

Some (Mis)facts about Myopic Loss Aversion*

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Abstract

Gneezy and Potters (1997) run an experiment to test the empirical content of Myopic Loss Aversion (MLA). They find that the attractiveness of a risky asset depends upon the investors' time horizon: consistently with MLA, individuals are more willing to take risks when they evaluate their investments less frequently. This paper shows that these experimental findings can be easily accommodated by the most standard version of Expected Utility Theory, namely a CRRA specification. Additionally, we use four different datasets to estimate a CRRA model and two alternative MLA versions, together with various mixture specifications of the two competing models. Our econometric exercise finds little evidence of subjects' loss aversion, which provides empirical ground for our theoretical claim.

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1 Introduction

Benartzi and Thaler (1995) propose Myopic Loss Aversion (MLA hereafter) as an explanation to the so-called *equity premium puzzle*. This term was coined by Mehra and Prescott (1985), when they estimate that investors should have relative risk aversion coefficients in excess of

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30 to explain the historical risk premium. Benartzi and Thaler (1995) explain MLA by two features, *i) loss aversion* and *ii) mental accounting*. According to loss aversion (Kahneman and Tversky, 1979), individuals compute gains and losses from a *reference point*, and tend to weigh losses more than gains. Mental accounting (Thaler, 1985) refers to the implicit methods that individuals use to code their financial outcomes. Specifically, it refers to how often transactions are evaluated over time, that is, whether they are evaluated as portfolios, or individually. Benartzi and Thaler (1995) prove that MLA individuals are more willing to take risks if they evaluate the results of their investments less frequently.

Several authors have tested MLA in the lab. Thaler *et al.* (1997) find that subjects are loss averse and that, consistently with MLA, risk-taking behavior increases when information is given less frequently. Gneezy and Potters (1997, GP97 hereafter) design an experimental *Investment Game* where individuals face a sequence of nine independent and identical lotteries. Each lottery gives a probability of $\frac{1}{3}$ to win 2.5 times the amount bet, $x \in [0, W]$, and a probability of $\frac{2}{3}$ of losing it. The expected monetary payoff of the induced lottery corresponds to $\frac{1}{6}x \geq 0$, which implies that a risk neutral individual should invest the full endowment, W , at all times. In one treatment (“High Frequency”, HF) subjects play the nine rounds one by one. At the beginning of each round they have to decide how much to bet. Then, before moving to the next round, they are informed about the lottery outcome. In the other treatment (“Low Frequency”, LF) subjects play rounds *in blocks of three*. They must bet the same amount for the three lotteries in the same block. They are informed about the lottery outcomes at the end of rounds 3, 6, and 9. GP97 find that, consistently with MLA, subjects bet significantly more in the LF treatment. In particular, in the LF treatment they bet on average a 33% more than in the HF treatment.

GP97 Investment Game has become a reference in the field and has been replicated by papers such as those of Haigh and List (2005, HL05), Bellemare *et al.* (2005), Langer and Weber (2005) and Iturbe-Ormaetxe *et al.* (2014, IPT14). Figure 1 reports the bet

distributions (averages by subject, normalized on a 0-100 scale) of the four datasets object of this study, disaggregated by treatment. As Figure 1 clearly shows, all these papers confirm GP97 main finding: people invest more when their so-to-speak “myopia” is corrected.

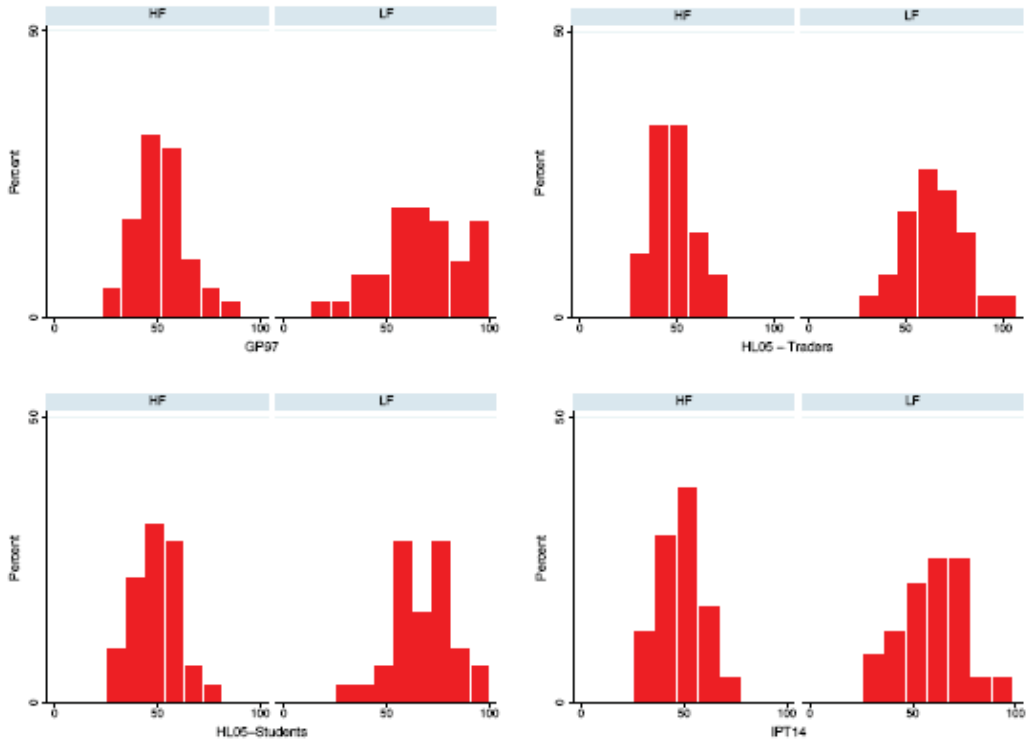


Figure 1. Bet distributions in Investment Games

The increasing popularity of MLA, together with its intuitive appeal, lies on the widespread belief that expected utility theory cannot explain the evidence of GP97-like experiments: “*At the same time, subjective expected utility theory does not predict a systematic difference in risk taking between the two treatments in our setup.*” (GP97 , p. 633).¹ The starting point of this paper is a proof that what seems to be a commonplace in the literature (that is, the inconsistency between expected utility maximization and the experimental

¹Along the same lines, HL05 claim: “*First, our findings suggest that expected utility theory may not model professional traders’ behavior well*” (p. 531). By contrast, Harrison and Rutström (2008) defend that, although a CRRA specification cannot explain the behavior observed by GP97, expected utility can explain the data using other parametrizations. In particular, they use the so-called *expo-power* utility function from Saha (1993) and Holt and Laury (2002).

evidence from these investment games) is -indeed- *false*. Instead, Proposition 1 proves that the most standard version of expected utility -namely, a Constant Relative Risk Aversion (CRRA) utility function- can explain the experimental evidence of GP97, as well as that from all its replications. Precisely, we provide a sufficient condition -namely, a lower bound for the return of the investment- that guarantees that any risk averse individual with a CRRA utility function will be willing to take more risk in the LF treatment than in the HF treatment. Under risk neutrality or risk loving, individuals bet all their endowment in both treatments.

