risk preferences, including Holt and Laury (2002) study the effect of raising stakes in lottery choices. In the present paper, decisions in T3 have higher stakes than those in T1, and the finding that a change in the stakes leads to a change in behavior is consistent with Holt and Laury (2002). On the other hand, Holt and Laury (2002) does not explore the effect of choice bracketing on behavior. Unlike Holt and Laury (2002), the experiment in this paper provide a first step toward a unified explanation of the effect of changing evaluation periods that is rooted in random choice, as opposed to specific functional forms.

Read et al. (1999) argue that "broad bracketing allows people to take into account all the consequences of their actions, it generally leads to choices that yield higher utility." Seen in this light, the result that broad bracketing might lead to either more or less risk-taking, depending on what decision is more likely to be associated with higher utility, is not surprising. Haisley et al. (2008), for instance, show that when making the decision to play a real-life lottery, subjects show myopic loss seeing, i.e. a smaller willingness to take risks when the decisions are aggregated. While a connection between myopic loss aversion and stochastic choice has previously been made in BP2010, no prior study provided an experimental test of a random choice model in the context of aggregated lottery decisions.

While the present paper focuses on the effect of deciding in blocks, the basic idea of exploring the implications of random choice for behavioral theories can be extended to other domains. Wilcox (2017) argues that random choice might be wrongly interpreted as probability weighting function. Tversky (1969) makes a connection between random choice and violations of transitivity, while Regenwetter et al. (2011) write 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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