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Diminishing marginal myopic loss aversion: A stress test on investment games experiments ☆

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ABSTRACT

We measure the marginal effects of two crucial dimensions of the Investment Game design of Gneezy and Potters (1997, GP97) and its replications: *time frequency* and *time horizon*. To this aim, we randomize between subjects five different time frequencies: 1 round ("High Frequency" in GP97), 3 rounds ("Low Frequency"), but also 6, 9 and 12 rounds. As for time horizon, we compare the baseline GP97 horizon (9 rounds) with smaller (3 and 6 rounds), but also higher (12 rounds) alternatives. We find that, holding the time horizon constant, subjects invest more when they evaluate their investments less frequently, but this result is significant only when time horizon is sufficiently long. We also find that lower frequencies increase the marginal investment at a decreasing rate. As for time horizon, we find that, holding time frequency constant, the higher the horizon, the lower the investment (although, as in the previous case, investment lowers at a decreasing rate). Our reduced form results also show that subjects' behavior is sensitive to the endowment stock provided along the experiment, independently of time frequency.

1. Introduction

Myopic Loss Aversion (MLA hereafter, Benartzi and Thaler, 1995) is one of the prominent theoretical conjectures arising from Behavioral Economics. It nicely combines two fundamentals of the behavioral approach to individual decision making: loss aversion (Kahneman and Tversky, 1979) and mental accounting (Kahneman and Tversky, 1984; Thaler 1985). According to MLA, investors take more risk when they evaluate their portfolios less frequently.

Without any doubt, the popularity of MLA within and beyond the boundaries of Behavioral Economics also comes from the convincing evidence provided by Gneezy and Potters' (1997, GP97) experiment, a classic in the field. GP97 presents a simple investment game in which subjects face a sequence of 9 iid lotteries. Each one of these lotteries gives a probability of $p = 1/3$ of winning $\alpha = 2.5$ times the amount invested, and a probability of 2/3 of losing it. Two alternative treatments are distributed between subjects: in the High Frequency (HF) treatment, subjects make their investment decision at each round after receiving feed-back on the outcome of the previous investment decision. By contrast, in the Low Frequency

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(LF) treatment subjects make their decision every 3 rounds, after receiving feed-back on the last sequence of 3 investment rounds. As it turns out, this design feature has an important impact on risk-taking behavior: consistently with MLA, subjects invest some 17% more in the LF treatment (67.6% of the total endowment) rather than in the HF treatment (50.6%).

Along the years, GP97 experimental design has become a classic and has been replicated by various authors who have consistently confirmed the MLA conjecture (see, among others, Haigh and List 2005, Bellemare et al. 2005, Sutter 2007, Fellner and Sutter 2009, Eriksen and Kvaloy 2010, Iturbe-Ormaetxe et al. 2016, 2019). All these experiments replicate GP97 parametrization *exactly*, namely, *(i) a time horizon* of 9 rounds, *(ii)* two *time frequencies* of 1 ("High", HF) and 3 ("Low", LF) and the basic parameters of the one-round lottery (investment return and winning probability).[1] In this respect, the experimental evidence so far lacks of "stress tests" of the GP97 design, exploring the behavioral properties of investment game experiments outside GP97 parametrization, with specific reference to time frequencies and time horizon.[2]

Designing one of such stress tests is the main purpose of this paper. More specifically, our objective is twofold. First, we aim at providing a robustness check by randomizing between subjects 5 different time frequencies: 1 round ("F1"), 3 rounds ("F3") but also 6, 9 and 12 rounds ("F6", "F9" and "F12", respectively). To implement this, we also need to randomize across different time horizons of the investment game. Specifically, we contrast the baseline GP97 horizon (9 rounds, "H9") with smaller (3 and 6 rounds: "H3" and "H6", respectively) and higher (12 rounds, "H12") alternatives. These extensions also provide valuable information on both frequency and horizon effects. To the best of our knowledge, randomizing time horizons in a GP97 experimental environment is a novel contribution of this paper. This allows us to test a key component of MLA, namely, *myopia.* In fact, since myopia assumes that each investment decision is taken independently (i.e., with no links with past and/or future decisions), the number of investment rounds (which also affects the cumulative endowment at subjects' disposal within the experiment) should not matter.