The key assumption of Proposition 1 is that, consistently with standard utility theory, subjects' monetary endowment is added to the lottery gains and losses, so that *all monetary payoffs in the experiment are non-negative*. By contrast, MLA *sets the reference point at the initial endowment*, from which gains and losses are evaluated. This is the key difference between the two competing models: one which takes an *ex-ante* view (i.e., the endowment is also taken into account when evaluating the lottery payoffs), and another one which takes an *ex-post* view (i.e., subjects evaluate the lottery outcomes as gains and losses with respect to the value of the endowment).² This difference is crucial when comparing the two models, once we have proved that a CRRA utility function plus expected utility maximization is consistent with the experimental evidence on these investment games. All the literature following GP97 takes for granted the ex-post view, so that the “bad outcome” in the lottery is associated with a loss. By contrast, by the ex-ante view, loss aversion plays no role in these experiments: since bets are constrained not to exceed their endowments, subjects cannot -technically- “lose money” in the experiment (as in *any experiment* approved by any Ethics Committee, for that matters).³ Put it differently, the issue addressed in this paper is not

²Mas-Colell *et al.* (1995, page 170), when describing how expected utility works, rely on the so-called *consequentialist* premise: “We assume that for any alternative, only the reduced lottery over final outcomes is of relevance to the decision maker.”

³Similar considerations hold for the so-called *bankruptcy game experiments*, which mimic situation in which claimants have to negotiate on how to share a fixed loss, measured as the difference between the sum of their claims and the total value of the estate (Herrero *et al.*, 2010).

directly related with the empirical content of MLA per se, but is about whether investment game experiments are the appropriate protocols to test the external validity of MLA.

To tackle this question, we rely on a structural estimation exercise, using the original data from the experiments of GP97, HL05 and IPT14, for a total of 249 subjects. Our estimation approach is twofold. We first use our data to estimate, separately, CRRA and MLA parameters. Two alternative versions of MLA are considered: *i*) a model that -by analogy with Iturbe-Ormaetxe *et al.* (2011)- posits a piecewise linear value function with two different slopes, one for the gain and one for the loss domain, respectively; *ii*) another model that -by analogy with Tversky and Kahneman (1992)- posits loss aversion and just one curvature, the same for gains and losses.

We then compare CRRA with each one of our two MLA parametrizations by estimating binary mixture models in which: *i*) we evaluate the ex-ante probability that each individual decision is generated by either competing model, CRRA or MLA, and *ii*) the ex-post probability -conditional on the pool *i*) estimations- that each individual subject behaves according with either competing model, CRRA or MLA. Finite mixture models have become increasingly popular to test the empirical content of competing behavioral theories and seem ideal also for our empirical exercise.⁴

The remainder of this paper is organized as follows. Section 2 frames GP97 investment game as a standard expected utility maximization problem, assuming a CRRA utility function and an ex-ante reference point, i.e., integrating gains and losses with the initial endowment. As Proposition 1 shows risk averse individuals invest more in LF than in HF, provided that the expected return of the investment is sufficiently high. Section 3 reports our estimation exercise, in which we first estimate separately maximum-likelihood parameters for the two competing models, CRRA and MLA, in its two alternative versions. In this case, *our estimations cannot reject the null* of $\lambda = 1$, i.e., absence of loss aversion, except in the

⁴See Harrison and Rutström (2009) for the methodology we apply to estimate model *i*) and Conte *et al.* (2010) and -especially- Bruhin *et al.* (2010) for the methodology we apply to estimate model *ii*).

case of the piecewise linear version *i*) of MLA. These results are consistent with those of Santos-Pinto *et al.* (2014), who also find no evidence of loss aversion looking at experimental data on lotteries involving both gains and losses. Like in their case, our experimental evidence seems to suggest that subjects frame negative outcomes as “*lesser gains*”, rather than “*true losses*” (p. 7). We then look at our mixture probability estimates, where we find that the estimated probability of MLA (against CRRA) is significantly bigger than zero, but also significantly smaller than 1/2 (roughly, 1/3, depending on the model and the dataset being used), except in Model (ii), the one with loss aversion and just one curvature, where the estimated mixture probability is around 50%. Section 4 discusses our results in light of the cited literature, and its relation with the antecedents that, in our opinion, have created the misconception that this paper aims to correct. Finally, Section 5 concludes, followed by an Appendix containing supplementary theoretical results.

2 Theory

We begin by presenting in detail the GP97 investment game in a slightly more general framework. Individuals receive an endowment W and are asked how much they want to invest in a risky option. The amount invested, $x \leq W$, yields a return of $(1 + \alpha)x$, $\alpha > 0$, with probability p and is lost with probability $1 - p$. Individuals keep money not invested, $(W - x)$. The payoffs with this lottery are, therefore, $(W + \alpha x)$ with probability p and $(W - x)$ with probability $1 - p$. In GP97’s experimental parametrization, $\alpha = \frac{5}{2}$ and $p = \frac{1}{3}$.

In treatment HF subjects play nine rounds one by one. In each round they have to choose how much of their endowment W they want to bet, and then they are informed about the realization of the lottery. In the other treatment, LF, they play rounds in blocks of three. At the beginning of round 1 they choose how much of W to bet in rounds 1, 2, and 3. That is, the amount bet must be the same for each one of the three rounds. At the end of round 3 they are informed about the outcome of the three lotteries. Then, they have to decide again

at the beginning of rounds 4 and 7. Since subjects are deciding how much to bet in three identical lotteries, there are four possible outcomes, depending on whether they win in 3, 2, 1, or 0 lotteries. Let x be the amount bet in each one of the three lotteries within a block. Payoffs are $(3W + 3\alpha x)$ with p^3 , $(3W + (2\alpha - 1)x)$ with $3p^2(1 - p)$, $(3W + (\alpha - 2)x)$ with $3p(1 - p)^2$, and $(3W - 3x)$ with $(1 - p)^3$.

A risk averse individual will always choose $x = 0$ if $p \leq \frac{1}{1+\alpha}$ (or $\alpha \geq \frac{1-p}{p}$) since in that case the expected value of the bet will be less or equal than W . The expected value with n repetitions of the lottery is $nW + n(p\alpha - (1 - p))x$. Then, to have $x > 0$ we need to assume that $p > \frac{1}{1+\alpha}$ or that $\alpha > \frac{1-p}{p}$. With GP97's parametrization, we have $\frac{1}{3} = p > \frac{1}{1+\alpha} \approx 0.286$.

We now consider a subject with a standard utility function with Constant Relative Risk Aversion (CRRA):

$$u(y) = \frac{y^{1-\rho}}{1-\rho}, \quad (1)$$

where $\rho \neq 1$. When $\rho = 1$, we take $u(y) = \ln(y)$. The case $\rho = 0$ corresponds to risk neutrality.

As for the HF treatment, let $U_{HF}(x)$ denote the expected utility of the lottery induced by an investment equal to $x \in [0, W]$:

$$U_{HF}(x) = p \frac{(W + \alpha x)^{1-\rho}}{1-\rho} + (1-p) \frac{(W - x)^{1-\rho}}{1-\rho}. \quad (2)$$

We know that an individual with a CRRA utility function will always invest a fixed fraction of her endowment, W . In the case of the HF treatment and assuming risk aversion ($\rho > 0$), we can easily solve for the optimal solution. In particular, we get:

$$x_{HF}^* = \frac{1 - \Omega}{1 + \alpha\Omega} W, \quad (3)$$

where $\Omega = \left(\frac{1-p}{\alpha p}\right)^{1/\rho}$. Here $\Omega < 1$ as long as $\alpha > \frac{1-p}{p}$. It is easy to check that, under risk-neutrality or risk loving ($\rho \leq 0$), we have $x_{HF}^* = W$. We also check that, as ρ goes to infinity, x_{HF}^* goes to zero.

