Preference for Skew in Lotteries: Evidence from the Laboratory⋆

Thomas Åstebro[a], José Mata[b], Luís Santos-Pinto[c,†]

[a]Haute École Commerciale, Paris
[b]Faculdade de Economia, Universidade Nova de Lisboa
[c]Faculty of Business and Economics, University of Lausanne

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Abstract

Using a laboratory experiment we investigate how skew influences choices under risk. We find that subjects make significantly riskier choices when the distribution of payoffs is positively skewed, these choices being driven in part by the shape of the utility function but also by subjective distortion of probabilities. A utility model with probability distortion calibrated on laboratory data is able to explain why most gamblers in public lotteries buy only a small number of tickets.

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†Corresponding author. Luís Santos-Pinto. Faculty of Business and Economics, University of Lausanne, Extranef 211, CH-1015, Lausanne, Switzerland. Ph: 41-216923658. Fax: 41-216923435. E-mail address: LuisPedro.SantosPinto@unil.ch.

In settings where risky decisions have to be made many people favor riskier options which offer a small probability of large gains, that is, where the distribution of payoffs has positive skew. For example, people tend to overbet on the long-shot horse with low probability of winning large returns rather than the favorite with the greatest expected return (Joseph Golec and Maury Tamarkin, 1998). And when people buy lottery tickets, David Forrest, Robert Simmons and Neil Chesters (2000) and Thomas Garrett and Russell Sobel (1999) show that people are more concerned with the size of the top prize than the expected value of the lottery. Positive skew may affect significant life choices, not just gambling. Three-quarters of all people that enter self-employment face higher variance and skew but lower expected return than in employment (Barton Hamilton, 2000.) Further, 97% of inventors will not break even on their investments but face a very skew distribution of returns conditional on succeeding (Thomas Åstebro, 2003.) Financial markets also provide evidence that is consistent with skew loving choices. For example, risk aversion implies that people should hold diversified portfolios. However, Marshall Blume and Irwin Friend (1975) find that most households hold undiversified portfolios with a high proportion of stocks with high positive skew. Also, securities that make the market portfolio more negatively skewed earn positive 'abnormal' average returns.[1]

This paper uses a laboratory experiment to test how positive skew influences risky choices. Betting in state lotteries, sports or lottery-type stocks may be explained by overestimation of the probability of attaining favorable outcomes due to optimism, pleasure from gambling, and/or anticipatory feelings.[2] The decision to become an entrepreneur or an inventor may be a result of preferences for being one's own boss or of overly confident perceptions of skill. Empirical research on the impact of positive skew on choice under risk and uncertainty has not been able to fully control for these various explanations and experimental work focusing on risk aversion has largely neglected

[1] The estimates for the annualized premium range from 2.5% to 3.6% (see Alan Kraus and Robert Litzenberger 1976 and Campbell Harvey and Akhtar Siddique 2000, respectively). See also Todd Mitton and Keith Vorkink (2007). Alok Kumar (2009) shows that the propensity to gamble and investment decisions are correlated. Individual investors prefer stocks with lottery features, and like lottery demand, the demand for lottery-type stocks increases during economic downturns.

[2] See John Hey (1984), John Conlisk (1993), and Andrew Caplin and John Leahy (2001). While some of these hypotheses are empirically supported, most of them are simply qualitative in nature and explain gambling in state lotteries without quantifying it.

skew.

Common to all of aforementioned risky decisions is that pleasure may be derived from the activity (be it gambling or not having a boss). Our experiment asks subjects to make choices between pairs of lotteries. By offering choices between alternatives which are essentially identical with respect to this characteristic we are able to rule out explanations based on the pleasure associated with the activity under scrutiny. In addition, the fact that the probabilities associated with success are objectively determined and known rules out explanations that rely on overconfidence about skill. The experimental design allows us to focus on preference for skew as an explanation for risky choices.

We ask subjects to make several sequences of 10 pairwise choices between a safe and a risky lottery and we count the number of safe lottery choices. The design is based on Charles Holt and Susan Laury (2002) with three important modifications. First, we consider lotteries that have more than two outcomes, so that we can use the third moment around the mean to manipulate skew and variance separately. Second, we use a graphical display to represent lottery payoffs. Third, we consider three different skew treatments.

In all skew treatments the safe lotteries have symmetric prize distributions, while the degree of skewness varies for the risky lotteries. In the first treatment – the "zero skew" condition – the risky lotteries also have symmetric prize distributions. In the second treatment – the "moderate skew" condition – all the risky lotteries have skew equal to 1.69 and in the third treatment – the "maximum skew" condition – skew is equal to 2.67 (the maximum possible skew in our framework). We perform the treatments under two monetary stakes conditions: low and high stakes (20 times higher than low stakes).

We find that the average number of safe choices decreases monotonically with an increase in skew indicating skew loving choices. The result holds in both stakes conditions. Increasing the monetary stakes leads to an increase in the average number of safe choices for all skew treatments. All these effects are statistically significant.

To explain these choices we resort to structural estimation of utility functions and focus on Expected Utility Theory (EUT) and Rank-Dependent Utility (RDU).[3] To perform the estimation we model RDU using the proba-

[3]Rank dependent utility models are able to accommodate probability-dependent risk attitude; that is, preferences are consistent with both risk-averse and risk-seeking behavior

bility weighting function due to Drazen Prelec (1998). This function accommodates the case in which individuals distort probabilities by overestimating small probabilities and underestimating large probabilities and vice-versa, and the case in which they estimate these probabilities accurately and RDU reduces to EUT. We perform this estimation under three different specifications for the utility function: power, hyperbolic absolute risk aversion (HARA), and expo-power. For all utility functions we find that RDU with probabilities of rare events overestimated and probabilities of frequent events underestimated explains the lottery choices of the subjects in the sample better than EUT.

In the final part of the paper we explore the consequences of our findings for gambling in state lotteries. Most theories find it difficult to explain why people buy only a small number of tickets. Using our estimated parameters we calibrate an agent's decision on the number of lottery tickets to buy. We show that buying a few lotto tickets is consistent with our representative parameter values.

Our findings do not imply that all agents are necessarily distorting probabilities, not even that only RDU agents will make skew loving choices. Skew loving choices can come from probability distortion or from the shape of the utility function of EUT maximizers. By examining the specific choices made by subjects we are able to classify them as either RDU or EUT maximizers. For EUT subjects we further classify them according to their preferences for risk and skew, while RDU subjects are divided into those who overestimate small probabilities and underestimate large probabilities and those who display the reverse pattern. Overall, 2/3 of our subjects appear to be EUT and 1/4 RDU. The remaining 1/12 make inconsistent choices. Approximately 1/2 of the subjects in the sample make skew loving choices, and these come in roughly equal proportions from the EUT and RDU group.

The remainder of the paper is organized as follows. Section 1 explains the experimental design. Section 2 presents the findings. Section 3 presents the classification of our subjects according to the choices they make and contains estimates of representative utility functions. Section 4 discusses an application of the findings to gambling in public lotteries. Section 5 concludes the paper. Details on the experimental design are provided in an Appendix.

depending on the probability distribution of outcomes. If individuals overweight small probabilities and underweight medium to large probabilities in evaluating risky gambles, then they will make "risky" choices in gambles involving small probabilities of large gains.