We shall summarize here our main findings. As for the frequency dimension, we find that when the time horizon is "short" (H3 or H6), frequency effects are relatively small. By contrast, when time horizon is "long" (H9 or H12) subjects invest more in the F3 treatments with respect to the F1 treatments (this is the result GP97 and its replications are best known for). However, this frequency effect is reduced when we move from F3 to even higher frequencies. Here we see that investment increases at a slower pace, if it does not increase at all. As for the horizon dimension, we find the general result that, holding frequency constant, the longer is the horizon, the lower the investment. This -novel, to our knowledge- stylized fact is at odd not only with MLA (as we noticed earlier) but also with standard models of Expected Utility (take, e.g. the CRRA version of Mossin, 1968), by which a longer horizon would call for higher investment due to higher asset integration. Time horizon effects have been studied -using binary lotteries similar to those proposed by Samuelson (1963), Benartzi and Thaler (1999) and Klos et al. (2005). In both studies one of the results related to ours is that, when subjects have to estimate the probability of a loss for a lottery with multiple repetitions, they overestimate it by a wide margin. Although they understand that such loss probability is decreasing in the experimental horizon (see Fig. 4 below), this measurement error gets bigger as the horizon gets larger. This, translated in our decision frame, may lower average investment, compared to a situation in which such loss probabilities would have been identified correctly.[3]

The remainder of this paper is organized as follows. Section 2 lays out the design of our experiment, in which we randomize between subjects various time frequency and time horizon conditions, besides GP97 original parametrization (still maintaining GP97 original lottery parameters, both in terms of winning probabilities and investment returns). Section 3 reports some descriptive statistics of our experimental evidence. Specifically, we confirm, once again, the main findings of GP97 and their replications: subjects' willingness to invest is increased when frequency of decision is reduced. However, our evidence also highlights the fact that time horizon needs to be sufficiently long for this effect to be noticeable and that, for even longer horizons, this frequency effect gets weaker. As for the time horizon (Section 3.2), we find that, holding time frequency constant, the higher the horizon, the lower is the investment (although, as in the previous case, investment lowers at a decreasing rate). Section 4 complements our descriptive analysis with some reduced form tobit regressions in which we look for (and find) nonlinearities in the relations between investment and frequency/horizon effects. In Section 5 we discuss about the relation between our stylized facts and the underlying design of GP97 investment game experiments, with specific reference to the current accumulated stock of experimental capital and expectations of future returns (proxied by the endowment flow available in future investment rounds). As Table 3 clearly shows, dependence of investment on time horizon hides a stronger dependence of investment on both accumulated and perspective capital, suggesting that investors' loss aversion may lower their risk taking behavior as they accumulate (or expect to accumulate) enough experimental capital compared to some latent subjective referent upon which they condition their investment decisions. Finally, Section 6 con-

[1] As for the time horizon, the only exceptions are Hopfensitz and Wranik (2008) and Fellner and Sutter (2009) who implement a 15 and 18 period horizon, respectively. Consistently with the evidence reported here (see Table A.1 in Appendix A), they find that the average investment decreases in both treatments (33.3 in HF and 56.6 in LF compared with 50.6 and 67.6 in GP97).

[2] Other design features of GP97 have been the object of interest in the context of replication. For example, Bellemare et al (2005) and Fellner and Sutter (2009) test whether higher investment in the LF treatment is due to lower investment flexibility and/or information feedback. Their findings are not conclusive: while Bellemare et al (2005) find that is feedback rather than flexibility what matters most to yield higher investment in the LF treatment, Fellner and Sutter (2009) find that both design features seem to influence higher investment in the LF frame in the same direction.

[3] With an investment decision frame similar to GP97, Klos (2004) compares two time horizons, H1 and H2, when subjects have the chance to revise their investment decision after each period (i.e., under F1). He finds no significant difference in average investment across horizons in this case.

Table 1
Treatment random assignment (number of subjects for each treatment between brackets). Cells highlighted in light gray (H9-F1 and H9-F3) correspond to the parametrization of GP97 and its replications. Cells highlighted in dark gray correspond to treatments that are unfeasible by design (either because F (frequency) is higher than H (horizon), or because H is not a multiple of F.

H\F	F1	F3	F6	F9	F12	Tot.
H3	H3-F1 (43)	H3-F3 (36)				79
H6	H6-F1 (21)	H6-F3 (22)	H6-F6 (24)			67
H9	H9-F1 (24)	H9-F3 (24)		H9-F9 (24)		72
H12	H12-F1 (23)	H12-F3 (23)	H12-F6 (19)		H12-F12 (23)	88
Tot.	111	105	43	24	23	**306**

cludes, followed by two appendices containing additional statistical evidence, proofs (Appendix A) and the experimental instructions (Appendix B).

2. Methods and procedures

Fourteen experimental sessions were conducted at the Laboratory of Theoretical and Experimental Economics (LaTEx) at the Universidad de Alicante, involving a total of 306 participants, 154 males and 152 females. Our experimental design includes 12 between-subject treatments, as sketched in Table 1. All treatments follow closely some of the features of GP97 original design. For each investment round, subjects are given an endowment of 100 eurocents. They have to decide the amount, $x \in [0, 100]$, they wish to invest in a lottery, $L(x)$, whose payoffs are $100 + \alpha x$ or $100 - x$, with probability p or 1-p, respectively. In GP97 (and most of its replications) α and p are set equal to 5/2 and 1/3 as to make the expected return of the investment, $r(x) = x((1 + \alpha)p - 1) = \frac{x}{6}$, which is strictly increasing in the quantity invested, x. Financial rewards correspond to the cumulative monetary payoffs in the experiment.