We now turn to the LF treatment, where the associated lottery yields expected utility $U_{LF}(x)$ equal to:

$$U_{LF}(x) = p^3 \frac{(3W + 3\alpha x)^{1-\rho}}{1-\rho} + 3p^2(1-p) \frac{(3W + (2\alpha - 1)x)^{1-\rho}}{1-\rho} + 3p(1-p)^2 \frac{(3W + (\alpha - 2)x)^{1-\rho}}{1-\rho} + (1-p)^3 \frac{(3W - 3x)^{1-\rho}}{1-\rho}. \quad (4)$$

As in the HF case, we know that a CRRA individual will invest a fixed fraction of W in each individual lottery. However, in this case, a closed-form optimal solution, x_{LF}^* , cannot be found analytically. However, since $U_{LF}(x)$ is a strictly concave function of x when $\rho > 0$, what we can do is to compute its first derivative and evaluate it at the point $x = x_{HF}^*$. If $\left. \frac{\partial U_{LF}(x)}{\partial x} \right|_{x=x_{HF}^*} > 0$ ($\left. \frac{\partial U_{LF}(x)}{\partial x} \right|_{x=x_{HF}^*} < 0$), then $x_{LF}^* > x_{HF}^*$ ($x_{LF}^* < x_{HF}^*$), respectively.

Proposition 1 Suppose that $0 < p < 1$ and $p > \frac{1}{1+\alpha}$.

- (i) If $\rho \leq 0$, then $x_{LF}^* = x_{HF}^* = W$.
- (ii) If $\rho = +\infty$, then $x_{LF}^* = x_{HF}^* = 0$.
- (iii) If $0 < \rho < +\infty$, $\rho \neq 1$, and $\alpha \geq 2$ then $0 < x_{HF}^* < x_{LF}^* < W$.
- (iv) If $\rho = 1$ (i.e., $u(y) = \ln(y)$), then $0 < x_{HF}^* < x_{LF}^* < W$.

Proof. (i) Under risk neutrality ($\rho = 0$), both $U_{HF}(x)$ and $U_{LF}(x)$ are linear increasing functions on x . The solution is to bet the whole endowment in both cases. Under risk loving ($\rho < 0$), both $U_{HF}(x)$ and $U_{LF}(x)$ are strictly convex functions. We compute $\left. \frac{\partial U_{HF}(x)}{\partial x} \right|_{x=0}$ and $\left. \frac{\partial U_{LF}(x)}{\partial x} \right|_{x=0}$ and check that these two derivatives are strictly positive because of the condition that $p > \frac{1}{1+\alpha}$. This means that both $U_{HF}(x)$ and $U_{LF}(x)$ are strictly increasing functions on the whole domain $[0, W]$ and, therefore, they reach a maximum at W .

(ii) In the HF case, it is easy to check that, as ρ goes to infinity, x_{HF}^* goes to zero. In the LF case, we can prove that, as ρ goes to infinity the first derivative of $EU_{LF}(x)$ evaluated at $x = 0$ goes to zero, meaning that the optimum is $x_{LF}^* = 0$.

(iii) It is possible to write $\left. \frac{\partial EU_{LF}(x)}{\partial x} \right|_{x=x_{HF}^*}$ as follows:

$$\begin{aligned} \left. \frac{\partial U_{LF}(x)}{\partial x} \right|_{x=x_{HF}^*} &= 3W^{-\rho}(1+\alpha)^{-\rho}B\Omega^\rho \left(3^{-\rho}p^3\alpha + 3^{-\rho}(p-1)^3\frac{1}{\Omega^\rho} + \right. \\ &\quad \left. +(1-p)p^2(2\alpha-1)\left(\frac{1}{2+\Omega}\right)^\rho + (1-p)^2p(\alpha-2)\left(\frac{1}{1+2\Omega}\right)^\rho \right), \end{aligned} \quad (5)$$

where

$$B = \left(\frac{1+\Omega\alpha}{\Omega} \right)^\rho = \frac{(1+\Omega\alpha)^\rho}{\Omega^\rho} > 0, \quad (6)$$

and $\Omega = \left(\frac{1-p}{\alpha p} \right)^{1/\rho}$. Given that $\Omega < 1$, we have that $\left(\frac{1}{2+\Omega} \right)^\rho > \left(\frac{1}{3} \right)^\rho$, and $\left(\frac{1}{1+2\Omega} \right)^\rho > \left(\frac{1}{3} \right)^\rho$.

Moreover, since $\alpha \geq 2$ we get that:

$$\begin{aligned} \left. \frac{\partial EU_{LF}(x)}{\partial x} \right|_{x=x_{HF}^*} &> 3W^{-\rho}(1+\alpha)^{-\rho}B\Omega^\rho \left(3^{-\rho}p^3\alpha + 3^{-\rho}(p-1)^3\frac{1}{\Omega^\rho} + \right. \\ &\quad \left. +(1-p)p^2(2\alpha-1)3^{-\rho} + (1-p)^2p(\alpha-2)3^{-\rho} \right) \\ &= 3^{1-\rho}W^{-\rho}(1+\alpha)^{-\rho}B\Omega^\rho p(p^2\alpha - (1-p)^2\alpha + (1-p)p(2\alpha-1) + (1-p)^2(\alpha-2)) \\ &= 3^{1-\rho}W^{-\rho}(1+\alpha)^{-\rho}B\Omega^\rho p(2-p)(p+\alpha p-1) > 0, \end{aligned} \quad (7)$$

since $p > \frac{1}{1+\alpha}$. It can be shown that $\left. \frac{\partial EU_{LF}(x)}{\partial x} \right|_{x=W} = -\infty$, which, in turn, implies $x_{LF}^* < W$.

(iv) In the case in which $u(y) = \ln(y)$, we have $x_{HF}^* = \frac{p(1+\alpha)-1}{\alpha}W$. The first derivative of $U_{LF}(x)$ is

$$\frac{\partial U_{LF}(x)}{\partial x} = 3 \left(\frac{p^3\alpha}{3W+3\alpha x} + \frac{p^2(1-p)(2\alpha-1)}{3W+(2\alpha-1)x} + \frac{p(1-p)^2(\alpha-2)}{3W+(\alpha-2)x} - \frac{(1-p)^3}{3W-3x} \right). \quad (8)$$

Evaluating at $x = x_{HF}^*$ we get

$$\left. \frac{\partial EU_{LF}(x)}{\partial x} \right|_{x=x_{HF}^*} = \frac{1}{W} \frac{2\alpha(p(1+\alpha)-1)(1-p^2+p\alpha(2-p))}{(2(1-p)+p\alpha)(1+\alpha)(1-p+2p\alpha)} > 0, \quad (9)$$

as long as $\alpha > \frac{1-p}{p}$ and $0 < p < 1$. Notice that $\left. \frac{\partial EU_{LF}(x)}{\partial x} \right|_{x=W} = -\infty$, which, in turn, implies that also for the logarithmic case, $x_{LF}^* < W$. ■

Notice that the fact that $\alpha \geq 2$ is only a sufficient condition since, in the logarithmic case, we do not need that condition to obtain the result.

If we go back to GP97's parametrization it is obvious that $\alpha = \frac{5}{2} > 2$ and $\frac{1}{3} = p > \frac{1}{1+\alpha} \approx 0.286$ and, thus, the CRRA specification prescribes that individuals should invest more in the LF treatment than in the HF treatment, as long as the coefficient of risk aversion is strictly positive. Needless to say, it is easy to prove that MLA can also accommodate these results.⁵

Figure 2 plots the optimal bets corresponding to the HF treatment (thin line) and to the LF treatment (bold line), setting $W = 100$. We see that, except for the case of risk-neutrality ($\rho = 0$), an expected utility maximizer will always choose a higher bet in the LF treatment than in the HF treatment. We also see that, consistently with Proposition 1, the difference between x_{LF}^* and x_{HF}^* goes to zero as ρ grows large.