1 Experimental Design

The theory of choice under risk and uncertainty informs us that individuals make skew loving choices for two reasons: either they are expected utility maximizers with a preference for positive skew or they are non-expected utility maximizers who overestimate small probabilities of large gains and underestimate the probabilities of the remaining payoffs.

We know from Tsiang (1972) that an expected utility maximizer has a preference for positive skew if the third derivative of his utility of wealth is positive. As a manifestation of such preferences a risk averse individual will be prepared to accept a lower expected return (but not a negative one) or a higher level of overall riskiness if the distribution of payoffs is more skewed to the right.

To illustrate how EUT individuals can be classified according to their risk and skew preference consider an EUT individual with a power utility function $u(x) = x^{1-\beta}$, with $x > 0$. This utility function implies risk preference for $\beta < 0$, risk neutrality for $\beta = 0$, and risk aversion for $0 < \beta < 1$ (it also represents constant relative risk aversion for money). The third derivative is

$$u'''(x) = \beta(1 + \beta)(1 - \beta)x^{-\beta-2}. \tag{1}$$

From (1) we see that an individual with a power utility is risk neutral and skew neutral when $\beta = 0$. When $\beta < -1$ he is highly risk loving and skew seeker, when $\beta = -1$ he is very risk loving and skew neutral, and when $-1 < \beta < 0$ he is mildly risk loving and skew averse. For $0 < \beta < 1$ such an agent is risk averse and skew seeker. In short, a risk loving agent with a power utility can be skew averse, neutral, or seeker but a risk averse agent with a power utility must be a skew seeker.

Can risk a averse individual be averse to skew? The answer is yes. Tsiang (1972) also shows that decreasing absolute risk aversion implies a preference for skew but that the converse is not true.[4] Hence, a necessary (but not sufficient) condition for a risk averse individual to be averse to skew is that he displays increasing absolute risk aversion.

A non-expected utility maximizer can make "skew loving" choices due to probability distortion. This type of behavior is captured by rank dependent

[4]An individual displays decreasing absolute risk aversion if $u'''(x) > \frac{[u''(x)]^2}{u'(x)}$ and prefers skew if $u'''(x) > 0$.

utility (RDU) theory which assumes that individuals subjectively distort probabilities via a probability weighting function.[5]

The most commonly used probability weighting functions are concave for small probabilities and convex for moderate and high probabilities. This pattern is called inverted s-shaped probability weighting. The pattern implies that subjects pay more attention to the best and worst outcomes, and little attention to intermediate outcomes. An RDU individual with an inverted s-shaped probability weighting function simultaneously can make "risk loving" choices in gambles that yield large gains with small probabilities such as in public lotteries and "risk averse" choices in gambles that yield large losses with small probabilities, a phenomenon relevant for insurance (see Quiggin 1982).

In this work we seek to find out whether people make "skew loving" choices or not in a controlled laboratory environment. Additionally, we want to know whether these "skew loving" choices are driven by EUT's preference for skew or RDU's probability distortion. To do this we use sequences of random lottery pairs in which the subject chooses one of the lotteries in each pair. Subjects face multiple pairs in sequence. At the end of the experiment one of the pairs is randomly selected for payoff and the subject's preferred lottery is then played out as the reward.

This methodology is based on Holt and Laury's (2002) [hereon HL] study of the trade-off between risk and return and avoids the willingness to pay / willingness to accept biases of certainty equivalent and auction methods. In HL, subjects are given the choice between the pairs of lotteries displayed in Table 1.

insert Table 1 here

It is expected that subjects start by choosing the safe lottery (S) in the top row as it has both higher expected value and lower variance. As one proceeds down the table, the expected values of both lotteries increases, but the expected value of the risky (R) lottery increases more. When the probability of the high-payoff ticket in the R choice increases enough (moving down the table), a person should cross over to choose R.

[5]Rank-dependent models were introduced by John Quiggin (1982) for decision under risk (known probabilities) and by David Schmeidler (1989) for decision under uncertainty (unknown probabilities).

Different persons will switch at different points, the switching point being determined by the degree of risk aversion. For example, a risk-neutral person would choose S four times before switching to R. Even the most risk-averse person should switch over by decision 10 in the bottom row, since R then yields a sure payoff of $3.85. HL find that most people make slightly risk averse choices under low stakes and that when stakes are increased the number of safe choices increases significantly.

Our design departs from HL's in three main aspects. First, we consider lotteries that can have from two to ten different prizes. Increasing the number of prizes allows us to control for the mean, variance, and skew of the sequences of lotteries. Second, lotteries are presented in a graphical display rather than in a table.[6] Third, we consider three different skew treatments. In the first skew treatment the safe and risky lotteries have symmetric prize distributions. We call this treatment the "zero skew" condition. In the second treatment – "moderate skew" – the safe lotteries are symmetric and the risky lotteries all have skew equal to 1.69. In the third treatment – "maximum skew" – the safe lotteries are symmetric and the risky lotteries all have skew equal to 2.67.

Figure 1 shows our graphical representation for the first choice between S and R in HL's lotteries. Each of the lines in HL's table is depicted in two graphs of the kind in Figure 1. People are presented with the 10 choices in sequence and are provided with a review section where any decision may be revisited.

insert Figure 1 here

Figures 2 to 4 show the first choice between S and R for each of three skew treatments. The different patterns that emerge are due to the skew of the corresponding lotteries.

insert Figures 2 to 4 here

[6] Researchers have found graphical display of data sometimes to be superior to tabular display in terms of decision accuracy. The advantage seems to depend on data structure and task complexity, where for either simple or very complex tasks or unclear data structures there seems to be little advantage of graphical display. See, e.g. Cheri Speier (2006), Joachim Meyer, Marcia Shamo, and Daniel Gopher (1999), John Schauenbroeck and Krishnamurty Muralidhar (1991) and Mark Hwang and Bruce Wu (1990).

The first comparison we will make is between the results obtained when the experiment is conducted offering the same choice options with the tabular display of HL and with our graphical display. We then introduce skew systematically. We modify the lotteries to have the same mean and variance as in HL, but while the safe option has no skew, the risky option has skew equal to 0, 1.69 and 2.67 in the different treatments. We focus on positive skew, but our exercise could be extended to lotteries with negative skew.

If the expected payoffs were to be maintained the higher levels of skew would lead to some negative payoffs. We therefore add $1 to HLs payoffs. We test whether there is any effect of adding $1. We also introduce lotteries with 20 times the payoffs to study the impact of skew under large stakes. We randomize subjects' allocation to treatments and the order of treatments.

Instructions were kept identical to those in HL, with some necessary revisions to account for the difference in presentation formats and the fact that the task was conducted online rather than with paper and pencil. Subjects also took a knowledge test on their understanding of the instructions and had to pass to move forward to the experiment.

Table 2 presents the different treatments. There are three basic treatment sequences: i) subjects perform 1 set of HL prize distribution choices (T1-T4) followed by 3 sets of low stakes choices with 3 skews and then draw a prize from one of the 4 sets; ii) Subjects perform 3 sets of high stakes choices with 3 different skews and then draw a prize from one of the 3 sets; iii) Subjects perform 3 sets of low stakes choices with 3 different skews. Subjects are then given the option between (A) drawing a final prize from the three low stakes distributions and finishing the experiment or (B) not drawing a prize and moving on to the high stakes choices. If subjects choose option (B) they will do the three sets of high stakes choices with 3 skews and draw a prize from those. All subjects presented with this option chose (B).