Our experimental treatments randomize -between subjects- the basic GP97 layout across the time frequency and time horizon dimensions. As for time frequency, in all F1 treatments (frequency=1), subjects play rounds one by one. They invest in each round, then the lottery is carried out and they know the outcome and invest for the next round. In F3 treatments subjects invest for three consecutive plays of the same lottery. Then, after the 3 iid lotteries are carried out and subjects know the outcomes, they have to decide the investment for the following three rounds. In F6 treatments subjects take one decision for every 6 successive rounds, in F9 one decision for the 9 rounds and in F12 one decision for the 12 rounds. As for time horizon, we complement the standard GP97 layout (9 periods) with shorter (3 and 6 periods, H3 and H6, respectively) and longer (12 periods, H12) alternative.[4]

As for time frequency, in all F1 treatments (frequency=1), subjects play rounds one by one. They invest in each round, then the lottery is carried out and they know the outcome and invest for the next round. In F3 treatments subjects invest for three consecutive plays of the same lottery. Then, after the 3 iid lotteries are carried out and subjects know the outcomes, they have to decide the investment for the following three rounds. In F6 treatments subjects take one decision for every 6 successive rounds, in F9 one decision for the 9 rounds and in F12 one decision for the 12 rounds.

The two highlighted cells of Table 1 correspond to GP97 original treatments ("HF" vs "LF", in GP97 terminology). In addition, we also explore 10 additional treatment configurations in which time horizon (time frequency) varies from 3 to 12 (1 to 12), respectively.

3. Descriptive statistics

3.1. Frequency effects

In our descriptive analysis, we shall look at the frequency dimension first. Fig. 1 tracks average investment across treatments by time horizon. In the treatments with a time horizon of 3 or 6 rounds (H3 or H6, respectively), we find no sig-

[4] Clearly, randomization across time frequencies and horizons cannot be independent across dimensions, but it is constrained by the fact that, for some (F,H) pair, either F may be higher than H, or because H may not a multiple of F (these situations correspond to the dark grey cells of Table 1). In this respect, the term "randomization" has to be interpreted with respect to the fact that, within the set of feasible (F,H) pairs, the assignment of a subject to a specific treatment is completely random.

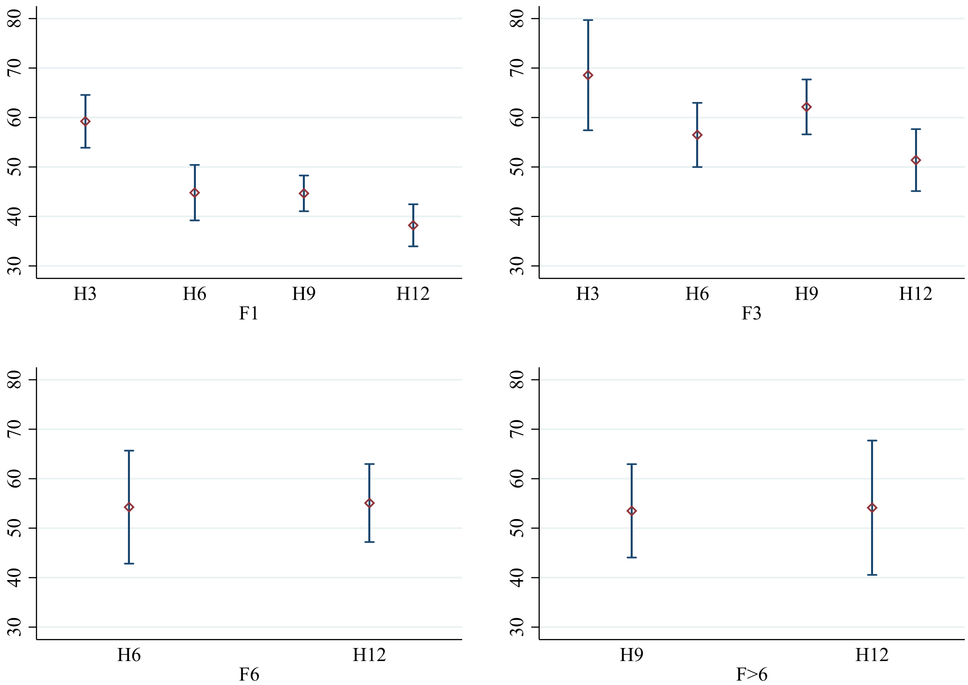

Fig. 1. Distribution of average investment by time frequencies (diamonds track average investment per treatment, bars identify 95% confidence intervals).

nificant differences in average investment between frequencies F1 and F3. Mann-Whitney (MW) non-parametric statistics cannot reject the nulls H_0: H3-F1 = H3-F3 ($p = 0.13$) and H_0: H6-F1 = H6-F3 ($p = 0.32$).