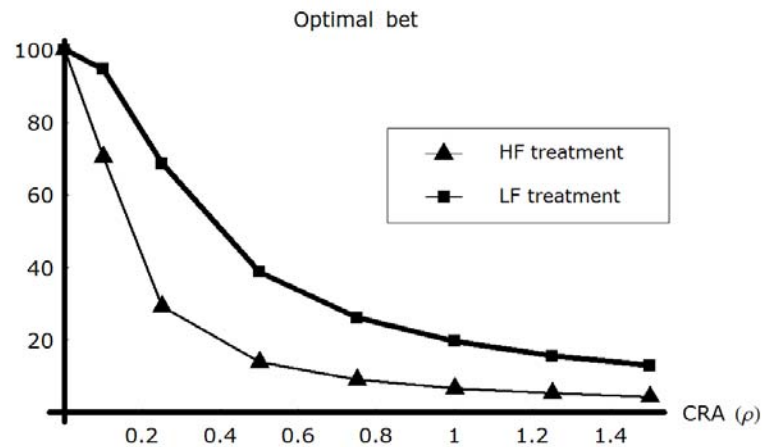


Figure 2: Optimal choice in HF and LF treatments

Although our theoretical result in Proposition 1 is for a particular parametric family of utility functions, namely the CRRA family, this is the most standard version of expected utility.⁶

⁵See the Appendix for details.

⁶Chiappori and Paiella (2011) find strong empirical support for CRRA utility functions.

3 Estimations

We briefly outline our empirical strategy in which we use an approach similar to that of Harrison and Rutström (2009) and Santos-Pinto *et al.* (2014).⁷

Our statistical model can be summarized as follows. Every individual i has to choose an amount to bet among m alternative possibilities in every round t . Her utility when choosing the alternative j in round t is:

$$V_{ijt} = U_{ijt}(\beta) + \varepsilon_{ijt}, \quad (10)$$

for $j = 1, 2, \dots, m$, $t = 1, 2, \dots, T$, and $i = 1, 2, \dots, N$. Here β represents the unknown utility parameters. The terms U_{ijt} and ε_{ijt} denote deterministic and random components of i 's utility, respectively. Depending on the structure of our theoretical model and the treatment, we shall propose different expressions for the deterministic component, U_{ijt} . According with our random utility model, individual i selects alternative j in round t with probability:

$$\begin{aligned} P_{ijt} &= \Pr[V_{ijt} \geq V_{ikt}, \text{ for all } k \neq j] = \\ &= \Pr[\varepsilon_{ikt} - \varepsilon_{ijt} \leq U_{ijt} - U_{ikt}, \text{ for all } k \neq j]. \end{aligned} \quad (11)$$

We assume that the errors ε_{ijt} are independent across choices and periods and are distributed as type I extreme values:

$$\Pr[\varepsilon \leq z] = \exp(-\exp(-z)). \quad (12)$$

Under this distributional assumption, the probability of choosing alternative j follows the conditional multinomial Logit model:

$$P_{ijt} = \frac{\exp(U_{ijt}(\beta))}{\exp(U_{i1t}(\beta)) + \exp(U_{i2t}(\beta)) + \dots + \exp(U_{imt}(\beta))}. \quad (13)$$

Assuming that the individual chooses the alternative j^* , the probability of the observed sequence of choices of individual i is:

$$P_i(\beta) = \prod_{t=1}^T P_{ij^*t}(\beta). \quad (14)$$

⁷Following Harrison and Rutström (2008), the estimations in this section assume that the objective function is linear in probabilities.

Let $L_i(\beta) = \log P_i(\beta)$ denote individual i 's contribution to the “grand” likelihood function for the entire sample, $L(\beta)$, calculated as

$$L(\beta) = \sum_{i=1}^N L_i(\beta). \quad (15)$$

We estimate first an expected utility model with the CRRA specification (1) we used to prove Proposition 1:

$$u(y) = \begin{cases} y^{1-\rho_+} \\ 1-\rho_+ \end{cases}, \quad (16)$$

where ρ_+ denotes the CRRA parameter. As for MLA, we consider two alternatives. The first one is a simple piecewise linear utility function:

$$u(y) = \begin{cases} y & y \geq 0, \\ \lambda y & y < 0, \lambda \geq 1, \end{cases} \quad (17)$$

where loss aversion implies a lower bound on λ . This parametrization has already been used for structural estimation purposes (see Iturbe-Ormaetxe *et al.*, 2011). The second model allows for a curvature of the value function, but imposes the same CRRA parameter, $\rho \in R$, in both domains, gains and losses:⁸

$$u(y) = \begin{cases} \frac{y^{1-\rho}}{1-\rho} & y \geq 0, \\ -\lambda \frac{(-y)^{1-\rho}}{1-\rho} & y < 0, \lambda \geq 1. \end{cases} \quad (18)$$

The parametrization in (18) has also been used for structural estimation purposes (take, for example, Tversky and Kahneman, 1992). Table 1 reports our estimation results, for the pool data and for each one of the four datasets separately.

Table 1. Structural estimation I: CRRA *vs* MLA

⁸Köbberling and Wakker (2005) warn that the full-fledged MLA model proposed by Benartzi and Thaler (1995), with loss aversion and two curvatures, cannot be identified. As Wakker (2008, Chapter 9) says: “..there is no clear way to define loss aversion for power utility unless the powers for gains and losses agree.”

As for Model (16), we find a moderate level of risk-aversion, with estimates of ρ_+ that go from 0.150 (HL05, Traders) to 0.192 (IPT14).⁹ In this case, we cannot reject the null that the estimated CRRA parameters are constant across datasets (neither the pairwise comparisons, nor the joint test).

As for Model (17), we first notice that the estimated values for λ are always significantly above 1.¹⁰ This seems to suggest that subjects are loss averse. Again, we find that the estimates from the four datasets are very similar. The minimum estimation we find is 1.269 and corresponds to the individuals from GP97. The maximum is 1.285 and is the one we get using IPT14 data. Also in this case, differences of the estimated λ across datasets are not significant.

Moving to Model (18), we first notice that the estimated values of ρ are higher than in Model (16). More strikingly, in the estimates of Model (18) *loss aversion, essentially, disappears* since the (imposed) lower bound on λ seems binding in all cases. Put it differently, imposing (piecewise) linearity in the value function seems to overestimate the impact of loss aversion. In this respect, our findings are analogous to those of Andersen *et al.* (2008) in the case of time preferences, where the estimated discount rate increases substantially when the value function is no longer constrained to be linear.

We now move to binary mixture models, where we follow the complementary approaches proposed by Harrison and Rutström (2009) and Santos-Pinto et al. (2014). Let π and $1-\pi$ denote the ex-ante probability that a decision in the experiment is being generated by a MLA model (17-18) or by a CRRA model (16), respectively. Thus, the grand likelihood function, $GL(\cdot)$, can be written as the probability weighted average of the conditional likelihoods of the two models, $P_i^{CRRRA}(\beta_{CRRRA})$ and $P_i^{MLA}(\beta_{MLA})$, respectively:

⁹These results are very similar to those obtained by Harrison and Rutström (2009) who estimate a CRRA function using data from a Random Lottery Pair experiment (Hey and Orme, 1994). Indeed, they propose a CRRA function $u(x) = x^r$, and get an estimate of between 0.87 and 0.89, depending on the specification.