Using posters we recruited 148 students at the University of Waterloo during the Spring 2008. These were randomly allocated across 10 treatments in six pre-determined treatment sequences as outlined in Table 3. Each of the sequences in the table was performed by at least 24 subjects. At the end of the experiment one prize is chosen randomly and subjects were awarded their prize plus a $5 participation fee.

insert Table 2 here

insert Table 3 here

Subjects in our sample are briefly described in Table 4. Some of the subjects did not respond to all of the demographics questions, the number of observations available for each item being presented along with the corresponding summary statistics.

insert Table 4 here

2 Findings

2.1 Skew and Incentive Effects

Table 5 shows the mean number of safe choices under the different conditions. We see that the number of safe choices decreases with an increase in skew in both the low stakes and high stakes condition. Thus, on average, subjects make skew loving choices. We also find that increasing the stakes increases the average number of safe choices for all skew conditions.

insert Table 5 here

We performed OLS regressions with the number of safe choices as the dependent variable and included dummies for moderate and maximum skew, and for high stakes (see Table 6). We find that the number of safe choices decreases by 0.34 from zero skew to moderate skew and by 0.67 from zero skew to maximum skew. When confronted with high stakes lotteries subjects make significantly less risky choices. The least squares regression provides easy interpretation of estimated coefficients. The coefficient 3.904 for the constant in column (i) implies that under low stakes and no skew subjects make on average 3.9 safe choices - which is risk neutral behavior.[7]

[7] As a robustness check, we also ran an ordered-Probit where the dependent variable is the number of times the safe choice was made. The results from such a model are more difficult to interpret, since the marginal impact of the coefficients depend on the level of the covariates and the specific choice being considered. The qualitative results did not

insert Table 6 here

Our main results are robust to including socio-demographic characteristics described in Table 4. The high stakes coefficient decreases somewhat from 0.60 to 0.46, but it remains significant. By design, all subjects perform all skew conditions and skew conditions are, therefore, orthogonal to subjects. The minor differences that we observe when including the demographics are therefore due to the fact that observations in different columns of Table 6 are not exactly the same, as we do not observe all characteristics for all subjects. This estimation reveals that males and non-white individuals make riskier decisions than females and whites, respectively. All other characteristics, except those related to income, are non-significant once controlling for everything else in the model. Socio-demographic characteristics does not seem to be important.[8]

Since all subjects make repeated decisions under different conditions we can also estimate individual random and fixed effects models. These estimations deliver the same coefficients for skew conditions, but the precision is significantly increased because the panel-data models correct for heterogeneity in risk preferences, which appears to be large. Increased precision means that the effect of moderate skew is now significant at the 1% level, rather than at the 5% level. The high stakes coefficient is approximately 0.5, with p-values below 1% (see Table 6).

2.2 Robustness

Our subjects perform their choices in different sequences (recall Table 3). Moreover, some of them went through the initial round which tested framing effects. We would therefore like to know whether choices are affected by order and by the initial treatment. The inclusion of such controls in the regression does not change the results regarding skew. Moreover, the controls are not jointly significant. The set of four dummies indicating which initial treatment (if any) the subject had performed has a p-value of 0.113, while the p-value

present changes from those in Table 6.

[8]A reason for including the individual characteristics explicitly is that the response of individuals to skew might depend on demographics. To test this we included interactions between the skew variables and each of the demographic characteristics that are captured by a dummy (gender, decision maker in the house, race, graduate student status, major, full time student status). In all cases we cannot reject the null that the effects are identical.

for the five order dummies is 0.099. Thus, we conclude that there is no meaningful order effect.

We have noted earlier that previous research has found graphical display of data to be superior to tabular display, in particular when the tasks are neither very simple nor very complex. Subjects making fully consistent choices would never switch back and forth between the safe and risky options. Some of them, however, did. We find that subjects switch back and forth in fewer cases in our graphical display as compared to the tabular display. 32% of the subjects switched back and forth when data was presented in the tabular display, and only 6% did so in the graphical display, which seems to indicate that the graphical display is cognitively superior to the tabular display for this task.[9]

There seems to be some indication in our data that the tabular display leads subjects to make a somewhat larger number of safe choices. This may be due to a lesser ability to fully understand the data in the tabular (T1 and T3) than in the graphical display (T2 and T4), as indicated by the higher proportion of switching back and forth for the tabular display. The observed average number of safe choices is 5.3, 3.2, 4.6 and 3.6 for treatments T1 to T4, respectively. We reject the hypothesis that the mean number of safe choices in T1 is equal to that in T2, but not that T3 is equal to T4. For all samples, except for T1, we cannot reject the hypothesis of risk neutral behavior. Finally, adding one dollar to the prizes has a small and not significant effect. However, as we have seen, multiplying the stakes by a factor of twenty has a significant effect.

3 Explaining the Findings

The results obtained in the zero skew treatment are consistent with findings in Holt and Laury (2002, 2005), Glenn Harrison, Eric Johnson, Melayne McInnes, and Elisabet Rutström (2005), and Glenn Harrison, Morten Lau and Elisabet Rutström (2007). The only difference is that we find slightly

[9]We checked the robustness of our regression results by defining two additional variables. One is defined as the decision before the one in which subjects make their first risky decision. The other is their last safe decision. The three variables are identical for subjects that never go back and forth. Results did not show any remarkable changes, except that the effect of being in the moderate skew condition is somewhat more imprecisely estimated, in particular when the variable is their last safe decision.

less risk aversion than they do.

The large number of risky choices observed in the maximum skew condition could be explained by EUT if most individuals were risk seekers. But that would contradict the safe choices observed in the zero skew condition. Thus, the choices made in the zero skew and in the maximum skew conditions are at odds with expected utility. To obtain greater insight into subjects' behavior we need to analyze individual choices rather than treatment average responses.

3.1 Subject Classification

3.1.1 A procedure for classifying subjects

Our experimental design offers a simple way to distinguish EUT subjects from RDU subjects by examining individual lottery choices across the skew treatments. In our design, a risk-neutral person makes 4 safe choices in all treatments, a risk averse person makes 4 or more safe choices in all treatments and 5 or more safe choices in at least one treatment, and a risk seeking person makes 4 or fewer safe choices in all treatment and 3 or fewer safe choices in at least one treatment. Hence, if, for example, we observe someone making 5, 4 and 3 safe choices in the zero, moderate, and maximum skew treatments, respectively, then we know that this person violates EUT's assumption that preferences towards risk should be independent of probabilities. However, the choices 5, 4, and 3 are consistent with RDU.