In contrast, we do find differences between F1 and F3 in treatments with horizons of with 9 and 12 rounds (H9 and H12).[5] Both MW tests, in this case, reject the null at 5% confidence. However, when we compare F1 with F6, F9 or F12 in treatments with horizons H9 and H12, we can only reject at 1% the null for treatments H12-F1 and H12-F6. In all other cases, we can only reject the null at 10% confidence for treatments H9-F1 and H9-F9 ($p = 0.0560$) and for H12-F1 and H12-F12 ($p = 0.0728$). That is, in the extreme cases when subjects evaluate their investments only once average investments increase but the difference is only weakly significant.

To summarize, subjects invest more when they take fewer decisions, but this is not true for the extreme situations when they take only one decision for the total investment. In addition, keeping time horizon constant, marginal investment increases with our frequency variable (i.e., when the frequency of decisions decreases) at a decreasing rate, to become negative when time horizon is long enough.

3.2. Horizon effects

Fig. 2 recompiles the same information as in Fig. 1 by reporting mean investments per treatment keeping frequency constant and varying time horizon. As Fig. 2 shows, holding time frequency constant, aggregate investments decrease with time horizon at a decreasing rate: being the strongest when horizon moves from 3 to 6 rounds.

4. Reduced form regressions

Our descriptive analysis offers two clear testable conjectures that we now look in more detail. The first one relates to frequency effects. This is the core of the MLA hypothesis: once we reduce the number of decisions (i.e., our frequency variable increases) we should expect investment to grow. In this respect, the descriptive analysis of Section 3.1 confirms this conjecture but, at the same time, also highlights that marginal investment grows at a decreasing rate (to become negative at times). In other words, descriptive data seem to show a non-linear relationship between frequency of decisions and investment behavior. The second conjecture is -to the best of our knowledge- novel and relates to the existence of a *horizon*

[5] Treatments H9-F1 and H9-F3 replicates the GP97's experiment with the same number of periods. GP97 obtain an average investment of 50.5% in HF and 67.4% in LF treatments. This is much in line with our results since we find 44.67% in HF and 62.14 % in LF for the same time horizon (see Table A.1 in the Appendix).

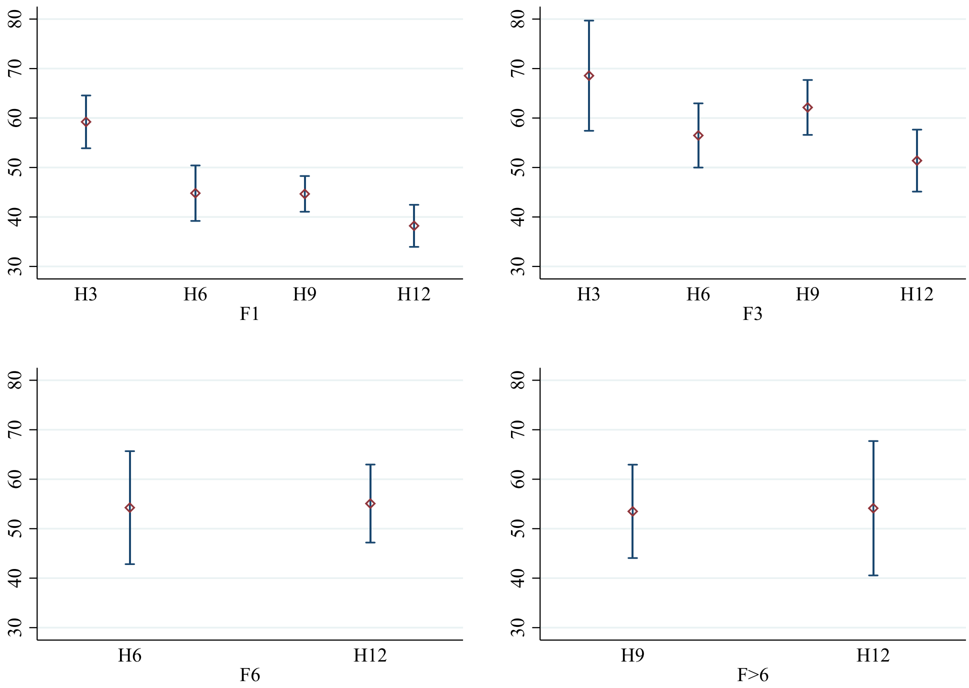

Fig. 2. Distribution of average investment by time horizon. Diamonds track average investment per treatment; bars identify 95% confidence intervals.

effect. What the evidence of Fig. 2 seems to suggest is that when we increase the time horizon of the investment game, average investment decreases. Again, Fig. 2 seems also to suggest that investment decreases at a decreasing rate.