¹⁰In Table 1, the “stars” associated with the estimated coefficients for λ report the confidence level of a t -test where the null hypothesis is $\lambda = 1$.

$$GL(\beta_{CRRA}, \beta_{MLA}, \pi) = \sum_{i=1}^N \log [P_i^{CRRA}(\beta_{CRRA})(1 - \pi) + P_i^{MLA}(\beta_{MLA})\pi], \quad (19)$$

where the full set of parameters, $\{\beta_{CRRA}, \beta_{MLA}, \pi\}$, is estimated simultaneously.

Table 2. Structural estimation II: Mixture models

Table 2 reports our estimation results. In the first panel (MLA_LIN) we confront CRRA with Model (17). In the second panel (MLA_1) we confront CRRA with Model (18), imposing $\rho_+ = \rho$ (that is, the same curvature for both models). In the third panel (MLA_2) we confront CRRA with a model as Model (18), imposing two curvatures one for gains - ρ_{ho+} , common to both models- and one for losses, ρ_{ho-} , respectively.¹¹ As Table 2 shows, the mixture probability for the MLA is below 30 % overall in models (MLA_LIN) and (MLA_2), and it is around 50 % in model (MLA_1). Put it differently, the mixture probability of CRRA is at least as those of our MLA parametrizations. However, in all models, *the estimated loss aversion is null*, this time also for the estimates of Model (MLA_LIN).

To summarize the results of our pool estimations, our data provide empirical support for both competing models, CRRA and MLA, although the estimated parameters of the latter cannot reject the null of absence of loss aversion. In this respect, our findings are consistent with those of Santos-Pintos *et al.* (2014), who also cannot reject the null of $\lambda = 1$ using mixture models involving expected utility and alternative value function parametrizations.

There is a caveat here. Model (19) derives the ex-ante mixture probability that each *individual decision* is being generated by either competing behavioral model, CRRA or MLA. We can also use Model (19) estimates to compute the ex-post probability that each individual subject's behavior is being generated by either competing model, by applying directly Bayes' Rule on each individual subject's contribution to the random utility model density function:

¹¹Since ρ_{ho+} is the same for both CRRA and MLA, it can now be identified.

$$\tau_i = \frac{\pi P_i^{MLA}(\beta_{MLA})}{(1 - \pi)P_i^{CRRRA}(\beta_{CRRRA}) + \pi P_i^{MLA}(\beta_{MLA})}. \quad (20)$$

Figure 3 shows three histograms reporting the distribution of τ_i corresponding to the three mixture models evaluated in Table 2. As Figure 3 shows, in the `MLA_LIN` case, the finite mixture model classifies subjects cleanly into either `CRRRA` (60%, approximately) or `MLA` (40% approximately), respectively. In this case, these ex-post probabilities of `MLA` type-membership are either close to 0 or close to 1, with a majority of `CRRRA`-type subjects. Similar considerations hold for `MLA_2` case where, for 95% of the population, we have $\tau_{MLA} < 0.4$, although the classification is not as clear-cut as in the `MLA_LIN` case.

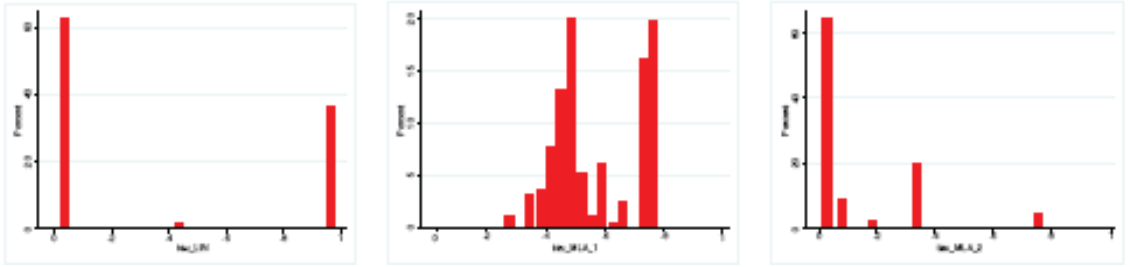


Figure 3. Posterior probability of being of `MLA` type

By analogy with the results of Table 2, the case of `MLA_1` is the one for which the ex-post mixture probability estimation fails to come up with an unambiguous classification, and many subjects exhibit a τ close to $1/2$ (also the median τ roughly equals 0.5).

To summarize, our econometric exercise nicely complements Proposition 1: not only a standard model of expected utility can explain the experimental evidence on Investment Games at least as well as one that posits `MLA`, but it is also consistent with subjects' (aggregate and individual) behavior. Our results indicate that the most standard version of an expected utility model yields the same prediction as a `MLA` model: people invest more in the `LF` treatment than in the `HF` treatment. More research is needed to disentangle whether the fact that individuals take more risks when they evaluate their investments less frequently

is due to loss aversion, risk aversion, or probably a mixture of both.

4 Discussion

Two arguments have been suggested in the literature to justify the inability of expected utility to explain the difference in behavior between the HF and the LF treatment. The first one relies on a classical example from Samuelson (1963). The second one comes from the work of Gollier *et al.* (1997). We will present both arguments in turn and will argue why they cannot be applied to GP97 experimental design.

4.1 Samuelson's offer

Paul Samuelson posed this question to a colleague:

Would you take a bet with a 50% chance of winning \$200 and a 50% chance of losing \$100?

The colleague turned down the bet, but told he was willing to accept a string of 100 such bets. Samuelson proved that this behavior is inconsistent with expected utility theory. In particular, Samuelson (1963) proved that if that bet is rejected for any wealth level between $[W - 10000, W + 20000]$, where W is the initial wealth level, any sequence of $n \leq 100$ such bets should also be rejected. The intuition of the proof is as follows. Suppose you have already played ninety nine bets and are facing bet one hundred. You should reject this bet, since it is just the original bet you had originally rejected. Now let us move one step behind. You have already played ninety eight bets and are facing bet ninety nine. By backward induction, you anticipate this is the last bet, since you know you will reject bet one hundred. Then, you should reject as well bet ninety nine. Applying the same argument, we end up proving that you will reject the first bet. Interestingly enough, this proof makes no use of Expected Utility.

The crucial assumption in Samuelson's argument is that the single lottery has to be

rejected for a large range of wealth levels. In particular, this assumption rules out CRRA utility. Take, for instance, $u(y) = \ln(y)$. It is immediate to check that an individual with this utility function will accept the single lottery as long as her initial wealth is greater than 200. In fact, Samuelson himself warned against extrapolating his theorem.

Samuelson's paper generated a large literature trying to generalize it. Pratt and Zeckhauser (1987) call a utility function "proper" if the sum of two independent undesirable gambles is inferior to either of the gambles individually. They provide sufficient conditions and separate necessary conditions on utility functions for them to be proper. Kimball (1993) proposes a stronger condition called "standard" risk aversion that is easier to characterize. If a utility function satisfies standard risk aversion, a decision maker who rejects a bet will always reject a sequence of bets. Kimball (1993) shows that necessary and sufficient conditions for a utility function to be standard are decreasing absolute risk aversion and decreasing absolute prudence. This amounts to say that $-u''(y)/u'(y)$ and $-u'''(y)/u''(y)$ are decreasing function of y .

However, Samuelson (1989) himself gave examples of utility functions for which a single bet is unacceptable, but a sufficiently long finite sequence of bets is eventually accepted. Nielsen (1985) proposed necessary and sufficient conditions for a concave function to accept a sequence of bounded good lotteries. Basically, what is needed is that the utility function cannot decrease too fast towards minus infinity.

Ross (1999) extends Nielsen's results to sequences of good bets that are independent, although not necessarily bounded or identically distributed. Finally Peköz (2002) shows that, when the decision maker has the option to quit early, a sufficiently long sequence of lotteries will always be accepted under very mild assumptions on the utility function and the individual bets.