Let x_{st} denote the number of safe choices of a subject in skew treatment $s \in \{5, 6, 7\}$ and in stake treatment $t \in \{L, H\}$, where s represents treatments T5, T6, and T7, and t represents low and high stakes. We classify a subject as making consistent choices if his choices satisfy one of the following six conditions for $t = L, H$: (C1) $x_{5t} \geq x_{6t} \geq x_{7t}$, (C2) $x_{5t} \geq x_{6t} - 1 \geq x_{7t}$, (C3) $x_{5t} \geq x_{6t} + 1 \geq x_{7t}$, (C4) $x_{5t} \leq x_{6t} \leq x_{7t}$, (C5) $x_{5t} \leq x_{6t} - 1 \leq x_{7t}$, (C6) $x_{5t} \leq x_{6t} + 1 \leq x_{7t}$. Condition (C1) says that the number of safe choices (weakly) decreases along the skew treatments. Conditions (C4) says that the number of safe choices (weakly) increases across the skew treatments. Conditions (C2), (C3), (C5) and (C6) allow subjects to make "mistakes" of -1 or +1 safe choices in the intermediate skew treatment.[10] To be classified

[10]For example, suppose an individual has chosen $(x_{5L}, x_{6L}, x_{7L}) = (4, 2, 3)$. The choices of this individual violate condition (C1) but satisfy condition (C3) and so the individual is classified as making consistently choices. However, an individual who has chosen

as making consistent choices we also require that the number of safe choices does not decrease across the low stakes treatments and increase across the high stakes treatments or the reverse for a subject who made choices under both low and high stakes.

We classify a subject as an RDU individual if his choices satisfy one of the six consistency conditions (C1)-(C6) and one of the following conditions for $t = L, H$: (R1) $5 \leq x_{5t}$ and $x_{7t} \leq 3$, (R2) $x_{5t} \leq 3$ and $5 \leq x_{7t}$, (R3) $6 \leq x_{5t}$ and $x_{7t} = 4$, (R4) $x_{5t} = 4$ and $6 \leq x_{7t}$, (R5) $x_{5t} = 4$ and $2 \leq x_{7t}$, (R6) $x_{5t} \leq 2$ and $x_{7t} = 4$. Condition (R1) says that the subject displays "risk averse" behavior in the zero skew treatment but "risk seeking" behavior in the maximum skew treatment and condition (R2) says the reverse. Condition (R3) says that the subject displays highly "risk averse" behavior in the zero skew treatment but "risk neutral" behavior in the maximum skew treatment and condition (R4) says the reverse. Condition (R5) says that the subject displays highly "risk seeking" behavior in the zero skew treatment but "risk neutral" behavior in the maximum skew treatment and condition (R6) says the reverse.

We classify an RDU subject as having an inverted s-shaped probability weighting function if his choices satisfy (R1), (R3), or (R5) and an s-shaped probability weighting function if his choices satisfy (R2), (R4), or (R6). It follows from conditions (R1), (R3), and (R5) that an RDU subject with an inverted s-shaped probability weighting function will make fewer safe choices in the high skew treatments than in the low skew treatments. Hence, all subjects who are classified as RDU with an inverted s-shaped probability weighting function are also classified as making skew loving choices. Similarly, all subjects who are classified as RDU with an s-shaped probability weighting function are also classified as making skew averse choices.

We classify a subject as making choices consistent with EUT if his choices satisfy one of the six consistency conditions (C1)-(C6) and do not satisfy any of the six RDU conditions (R1)-(R6). Such a subject is classified as a risk seeker if his average number of safe choices across all treatments is smaller than 4, risk neutral if it is equal to 4, and risk averse if it is greater than 4. A subject who makes choices consistent with EUT is classified as skew seeker if $x_{5t} - x_{7t} \leq -1$ for $t = L$ or $t = H$ and if $\sum_t x_{5t} - x_{7t} \leq -1$ when $t = L$

$(x_{5L}, x_{6L}, x_{7L}) = (4, 1, 3)$ is classified as making inconsistent choices since his choices can not be generated by EUT nor by RDU (s-shaped or inverted s-shaped probability weighting) allowing for a mistake of -1 or +1 safe choices in the intermediate skew treatment.

and $t = H$. A subject who makes choices consistent with EUT is classified as skew neutral if $x_{5t} = x_{7t}$ for $t = L$ or $t = H$ and if $-1 < \sum_t x_{5t} - x_{7t} < 1$ when $t = L$ and $t = H$. Finally, we classify a subject who makes choices consistent with EUT as skew averse if $x_{5t} - x_{7t} \geq 1$ for $t = L$ or $t = H$ and if $\sum_t x_{5t} - x_{7t} \geq 1$ when $t = L$ and $t = H$.

3.1.2 An example

Table 7 applies our classification to the choices of an RDU individual with a square-root utility with different values of probability distortion (the parameter η) and gives the subject classification for each case.

insert Table 7 here

Table 7 shows that an RDU individual with a square-root utility will make choices inconsistent with EUT if he has an inverted s-shaped probability weighting function with $\eta < 0.73$. We see that within this range of probability distortion the person displays highly skew loving choices: for $0.4 < \eta < 0.73$ he makes "risk averse" choices in the zero skew treatment and "risk seeking" choices in the maximum skew treatment–$(5,4,3)$, $(5,3,3)$, $(5,3,2)$ and $(5,2,2)$–and for $\eta < 0.4$ he makes "risk neutral" choices in the zero skew treatment and strongly "risk seeking" choices in the maximum skew treatment–$(4,2,2)$, $(4,2,1)$, $(4,1,1)$ and $(4,1,0)$. Note that if such an individual has $0.73 < \eta < 3$ his choices do not violate the EUT axioms and we classify him as making choices consistent with EUT. Hence, our design is likely to overestimate the actual number of EUT subjects and underestimate the number of RDU subjects.

Table 8 maps different possible safe choices of an EUT individual with a power utility along the three skew treatments with different values for the parameter β and gives the subject classification for each case.

insert Table 8 here

Table 8 shows that the theoretical skew preference classification and our skew choice classification coincide in all choices, except $(1,1,1)$, $(3,3,3)$ and $(5,5,5)$ for this particular utility function. If an individual is an EUT maximizer with a power utility function and he chooses $(5, 5, 5)$, then he must have $\beta \in (0.5, 0.9)$ and (1) implies skew seeking preferences. However, an EUT individual with a utility function that does not display a preference for skew can also choose $(5, 5, 5)$. We also see from Table 7 that an RDU individual with s-shaped probability distortion ($1 < \eta < 1.42$) and a square-root utility chooses $(5, 5, 5)$ since the effects of probability distortion and the shape of the utility function work in opposite directions.

3.1.3 Classifying subjects in our sample

Applying the classification to our sample we find a small number of subjects, 14 (9.5%), who make inconsistent choices. Table 9 displays the classification of subjects who made consistent choices. Most subjects, 98 (66.2%), make choices consistent with EUT and 36 (24.3%) make choices consistent with RDU.

insert Table 9 here

Among the subjects whose choices are consistent with EUT, 18 are risk neutral, 32 are risk averse and 48 are risk seekers. The risk neutral individuals are also neutral to skew. Among the risk averse, 22 are skew seekers, 9 are neutral to skew, and only 1 is skew averse. Finding that the majority of risk averse individuals are skew seekers is consistent with experimental evidence that shows that most people tend to exhibit decreasing absolute risk aversion. Among the risk seekers, 18 are skew seekers, 17 are skew neutral and 13 are averse to skew.

The vast majority of the RDU individuals (32 out of 36) display an inverted s-shaped probability weighting function. This result is consistent with experimental evidence showing that most individuals who subjectively distort probabilities tend to overestimate small probabilities and underestimate large ones.