In Table 2 we test our preliminary conjectures by running some Tobit regressions in which individual investment decisions are regressed against our treatment variables (F and H) together with their corresponding variables squared (F^2 and H^2, respectively). In regression (1) we use a cross-section of our dataset averaging investment for each individual participant; in regression (2) we use a cross-section of subjects' first investment decision; in regressions (3–6) we run random-effect tobit regressions of the individual investment decisions. Regression (3) has the same structure as (1); regression (4) also include period dummies in the set of covariates. Finally, in regression 5 (6), we control for possible dynamic trends in the data, including in the set of the covariates the investment period (squared), respectively.

As Table 2 shows, our descriptive analysis finds empirical validation in that the coefficients of F and H^2 (H and F^2) are always positive (negative), respectively, while first (second) order effects are always significant at 5% (10%) confidence, respectively. Comparing regressions (1) and (2), we see that first and second order effect are even stronger when we look only at subjects' first decisions, which cannot be affected by any prior risk realization. Finally, we also notice from regressions (5) and (6) that dynamic effects are weak, if not insignificant (see also Fig. 5 below).

Another possible way to deal with non-linearities is to consider the interactions between time frequency and time horizon treatment variables. Fig. 3 plots the average marginal effects of a random-effect Tobit regression in which individual investment is regressed against the corresponding time frequency, time horizon, and the interaction between the two covariates.[6] As Fig. 3 shows, the only significant movement of both marginal effects is for the first two values of F and H, respectively. Subsequently, no other significant change is detected.

5. Discussion

This section conjectures on some possible explanations for our "diminishing sensitivity" results, together with auxiliary interesting stylized facts uncovered by our augmented experimental design.

[6] Table A.2 in Appendix A reports the full estimated coefficients.

Table 2
Tobit regressions (I).

VARS	(1)	(2)	(3)	(4)	(5)	(6)
F	5.003**	6.117***	5.662**	6.940***	5.936**	6.188***
	(1.956)	(2.223)	(2.362)	(2.464)	(2.368)	(2.375)
F^2	−0.324**	−0.368**	−0.374*	−0.437**	−0.374*	−0.382*
	(0.161)	(0.183)	(0.201)	(0.206)	(0.201)	(0.201)
H	−8.566***	−11.02***	−8.331**	−8.775**	−8.609**	−9.106***
	(2.952)	(3.355)	(3.492)	(3.535)	(3.496)	(3.514)
H^2	0.436**	0.565**	0.405*	0.418*	0.405*	0.433*
	(0.193)	(0.2189)	(0.226)	(0.228)	(0.226)	(0.227)
per					0.562	2.058*
					(0.356)	(1.191)
per^2						−0.137
						(0.104)
const.	79.72***	84.50***	80.38***	76.99***	79.82***	78.66***
	(9.436)	(10.73)	(11.50)	(11.73)	(11.50)	(11.53)
sigma_u			28.19***	28.32***	28.21***	28.19***
			(1.817)	(1.812)	(1.816)	(1.815)
sigma_e	833.9***	1066***	28.70***	28.18***	28.63***	28.61***
	(75.94)	(102.6)	(0.856)	(0.842)	(0.855)	(0.854)
Random effects	NO	NO	YES	YES	YES	YES
Period dummies	NO	NO	NO	YES	NO	NO
Obs.	306	306	1100	1100	1100	1100
# of subjects	306	306	306	306	306	306

Robust st. err. (clustered within subjects in regr. 3–6) within parentheses.
* $p<0.1$.
** $p<0.05$.
*** $p<0.01$.