However, we want to stress that there are two crucial aspects in Samuelson's example that are different from the experimental design in GP97:

1. Accepting 100 bets means that you are willing to play **at most** 100 bets. That is, you can decide to withdraw before arriving to bet one hundred. This is crucial to apply backward induction.
2. Each individual bet is 0-1. You do not decide how much to bet, you only decide whether to take the bet or not.

If we drop point (1), that is, if once you accept to play 100 bets, you cannot withdraw (or, as in Benartzi and Thaler (1995), you do not watch the bet being played out) it is easy to see that Expected Utility explains easily Samuelson's colleague behavior. Consider the following simple example.¹² Suppose you own wealth W and are offered at most 2 bets. Your utility function is piecewise linear with a kink (see Gollier, 2001). In particular:

$$u(y) = \begin{cases} y & y \leq W \\ W + a(y - W) & y > W. \end{cases} \quad (21)$$

This function is increasing if $a \geq 0$ and it is concave if $a \leq 1$. It is easy to check that, as long as $1/3 < a < 1/2$, $EU(1 \text{ bet}) < EU(0 \text{ bets}) < EU(2 \text{ bets})$. An individual with this utility function that maximizes Expected Utility will reject one bet. When offered two bets, he will take them.

To sum up, we believe that Samuelson's example is not appropriate for this case. Once we adapt the example to our framework by eliminating the possibility of withdrawing before the last bet, expected utility provides an easy explanation for the behavior of Samuelson's colleague.

4.2 Gollier *et al.* (1997)

Gollier *et al.* (1997) study a standard portfolio problem. There are two periods and two different economies called *flexible* and *rigid*, respectively. In the flexible economy the individual invests at the beginning of period 1, receives her returns, and then decides how much

¹²See also Tversky and Bar-Hillel (1983) for another example.

to invest in period 2. In the rigid economy, period 2 decision must be made before knowing the results of period 1. In period 1 she decides how much to invest. The decision maker has initial wealth $\$W$ to invest in two assets, a risky asset and a safe asset. The returns of the risky asset are independent and identically distributed. Wealth at the beginning of period 2 is called $\$z$. The problem is to see the effect of flexibility on exposure to risk in period 1. Period 1 investment in the risky asset in the rigid and flexible economies are denoted by α_1^r and α_1^f , respectively. The authors are interested in finding whether $\alpha_1^r < \alpha_1^f$. This can never be the case with Constant Absolute Risk Aversion utility functions, since in that case $\alpha_1^r = \alpha_1^f$. For the case of CRRA utility they prove that $\alpha_1^r \leq \alpha_1^f$ if and only if the coefficient of relative risk aversion is less or equal than one. This result has been used by GP97 to suggest that expected utility implies that individuals should take more risks in the HF treatment than in the LF treatment. In particular they claim that these authors “*..derive sufficient conditions on the utility function for this information effect to have an unambiguous sign. Translated to our setting, their results indicate that constant relative risk aversion less than 1 would induce more risk taking in Treatment H than in Treatment L. Under constant absolute risk aversion there should be no treatment effect.*” (page 636, footnote 5).

However, there is a fundamental difference between the paper by Gollier *et al.* (1997) and the experimental set up of GP97. In the model of Gollier *et al.* (1997) the wealth that will be available for investment in the second period, z , is a random variable from the point of view of the beginning of period 1. If first period investment is successful, z will be large. If first period investment is unsuccessful, z will be low. On the contrary, in GP97 and the other papers that present similar experimental evidence, individuals receive the same amount W in each period to invest. This difference makes the results of Gollier *et al.* (1997) inapplicable to the framework of GP97.

5 Concluding remarks

Our econometric exercise nicely complements Proposition 1 in that both competing models, CRRA and MLA, are consistent with the experimental evidence on investment games. Our mixture estimations also suggest that both models have significant predictive power and suit the behavior of different groups of individuals.

Consistently with the cited literature, our estimation exercise also provides little empirical support to subjects' loss aversion. As we discussed in the introduction, this may be due to the fact that the entire experimental framework -together with the normative constraints imposed by Ethic Committees within Universities and Academic journals- makes it difficult to implement the experience of a loss in the lab, experience that is much more common in real life. More experimental research -possibly, in the field- is then needed to identify more neatly the motivation behind the fact that individuals take more risks when they evaluate their investments less frequently.

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Appendix

MLA Prediction

We assume that $p > \frac{1}{1+\alpha}$, $\alpha > 0$, the endowment is the reference point and the evaluation function is linear. The high frequency lottery is $HF = (\alpha x, p; -x, 1 - p)$. The low frequency lottery is:

$$LF = (3\alpha xp, p^3; (2\alpha - 1)x, 3p^2(1 - p); (\alpha - 2)x, 3p(1 - p)^2; -3x, (1 - p)^3).$$

In the HF treatment, a subject chooses to invest $x > 0$ if her coefficient of loss aversion λ is below a certain threshold. In particular, if:

$$\lambda < \lambda_{HF} = \alpha \frac{p}{1 - p}. \quad (22)$$

In the LF treatment, the same individual chooses $x > 0$ if:

$$\lambda < \lambda_{LF} = \frac{\alpha p^3 + (2\alpha - 1)p^2(1 - p) + (\alpha - 2)p(1 - p)^2}{(1 - p)^3}. \quad (23)$$

Now, we see that:

$$\lambda_{LF} - \lambda_{HF} = \frac{p(2 - p)(p(1 + \alpha) - 1)}{(1 - p)^3} > 0.$$

Investing in the LF treatment is, therefore, more attractive than investing in the HF treatment.

Dataset		ALL	GP97	HL05 - T	HL06 - S	IPT14
<i>i)</i> CRRA	rho_plus	0.162*** (0.0093)	0.152*** (0.0153)	0.150*** (0.0182)	0.164*** (0.0198)	0.192*** (0.0225)
	Log lik.	-4706.3656	-1606.8844	-1064.496	-1235.4153	-776.1103
<i>ii)</i> MLA_LIN	lambda	1.274*** (0.0054)	1.269*** (0.0089)	1.273*** (0.0115)	1.272*** (.0111)	1.285*** (0.0137)
	Log lik.	-5967.3055	-1974.4814	-1126.6427	-1643.9931	-1215.8118
<i>iii)</i> MLA_I	rho	0.569*** (0.0402)	0.595*** (0.0607)	0.4852** (0.2069)	0.604*** (0.0490)	0.530*** (0.0828)
	lambda	1 (1.16e-08)	1 (2.25e-09)	1 (2.79e-07)	1 (2.57e-09)	1 (6.15e-08)
	Log. Lik.	-3999.3533	-1339.7236	-807.34472	-1062.454	-786.375
	Obs.	1,491	495	324	384	288

Robust standard errors (clustered at the subject level) in parentheses - *** p<0.01, ** p<0.05, * p<0.1.