Overall, we find 72 subjects in our sample making skew loving choices, 44 making skew neutral choices, and 18 making skew averse choices. Among the 72 subjects who make skew loving choices, 32 are RDU individuals, 22 make choices consistent with EUT and risk averse preferences, and 18 make choices consistent with EUT and risk seeking preferences. Skew loving choices can, therefore, come either from probability distortion or the shape of the utility function. Both cases are present in meaningful numbers in our sample.

3.2 Estimation of Decision Models

We continue with structural estimation of decision models to compare alternative explanations for the experimental results. Consider a lottery $(p_1, x_1; ...; p_n, x_n)$, yielding outcome x_j with probability p_j, $j = 1, .., n$. The probabilities $p_1, ..., p_n$ are nonnegative and sum to one. According to RDU the utility of this lottery is evaluated as $\sum_{j=1}^{n} \pi_j u(x_j)$,where u is the utility function and the π_js are called decision weights. The decision weights are nonnegative and sum to one. Expected utility is the special case of the general weighting model where $\pi_j = p_j$ for all j. If $x_1 > x_2 > ... > x_n$, then

$$RDU(p_1, x_1; ...; p_n, x_n) = \sum_{j=1}^{n} \pi_j u(x_j),$$

where, for each j,

$$\pi_j = w(p_1 + ... + p_j) - w(p_1 + ... + p_{j-1}),$$

with $w(0) = 0$ and $w(1) = 1$. The function $w(p)$ is the decision weight generated by the probability p when associated with its best outcome. Thus, the decision weight π_j of outcome j depends only on its probability p_j and its rank.

To model probability distortion we use Prelec's (1998) probability weighting function:

$$w(p) = \exp(-(-\ln(p))^{\eta}), \text{ for } 0 < p \leq 1 \text{ and } 0 < \eta, \tag{2}$$

where the parameter η determines the degree of distortion of probabilities. When $\eta = 1$ there is no distortion of probabilities and we are back to EUT. If $\eta \in (0, 1)$, then the function captures the inverted s-shaped pattern and the further away η is from 1 the higher the degree of probability weighting. If $\eta > 1$, we have an s-shaped pattern where small probabilities are underestimated and large probabilities are overestimated.

To model the utility function we focus on hyperbolic absolute risk aversion (HARA), power, and expo-power utilities. These three utility functions represent different types of risk preferences and risk-skew trade-offs. Power utility is the benchmark approach in most empirical work on risk aversion.[11]

[11] See Harrison et al. (2005, 2007) and Harrison and Rutström (2008).

HARA utility nests power utility and provides a simple and flexible characterization of the trade-off between risk aversion and preference for skew. Expo-power utility offers a more flexible representation of risk preferences across different stakes than power or HARA utility.

Consider the utility function:

$$u(x) = (\alpha + x)^{1-\beta}, \tag{3}$$

where x is wealth, $\beta < 1$, and $\alpha + x > 0$. An individual with this utility function is risk seeking if $\beta < 0$, risk neutral if $\beta = 0$, and risk averse if $0 < \beta < 1$. This utility function belongs to the family of HARA utility functions.[12] The coefficient of relative risk aversion for HARA is

$$-\frac{u''(x)x}{u'(x)} = \frac{\beta}{1 + \alpha/x}. \tag{4}$$

From (4) we see that when $\alpha > 0$ and $\beta > 0$ the coefficient of relative risk aversion is increasing with wealth and is bounded above by β.

The trade-off between risk aversion and skewness preference is given a choice-theoretical characterization by Chiu (2005). He shows that if two lotteries are strongly skewness comparable, then the function $-u'''(x)/u''(x)$ has the interpretation of measuring the strength of an individual's preference for skew against his risk aversion. The higher the ratio $-u'''(x)/u''(x)$ the more important is the preference for skew and the less important is risk aversion.

From (3) we have that

$$-\frac{u'''(x)}{u''(x)} = \frac{1+\beta}{\alpha + x}, \text{ for } 0 < \beta < 1. \tag{5}$$

HARA utility nests power utility since setting $\alpha = 0$ in (3) gives us a power utility. Setting $\alpha = 0$ in (5) gives us

$$-\frac{u'''(x)}{u''(x)} = \frac{1+\beta}{x}, \text{ for } 0 < \beta < 1. \tag{6}$$

Comparing (5) to (6) we see that if $\alpha > 0$ and $\beta > 0$, then $\frac{1+\beta}{x} > \frac{1+\beta}{\alpha+x}$ for any given x. This means that, for any given wealth level, a risk averse

[12] The HARA family of utility functions was introduced by Robert Merton (1971). The HARA family has an Arrow-Pratt's coefficient of absolute risk-aversion that is an hyperbolic function of wealth since $-u''(x)/u'(x) = \beta/(\alpha + x)$.

individual with a power utility displays a stronger preference for skew relative to aversion to risk than a risk averse individual with a HARA utility.

The expo-power utility function was first proposed by Atanu Saha (1993) and is defined as

$$u(x) = \frac{1}{\phi}\left[1 - \exp\left(-\phi x^{1-\theta}\right)\right],$$

with $\phi > 0$ and $\theta < 1$. Expo-power utility converges to power utility when ϕ converges to 0. The expo-power function exhibits decreasing absolute risk aversion and increasing relative risk aversion when $0 < \theta < 1$ and $\phi > 0$. It exhibits increasing absolute and relative risk aversion when $\theta < 0$ and $\phi > 0$. Thus, expo-power utility is more flexible than HARA utility to capture different types of absolute risk aversion. The third derivative of the expo-power function is not as tractable as that of the HARA and so the function $-u'''(x)/u''(x)$ of the expo-power does not provide a simple characterization of the risk-skew trade-off.

Maximum likelihood methods are used to estimate the relevant parameters (see Harrison and Rutström, 2008 for a discussion of the empirical strategy). First we calculate the index

$$\nabla RDU = RDU_S - RDU_R,$$

where RDU_S is the rank dependent utility of the safe lottery and RDU_R is the rank dependent utility of the risky lottery. This latent index, based on latent preferences, is then linked to observed choices using a logistic cumulative distribution function $\Lambda(\nabla RDU_i)$. This "logit" function takes any argument between $\pm\infty$ and transforms it into a number between 0 and 1. Thus, with this logit link function we have

$$\Pr(Choice = S) = \Lambda(\nabla RDU).$$

3.3 Estimation Results

Table 10 reports maximum likelihood estimation results of the above decision models. For each utility function we report two specifications, one imposing the constraint that the RDU parameter η is equal to one and a second without such a constraint. First, η is significantly less than one when allowed to vary. Second, other than η, the results do not vary much between the constrained and unconstrained estimations. These are indications that the results are robust and do not depend on particular specifications. Third, across the utility models the HARA function fits the data best. Since HARA utility nests power utility, the comparison between the two amounts to a test of the significance of the coefficient α. This parameter is indeed significant and we conclude that the HARA generalization is useful. The expo-power function is non-nested with the HARA function but since the number of parameters is the same we can compare the two models based on their log likelihoods. The HARA function fits better than the expo-power function, both in the restricted and non-restricted estimations.