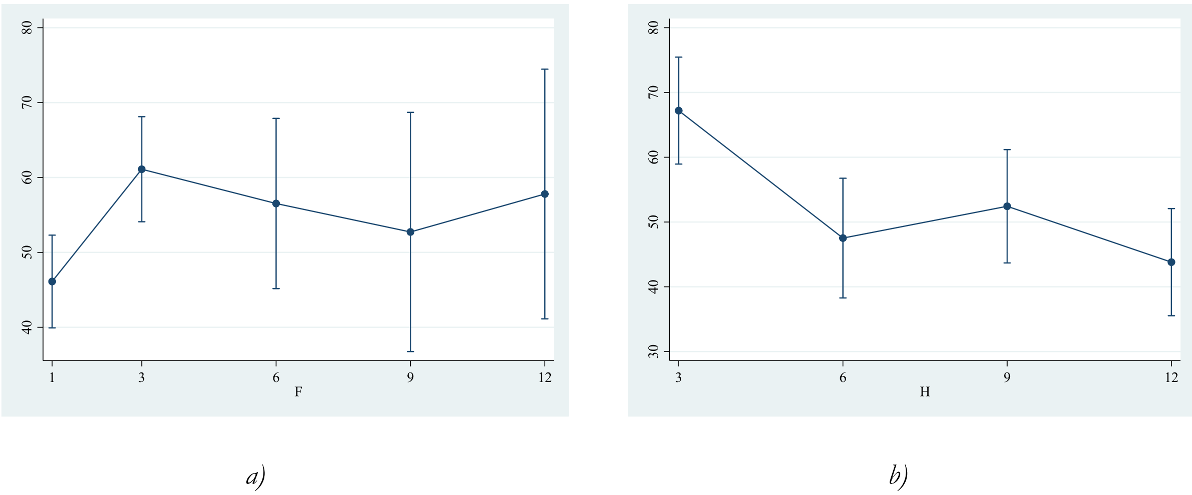

Fig. 3. Random-effect Tobit regression, marginal effects (linear prediction). Dependent Variable: individual investment. Covariates. *H, F, HxF*.

5.1. Frequency effects

As for the frequency marginal effects, we first notice that the impact of the frequency of decisions on the probability of a negative (cumulative) payoff is, on average, diminishing -not monotonically, though- as the interval between decisions increases. Remember that the classic storytelling behind the MLA rational for the GP97 results works as follows: if losses weigh more than gains, the probability of a negative (cumulative) payoff is higher in the HF treatment($\frac{2}{3} = 1 - p > (1-p)^3 = \frac{8}{27}$). In the GP97 case calculations are relatively simple because, in the LF treatment, a negative cumulative payoff can only be associated with three negative outcomes in a row. Under the same parameter setting (i.e., (α=5/2 and $p = 1/3$) Fig. 4 tracks the probability of a negative cumulative payoff as a function of the number of rounds where the same decision is kept constant, that is, the probability with which a binomial distribution of *n* iid lotteries with payoffs of α (-1) with probability of *p* (1-*p*), respectively, yields a negative cumulative outcome.

As Fig. 4 shows, this probability goes to 0 as *n* goes to infinity. This is a straightforward implication of the central limit theorem. However, this probability does not reach its limit monotonically since -at varying intervals that ultimately depend

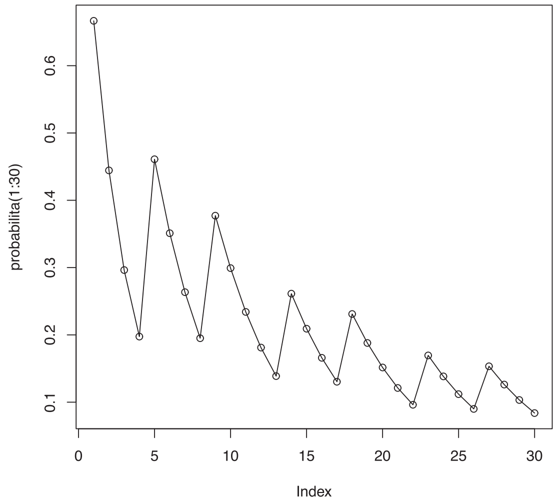

Fig. 4. Probability of a cumulative loss after n iid draws of a GP97 lottery (α=5/2 and p = 1/3).