Table 1

Dataset		ALL	GP97	HL05 - T	HL06 - S	IPT14
<i>i) MLA_LIN</i>	rho	0.285*** (0.0123)	0.305*** (0.0250)	0.305*** (0.0346)	0.288*** (0.0254)	0.254*** (0.0174)
	lambda	1 (4.86e-08)	1.0056 (0.1114)	1 (5.18e-09)	1.0735 (.0969)	1 (2.84e-08)
	pi	0.2590*** (0.0259)	.3058*** (0.0462)	.3032*** (0.0541)	.2715*** (0.0577)	.1388 (0.0501)
	Log lik.	-3264.371	-1072.5406	-679.2939	-868.3497	-622.5062
	rho	0.244*** (0.0083)	0.244*** (0.0141)	0.2586*** (0.0253)	0.239*** (0.0160)	0.237*** (0.0154)
<i>ii) MLA_1</i>	lambda	1 (3.17e-09)	1 (7.86e-09)	1 (3.24e-08)	1 (5.42e-09)	1 (1.56e-08)
	pi	0.5133*** (0.0333)	0.572*** (0.0565)	0.6478*** (0.0769)	0.5010*** (0.0653)	0.2790*** (0.0768)
	Log. Lik.	-3552.0401	-1176.4119	-758.1530	-940.3960	-659.0019
	rho_plus	0.274*** (0.011)	0.2833*** (0.0203)	0.259*** (0.0197)	0.287*** (0.0255)	0.2508*** (0.0166)
<i>iii) MLA_2</i>	rho_minus	0.966*** (0.0028)	0.965*** (0.0043)	0.971*** (0.0029)	0.6993** (0.2937)	0.957*** (0.00439)
	lambda	1 (0.0026)	1 (0.0001)	1 (0.0007)	1.9602 (.5481)	1 (0.0001)
	pi	.2725*** (0.0289)	.334663*** (0.0540)	.3790*** (0.0600)	.2726*** (0.0592)	.1381*** (.0501)
	Log. Lik.	-3263.6578	-1072.6447	-667.3834	-869.2339	-621.522
	Obs.	1,491	495	324	384	288

Robust standard errors (clustered at the subject level) in parentheses - *** p<0.01, ** p<0.05, * p<0.1.

Table 2

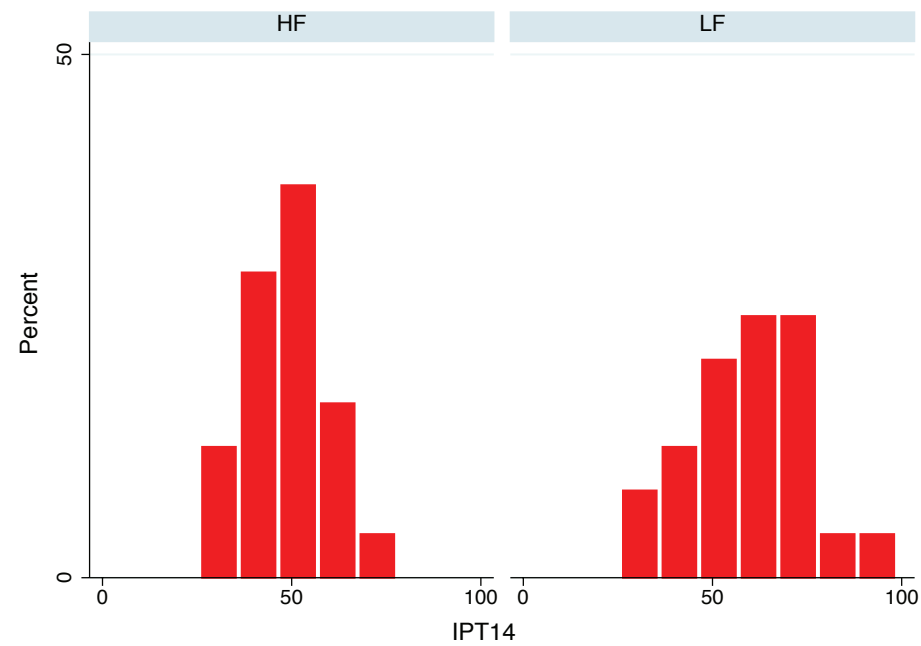
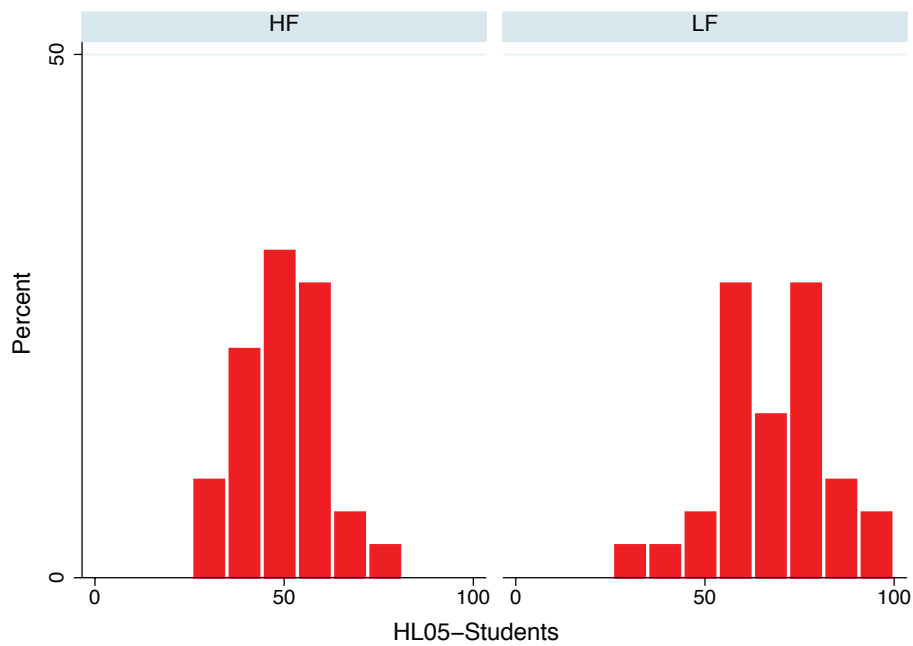
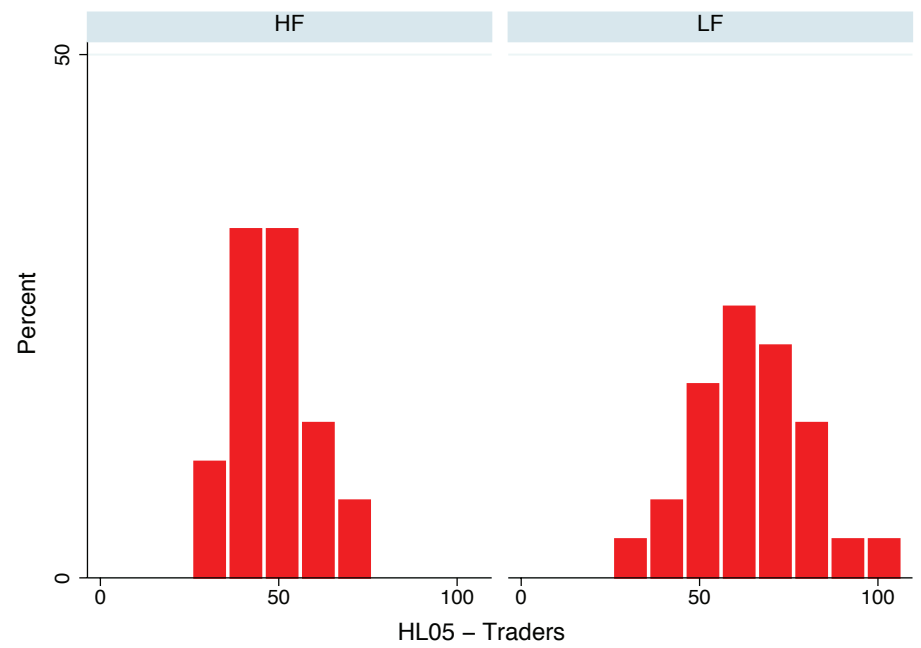
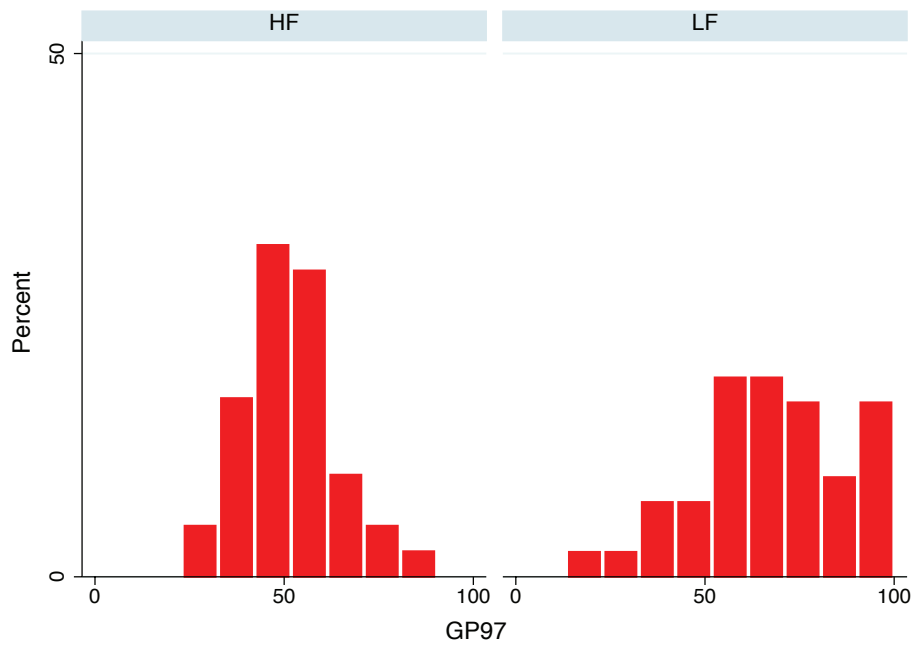