insert Table 10 here

So far estimations have not accounted for heterogeneity in subjects' preferences. To do so we split our sample according to the prior classification scheme and estimate separate decision models for individuals classified as EUT and RDU, respectively. Results are reported in Table 11. For EUT individuals η is always larger than for the pooled sample and quite close to unity, which implies low levels of probability distortion. For those classified as RDU η is always smaller than for the pooled sample, indicating greater probability distortion. These structural group-level results are thus consistent with our non-structural classifications of subjects.[13]

insert Table 11 here

4 Gambling in Public Lotteries

In this section we show that a rank-dependent utility model calibrated with our laboratory-derived estimates is able to explain several stylized facts of gambling in public lotteries. Research on gambling in public lotteries shows that:

1. Despite a return of only \$.53 on the dollar, public lotteries are extremely

[13] Of course, EUT and RDU subjects are not homogeneous. For example, among the RDU subjects 32 were classified as having inverted s-shaped probability weighting and 4 were classified as having s-shaped probability weighting.

popular.[14]

2. Most players only buy from 1 to 5 tickets on each lottery.

3. Ticket sales are an increasing function of the mean (better bets are more attractive ones), a decreasing function of the variance (riskier bets are less attractive), and an increasing function of the skew of the prize distribution (see Ian Walker and Juliet Young 2001).

4. Low-income individuals spend a higher percentage of their income on lottery tickets than do wealthier individuals (see Emily Haisley, Romel Mostafa, and George Loewenstein (2008) and the references therein).

To show that our laboratory-derived estimates can explain these stylized facts we start by formalizing the lottery ticket purchase problem. Let each lottery ticket win a unique prize of value G with probability p and be sold at price $c > pG > 0$.[15] Since buying a single lottery has negative expected value ($c > pG$) a risk neutral or a risk averse EUT agent will never buy a lottery ticket. The rank-dependent utility of buying n lottery tickets is

$$RDU(n) = [1 - w(np)]\, u(z - nc) + w(np)u(z + G - nc),$$

where z is initial wealth and $w(\cdot)$ is the probability weighting function, given by (2). The optimal n for a RDU agent is the solution to

$$\begin{aligned} &\max_n\, [1 - w(np)]\, u(z - nc) + w(np)u(z + G - nc) \\ &\text{s.t. } w(p) = \exp(-(-\ln(p))^\eta) \\ &\qquad nc \leq z \\ &\qquad u(z) \leq RDU(n) \end{aligned}$$

To calibrate the lottery parameters we set $G = \$10^6$, $p = 10^{-6}$, and $c = \$2$.[16] Thus, a person that buys a single state lottery ticket faces a lottery

[14] In a 2007 Gallup poll, 46 percent of Americans reported participation in state lottery gambling (see www.gallup.com/poll/104086/One-Six-Americans-Gamble-Sports.aspx).

[15] This is a simplified lottery. Real world public lotteries usually have multiple prizes (second prize, third prize, and others).

[16] For example, a "lottery ticket" in the lottery "Euromillions" is the selection and purchase of a combination of 5 digits (from 1 to 50) and 2 stars (from 1 to 9). Each ticket costs €2.00. The gross expected value of buying one ticket is approximately €.80. A ticket in the US lottery "Powerball" is the selection and purchase of a combination of five white balls out of 59 balls and one red ball out of 39 red balls. Each ticket costs \$1.00. The gross expected value of buying one ticket is approximately \$.59.

with mean $-\$1$, median $-\$2$, standard deviation $\$1,000$, and skew 1000. To calibrate the power utility we set $\beta = 0.5$ (an average of recent estimates, see HL) and $\beta = 0.75$, our estimate for the power-RDU model. We calibrate the HARA and expo-power utilities with the estimates obtained with the RDU model: $\alpha = 60.7$, $\beta = 0.73$, $\phi = 0.016$, and $\theta = 0.573$. We solve this problem for three levels of initial wealth–\$10, \$100 and $\$1,000$–and sixteen levels of the probability weighting parameter η.[17]

Table 12 summarizes the results. Each cell in the tables gives us the optimal number of lottery tickets that an RDU individual buys for each utility function, probability weighting level, and initial wealth level. The table shows that:

insert Table 12 here

i) Subjects only buy lottery tickets for sufficiently high levels of probability distortion (low η). The values of η in the table are within the range that have been found in the literature. For these values, subjects eventually buy lottery tickets in all cases. The number of tickets bought increases with the level of distortion.

ii) Increases in initial wealth lead to less than proportional increases in lottery ticket purchases for all specifications. This is consistent with the fact that low-income individuals spend a higher percentage of their income on lottery tickets than high income individuals.

iii) The number of lottery tickets bought is low and decreases with the concavity of the utility function.

iv) Functions that exhibit increasing relative risk aversion (like HARA and expo-power) generate the smallest predicted ticket purchases.

v) The HARA function with η close to our own estimate of .815 predicts a number of tickets purchased from 0 to 2.

[17]The literature has found a variety of estimates for the parameter η in the domain of gains. (Amos Tversky and Daniel Kahneman (1992) find $\eta = 0.61$, Colin Camerer and Teck Ho (1994) find $\eta = 0.56$, George Wu and Richard Gonzales (1996) find $\eta = 0.71$, Mohammed Abdellaoui (2000) find $\eta = 0.60$, and Glenn Harrison (2008) finds $\eta = 0.92$ and $\eta = 0.95$.

5 Conclusion

This paper use an laboratory experiment to examine the impact of skew in the distribution of payoffs on choices under risk. We offer individuals three sets of ten pairwise choices between a safe and a risky lottery. Across the sets we keep the skew of the safe lotteries fixed at zero and vary the skew of the risky lotteries. We find that subjects make more risky choices when the risky lotteries displays greater positive skew.

In the experiment subjects are given the objective probabilities of each lottery outcome. Yet, our findings reveal that many individuals make skew loving choices because they overestimate small probabilities and underestimates large probabilities. We estimate utility functions for the representative subject in our pool and use our estimated parameters to study the decision of an economic agent to buy state lottery tickets, a decision in which the agent also faces objective probabilities of winning. We find that such an agent may decide not only to buy lottery tickets but to restrict their purchase to a small number of them.

Knowing how individuals respond to risk, skew, and probabilities can be useful in a number of other settings such as household portfolio choices, the design of incentives in organizations (e.g. employee stock options and prizes in rank-order tournaments) and entry into entrepreneurship.

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7 Tables and Figures

Table 1: HL's Lotteries.

Option S	Option R	E(S)-E(R)
1/10 of \$2.00, 9/10 of \$1.60	1/10 of \$3.85, 9/10 of \$0.10	\$1.17
2/10 of \$2.00, 8/10 of \$1.60	2/10 of \$3.85, 8/10 of \$0.10	\$0.83
3/10 of \$2.00, 7/10 of \$1.60	3/10 of \$3.85, 7/10 of \$0.10	\$0.50
4/10 of \$2.00, 6/10 of \$1.60	4/10 of \$3.85, 6/10 of \$0.10	\$0.16
5/10 of \$2.00, 5/10 of \$1.60	5/10 of \$3.85, 5/10 of \$0.10	-\$0.18
6/10 of \$2.00, 4/10 of \$1.60	6/10 of \$3.85, 4/10 of \$0.10	-\$0.51
7/10 of \$2.00, 3/10 of \$1.60	7/10 of \$3.85, 3/10 of \$0.10	-\$0.85
8/10 of \$2.00, 2/10 of \$1.60	8/10 of \$3.85, 2/10 of \$0.10	-\$1.18
9/10 of \$2.00, 1/10 of \$1.60	9/10 of \$3.85, 1/10 of \$0.10	-\$1.52
10/10 of \$2.00, 0/10 of \$1.60	10/10 of \$3.85, 0/10 of \$0.10	-\$1.85

Table 2: Treatments.