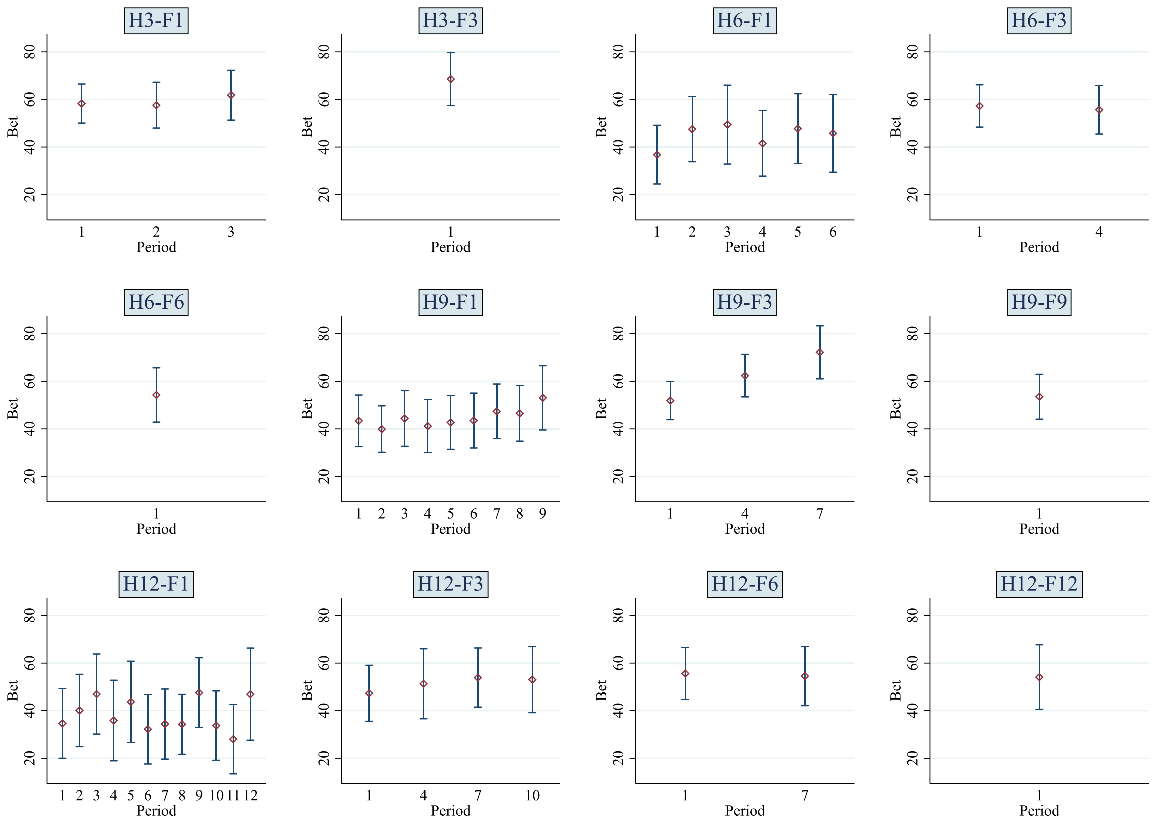

Fig. 5. Distribution of average investment by treatments and periods. Diamonds track average investment per treatment; bars identify 95% confidence intervals.

on α and p- the number of instances by which the cumulative payoff is negative (n losses, n-1 losses and 1 gain, n-2 losses and 2 gains, etc.…) increases with n. This consideration notwithstanding, as Fig. 4 clearly shows, the impact of these "peaks" on the overall dynamics vanishes as n increases. This may suggest that MLA subjects may become less sensitive to the probability of a loss as the frequency of decisions decreases, which is exactly what happens in our augmented experimental design.

Table 3
Tobit regressions (II).

VARS	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
F	5.587**	12.47**	5.908**	12.79**	5.143**	11.14*	5.164**	11.27*
	(2.348)	(6.154)	(2.353)	(6.154)	(2.317)	(5.855)	(2.317)	(5.830)
F^2	−0.371*	−1.314	−0.370*	−1.313	−0.305	−1.037	−0.304	−1.040
	(0.200)	(0.959)	(0.199)	(0.959)	(0.196)	(0.905)	(0.196)	(0.905)
H	−6.186*	−3.887	−5.676	−3.373	0.373	0.251		
	(3.567)	(4.335)	(3.575)	(4.343)	(1.033)	(1.123)		
H^2	0.398*	0.237	0.397*	0.236				
	(0.225)	(0.273)	(0.225)	(0.273)				
K_t	−0.0201***	−0.0201***						
	(0.00778)	(0.00781)						
k_t			−0.0217***	−0.0218***	−0.0218***	−0.0218***	−0.0196***	−0.0205***
			(0.00781)	(0.00784)	(0.00782)	(0.00785)	(0.00483)	(0.00541)
w_t			−0.0284***	−0.0285***	−0.0286***	−0.0286***	−0.0260***	−0.0271***
			(0.00895)	(0.00898)	(0.00896)	(0.00899)	(0.00549)	(0.00616)
cons.	80.18***	66.21***	79.50***	65.51***	62.48***	56.00***	63.40***	56.68***
	(11.43)	(13.73)	(11.43)	(13.73)	(6.127)	(8.195)	(5.580)	(7.612)
1-timers	YES	NO	YES	NO	YES	NO	YES	NO
Obs.	1100	993	1100	993	1100	993	1100	993
# id	306	199	306	199	306	199	306	199

Standard errors in parentheses.
* $p<0.1$.
** $p<0.05$.
*** $p<0.01$.

5.2. Horizon effects

The simple idea of a "horizon effect" goes at odds with that of "myopia": "*In general, narrow framing of decisions and narrow framing of outcomes tend to go together, and the combination of both tendencies defines a myopic investor*..." (Thaler et al., 1997, p. 648). In this respect, our rich randomization over frequencies and horizons seems ideal to investigate over the time-framing of our subjects' investment decisions.