Figure 1

Optimal bet

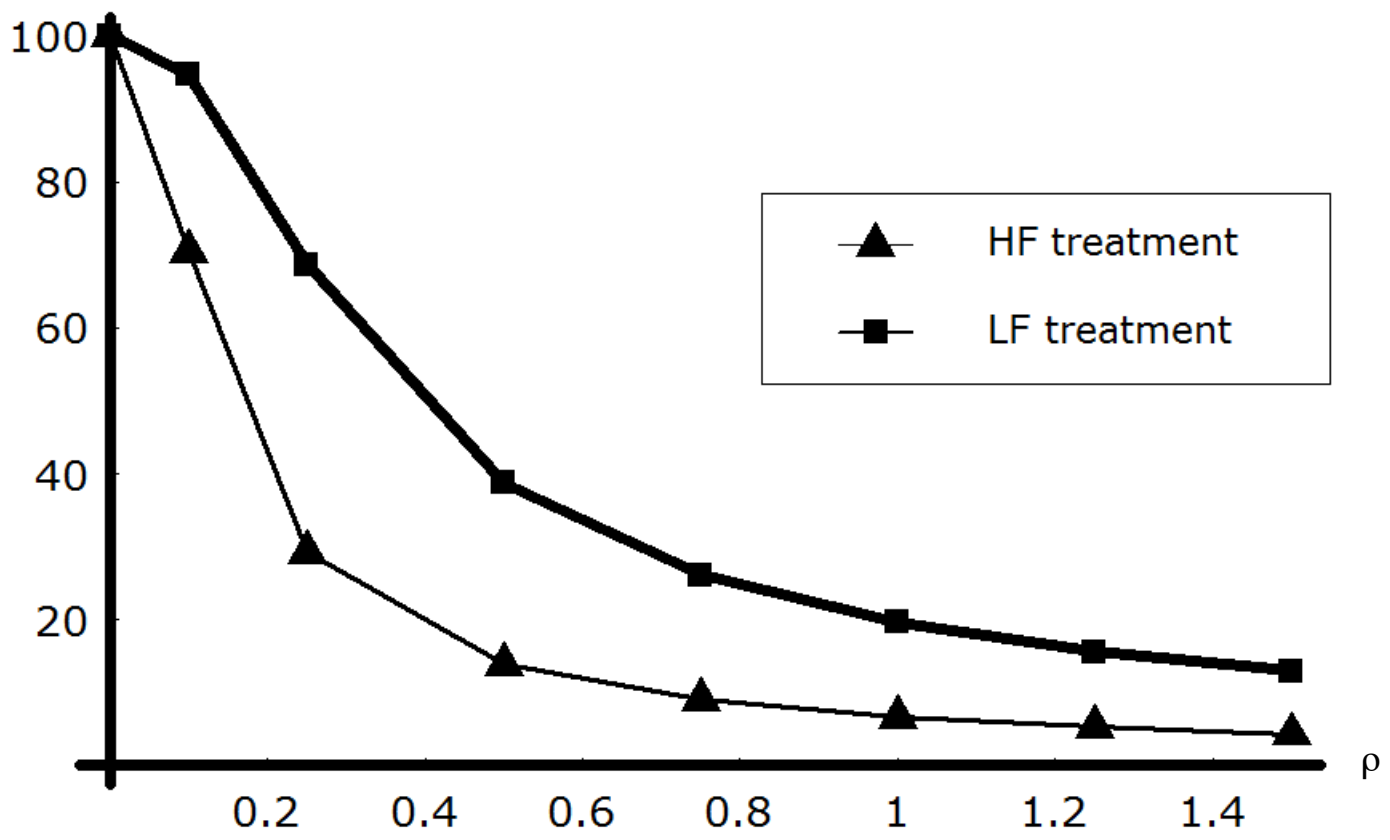


Figure 2

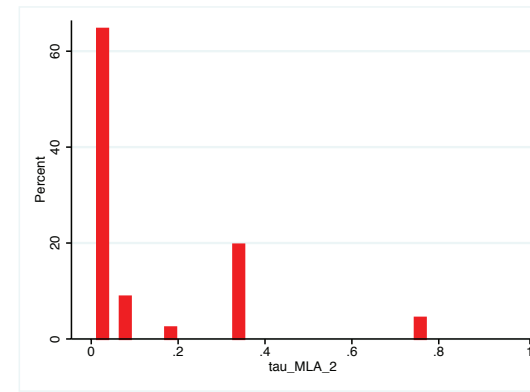
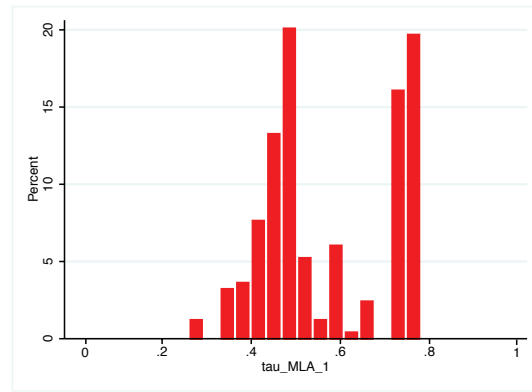
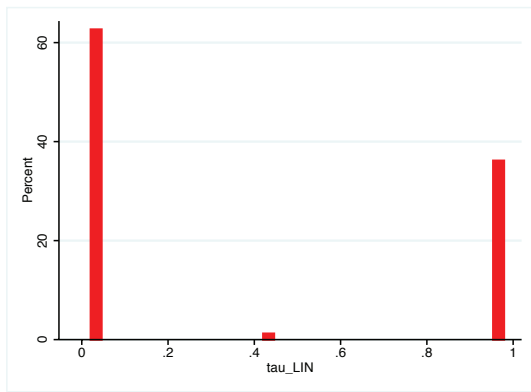


Figure 3