Legend	Treatment
T1	Tabular display of Holt and Laury's (HL) low-payoff treatment
T2	Graphical display of HL low-payoff treatment
T3	Tabular display of HL low-payoff treatment plus \$1.00
T4	Graphical display of HL low-payoff treatment plus \$1.00
T5L	Graphical display zero skew
T5H	Graphical display zero skew 20x (high payoff)
T6L	Graphical display moderate skew
T6H	Graphical display moderate skew 20x (high payoff)
T7L	Graphical display maximum skew
T7H	Graphical display maximum skew 20x (high payoff)

Table 3: Sequences of Treatments.

a i)	T1 first, then T5L, T6L and T7L randomized in 6 different orders
a ii)	T2 first, then T5L, T6L and T7L randomized in 6 different orders
a iii)	T3 first, then T5L, T6L and T7L randomized in 6 different orders
a iv)	T4 first, then T5L, T6L and T7L randomized in 6 different orders
b)	T5H, T6H and T7H randomized in 6 different orders
c)	T5L, T6L and T7L and then T5H, T6H and T7H randomized in 6 different orders

Table 4: Sample characteristics.

	Mean	Std. Dev	Obs.
Age	22.95	3.96	146
Height	1.73	0.10	140
People in the house	2.58	1.02	141
Male	0.67		147
Raised in Canada	0.62		147
Non white	0.63		148
Non main decison maker in house	0.47		148
Non married	0.92		148
Non full time student	0.07		148
Graduate student	0.23		148
Major in Economics or Business	0.25		139

Table 5: Average Numbers of Safe Choices with Real Stakes: Effect of Skew.

Number of subjects	Treatment	Low Stakes	High Stakes (20×)
124 subjects	Zero skew	3.86	
47 subjects	Zero skew		4.62
124 subjects	Moderate Skew	3.59	
47 subjects	Moderate Skew		4.11
124 subjects	Maximum Skew	3.25	
47 subjects	Maximum Skew		3.79

Table 6: Regression results: Effect of Skew and Stakes.

	OLS (i)	OLS (ii)	Random Effects (iii)	Fixed Effects (iv)
Constant	3.904	3.633	3.765	
	(0.128)	(1.032)	(1.452)	
Medium Skew	-0.339^b	-0.316^b	-0.316^a	-0.339^a
	(0.171)	(0.156)	(0.122)	(0.111)
High Skew	-0.673^a	-0.677^a	-0.677^a	-0.673^a
	(0.171)	(0.156)	(0.122)	(0.111)
High Stakes	0.603^a	0.458^a	0.516^a	0.536^a
	(0.156)	(0.153)	(0.153)	(0.175)
Age		-0.005	-0.013	
		(0.033)	(0.047)	
Male		-0.488^a	-0.405	
		(0.156)	(0.215)	
Raised in Canada		-0.168	-0.227	
		(0.167)	(0.228)	
Major in Economics or Business		-0.072	-0.021	
		(0.176)	(0.241)	
People in house		0.065	0.055	
		(0.064)	(0.091)	
Non main decison maker in the house		0.651	0.570	
		(0.229)	(0.322)	
Non white		-0.559^a	-0.588^b	
		(0.177)	(0.252)	
Non married		0.396	0.478	
		(0.338)	(0.479)	
Non full time student		-0.530	-0.463	
		(0.364)	(0.498)	
Graduate student		0.190	0.152	
		(0.263)	(0.370)	
$R^2/\bar{R}^2$	0.03/0.03	0.06/0.05	0.27/0.22	0.71/0.59
Subjects/observations	148/513	135/474	135/474	148/513

Note: Standard errors in parenthesis. Superscripts a and b indicate significance at the 1% and 5% level, respectively. Estimation in columns (ii) and (iii) also includes controls for income level, source of income and responsible for tuition.

Table 7: Pattern of probability distortion and lottery choices of an RDU subject with square root utility and Prelec's probability weighting function and corresponding EUT/RDU and skew choice classifications

Range of probability distortion for RDU $w(p) = e^{(-(-\ln p)^{\eta})}$	Pattern of Probability Distortion	Safe choices in T5,T6,T7	EUT/RDU choice classif.	Skew choice classif.
$1.90 < \eta < 3.00$	s-shaped	6,6,6	EUT	neutral
$1.80 < \eta < 1.90$	s-shaped	5,6,6	EUT	averse
$1.43 < \eta < 1.80$	s-shaped	5,6,5	EUT	averse
$1.00 < \eta < 1.43$	s-shaped	5,5,5	EUT	neutral
$0.97 < \eta < 1.00$	inverted s-shaped	5,5,4	EUT	seeker
$0.73 < \eta < 0.97$	inverted s-shaped	5,4,4	EUT	seeker
$0.69 < \eta < 0.73$	inverted s-shaped	5,4,3	RDU	seeker
$0.54 < \eta < 0.69$	inverted s-shaped	5,3,3	RDU	seeker
$0.47 < \eta < 0.54$	inverted s-shaped	5,3,2	RDU	seeker
$0.40 < \eta < 0.47$	inverted s-shaped	5,2,2	RDU	seeker
$0.37 < \eta < 0.40$	inverted s-shaped	4,2,2	RDU	seeker
$0.32 < \eta < 0.37$	inverted s-shaped	4,2,1	RDU	seeker
$0.16 < \eta < 0.32$	inverted s-shaped	4,1,1	RDU	seeker
$0.10 < \eta < 0.16$	inverted s-shaped	4,1,0	RDU	seeker

Table 8: Preferences for risk and skew and lottery choices of an EUT individual with a power utility and corresponding skew classification

Range of relative risk aversion for $u(x) = x^{1-\beta}$	Risk preference	Skew preference	Safe choices in T5,T6,T7	Skew choice classif.
$\beta < -5.10$	seeker	seeker	1,0,0	seeker
$-5.10 < \beta < -2.70$	seeker	seeker	1,1,0	seeker
$-2.70 < \beta < -2.00$	seeker	seeker	1,1,1	neutral
$-2.00 < \beta < -1.52$	seeker	seeker	2,1,1	seeker
$-1.52 < \beta < -1.49$	seeker	seeker	2,2,1	seeker
$-1.49 < \beta < -0.88$	seeker	neutral	2,2,2	neutral
$-0.88 < \beta < -0.86$	seeker	averse	2,2,3	averse
$-0.86 < \beta < -0.80$	seeker	averse	2,3,3	averse
$-0.80 < \beta < -0.32$	seeker	averse	3,3,3	neutral
$-0.32 < \beta < -0.30$	seeker	averse	3,3,4	averse
$-0.30 < \beta < -0.21$	seeker	averse	3,4,4	averse
$-0.21 < \beta < 0.25$	neutral	neutral	4,4,4	neutral
$0.25 < \beta < 0.40$	averse	seeker	5,4,4	seeker
$0.40 < \beta < 0.50$	averse	seeker	5,5,4	seeker
$0.50 < \beta < 0.90$	averse	seeker	5,5,5	neutral
$0.90 < \beta < 1.00$	averse	seeker	6,5,5	seeker

Table 9: Classification of Subjects in the Sample

	EUT			RDU		Total
	Risk Seeker	Risk Neutral	Risk Averse	Inverted S-shaped	S-shaped	
Skew Seeker	18	0	22	32	0	72 (54%)
Skew Neutral	17	18	9	0	0	44 (33%)
Skew Averse	13	0	1	0	4	18 (13%)
Total	98 (73%)			36 (27%)		134

Note: the 14 subjects who made inconsistent choices are not included.