Fig. 5 tracks the evolution of investment behavior across treatments and rounds. As Fig. 5 clearly shows, we cannot identify a clear dynamic trend in our data (with the exception of the LF treatment as in GP97, where average investment clearly grows over time). While investment does not seem to have a distinct dynamic pattern, we look for alternative variables that may explain our (marginally decreasing) negative horizon effect. A natural candidate to look at is the value of the portfolio, either in terms of its evolution as a function of investment decisions and lottery outcomes, but also in term of the anticipation of future endowments. This is relevant in our analysis for, at least, two reasons. First, because it directly affects the interpretation of the same concept of "myopia", and not only in the context of MLA. In fact, as we know from Mossin (1968), also for a wide class of utility functions (including, among others, CRRA) an expected utility maximizer finds optimal to treat each single-round decision myopically, that is, as if it were the last one. Individuals base each round's decision "*on that period's initial wealth and probability distribution of yields only, with the objective of maximizing expected utility of final wealth in that period while disregarding the future completely*" (Mossin, 1968, p. 223). In this sense, for standard portfolio theory investors are also myopic, in that they maximize utility over the action of the current round only. By contrast, they are not myopic in that they perform full asset integration: what they condition their current investment decision upon is the present value of their accumulated experimental income plus that of all future endowments.

In this sense, standard optimal portfolio behavior also involves *conditioning*, that is, adapting risk-taking behavior to the evolution of the present value of final portfolio (which clearly depends on the horizon of the experiment, rather than the frequency of decisions). On the other hand, dependency of investment on the portfolio value is somewhat neglected by the standard MLA rationale (see Appendix A for details).

Table 3 reports the estimated coefficients of some random-effect tobit models in which individual investment is regressed against frequency and horizon variables (as in Table 2) but also against three different proxies of the evolution of the portfolio over the experimental horizon: $k_t = 100t + \sum_{\tau<t} z_t$; $w_t = 100(H-t)$ and $K_t = k_t + w_t$. In words, k_t is the current value of the portfolio (excluding future endowments), where $z_t = \alpha x_t$ ($z_t = -x_t$) if the investment is (un)successful, respectively; w_t is the value of future endowments, and K_t is the present value of the final portfolio including future endowments not yet disposable at round t. While K_t corresponds to the expected value of "*final wealth*" upon which standard portfolio decisions are conditioned, our variables k_t and w_t split this value in its past (future) components, respectively.

To the extent to which K_t is highly correlated with H, models (1) to (8) exclude gradually H in the set of regressors. In addition, we also estimate our model both including all subjects (1-timers="YES"), but also excluding those who take only one decision throughout the experiment (treatments H3-F3, H6-F6, H9-F9 and H12-F12 see Table 1). As Table 3 shows, our results -significant negative effects of both accumulated and perspective capital on investment- are robust across all model specifications. The coefficients of k_t and w_t are similar in magnitude, although the effect of w_t is always higher (in absolute value, with the difference being significant at 10% confidence in all regressions, this indicating a marginally higher impact of accumulated experimental capital on current investment.

6. Conclusions

Diminishing marginal sensitivity is often invoked as a realistic auxiliary assumption in many behavioral domains, both within and outside standard economic theory (take, for example, the assumption of “gain and loss satiation”, one of the building blocks of Prospect Theory). Our main contribution is to highlight another domain that exhibits diminishing marginal phenomena: MLA. Both with respect to frequency and horizon effects. As for the former, we confirm GP97 main evidence with the caveat that *marginal effects are diminishing* when we further decrease the frequency of decisions. By randomizing choice frequencies, we also need to manipulate time horizons, which allows us to study the dynamics of investment game experiments along a complementary dimension. Our novel evidence highlights an intriguing stylized fact: average investment is *decreasing* in the time horizon dimension (again, with diminishing sensitivity).

Our “diminishing sensitivity” results may suggest that, when frequency/horizon are longer, subjects could be overestimating the probability of a loss (and, in consequence of that, lower their investment) as it has been observed by Benartzi and Thaler (1999) and Klos et al. (2005) in games with repetitions. Moreover, the estimates of Table 3 show a stronger dependence of investment on both accumulated and perspective capital. In a similar way the NY taxi drivers in Crawford and Meng (2011), investors’ loss aversion lowers their risk taking behavior as they accumulate (or expect to accumulate) enough capital compared to some latent referent that depends negatively (i.e., it is a substitute in the investment’s strategy) on both variables. This intriguing dependency of (both, accumulated and perspective) experimental capital and investment may prompt further “robustness checks” of the GP97 protocol beyond the scopes of this paper (for example, by manipulating subjects’ endowment in each round, keeping fixed horizon and frequency, or distributing the same aggregate endowment across different horizon/frequency pairs).

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jebo.2021.07.031.

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