Table 10: Estimation of Decisions Models - Pooled Data

	Power		HARA		Expo-Power	
Parameter						
α			45.11^{b}	60.70		
			(18.79)	(21.09)		
β	0.755	0.755	0.738	0.732		
	(0.015)	(0.015)	(0.019)	(0.019)		
ϕ					0.023	0.016
					(0.000)	(0.001)
θ					0.543	0.573
					(0.000)	(0.009)
η		0.928^{b}		0.815		0.864
		(0.036)		(0.038)		(0.035)
LL	-2249.6	-2246.7	-2219.9	-2199.1	-2243.0	-2227.5

Note: Clustered standard errors in parentheses. Superscript b indicate significance at the 5% level. All others are significant at the 1% level. Number of observations = 5330. Number of subjects = 148.

Table 11: Estimation of HARA Decision Model - Group Data

	Power		HARA		Expo-Power	
Parameter	EUT	RDU	EUT	RDU	EUT	RDU
α			114.17^{a}	72.82^{b}		
			(35.07)	(30.84)		
β	0.777^{a}	0.726^{a}	0.726^{a}	0.691^{a}		
	(0.019)	(0.024)	(0.026)	(0.031)		
ϕ					0.017^{a}	0.005^{a}
					(0.000)	(0.000)
θ					0.586^{a}	0.574^{a}
					(0.000)	(0.000)
η	1.181^{a}	0.858^{c}	0.905^{b}	0.742^{a}	1.034	0.777^{a}
	(0.059)	(0.073)	(0.040)	(0.066)	(0.037)	(0.061)
LL	-1965.82	-611.63	-1830.95	-581.89	-1898.50	-596.76

Note: Clustered standard errors in parentheses. Superscripts a, b, and c indicate significance at the 1%, 5%, and 10% levels, respectively. Number of observations (EUT/RDU) = 3990/1520. Number of subjects (EUT/RDU) = 98/36.

Table 12: Optimal Number of Lottery Tickets Bought by a RDU Individual as a function of the Estimated Models, Probability Distortion (η), and Initial Wealth (z)

	Power $(z+x)^{.50}$			Power $(z+x)^{.25}$			HARA $(60+z+x)^{.27}$			Expo-Power $\frac{1-\exp\left(-.016(z+x)^{.427}\right)}{.016}$		
$\eta\backslash z$	10	100	1000	10	100	1000	10	100	1000	10	100	1000
1.00	0	0	0	0	0	0	0	0	0	0	0	0
.975	0	0	0	0	0	0	0	0	0	0	0	0
.950	0	0	0	0	0	0	0	0	0	0	0	0
.925	0	0	0	0	0	0	0	0	0	0	0	0
.900	0	0	0	0	0	0	0	0	0	0	0	0
.875	0	0	0	0	0	0	0	0	0	0	0	0
.850	0	0	3	0	0	0	0	0	0	0	0	0
.825	0	1	8	0	0	1	0	0	1	0	0	0
.800	0	2	16	0	0	2	0	0	2	0	0	1
.775	1	3	28	0	0	3	0	0	4	0	0	1
.750	1	6	44	0	1	6	1	1	7	0	0	1
.725	1	9	63	0	1	9	1	1	11	0	0	2
.700	2	12	84	0	1	14	1	2	16	0	0	3
.675	2	16	105	0	2	19	1	3	22	0	1	5
.650	3	20	126	1	2	25	2	4	29	0	1	7
.625	3	23	148	1	3	31	3	6	37	0	1	9
.600	4	26	167	1	4	38	3	7	44	1	1	11

Figure 1 - Graphical representation for the first choice between S and R in HL lotteries

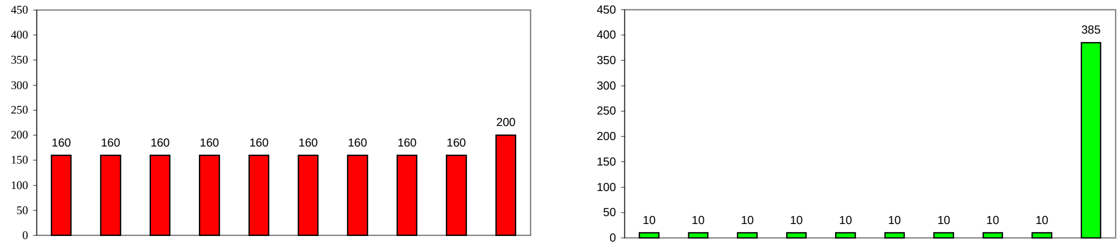

Figure 2 - Graphical representation for the first choice between S and R in the zero skew treatment

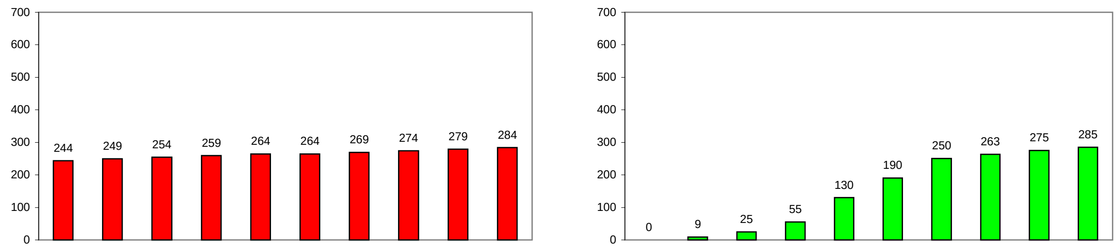

Figure 3 - Graphical representation for the first choice between S and R in the moderate skew treatment

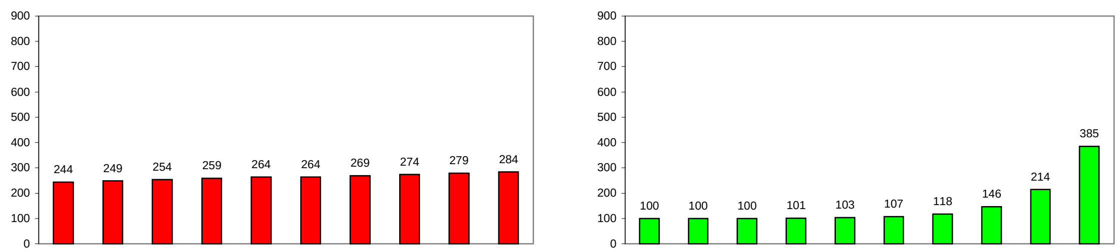

Figure 4 - Graphical representation for the first choice between S and R in the maximum skew treatment