

Preference for Skew in Lotteries: Evidence from the Laboratory*

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Abstract

A laboratory experiment investigates how positive skew influences risky choices. A new non-parametric method classifies subjects according to risk and skew preferences and test whether choices are compatible with expected utility. Both students and executives make riskier choices when lotteries display positive skew. Approximately half of the subjects make skew seeking choices, and half violate expected utility axioms. Students' and executives' preferences for skew are similar. Combining structural estimation with the non-parametric method, we find that skew seeking (averse) choices are driven by an interaction between concave (convex) utility and inverse s-shape (s-shape) probability weighting.

JEL Codes: D81; C91.

Keywords: Decision Making under Risk; Skew; Laboratory Experiment.

*We thank Vince Crawford, Florian Ederer, Ernst Fehr, Xavier Gabaix, Itzhak Gilboa, Glenn Harrison, Botond Koszegi, and Joel Sobel for helpful comments. We also thank seminar participants at HEC Paris, Lisbon Technical University, Ludwig-Maximilian University, Nova University Lisbon, Portuguese Catholic University, University of Nottingham, University of Lausanne, University of Zurich, the National Bureau of Economic Research Entrepreneurship Working Group Meeting 2009, 36thEARIE Conference, and the Royal Economic Society Conference in Surrey. Gordon Adomdza, Won Kno and Anisa Shyti provided research assistance. Support from HEC Foundation, NOVA FORUM and Fundação para a Ciência e Tecnologia is gratefully acknowledged.

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1 Introduction

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 (Golec and Tamarkin, 1998). And when people buy lottery tickets, Forrest, Simmons and Chesters (2000) and Garrett and Sobel (1999) show that people are more concerned with the size of the top prize than the expected value of the lottery.

Positive skew affects other economic choices besides gambling. Three-quarters of all people that enter self-employment face higher variance and skew but lower expected return than in employment (Hamilton, 2000.) Further, 97% of inventors will not break even on their investments but face a very skew distribution of returns conditional on succeeding (Åstebro, 2003.)

Financial markets also provide evidence that is consistent with skew seeking choices. For example, risk aversion implies that people should hold diversified portfolios. However, Blume and 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 (see e.g. Kraus and Litzenberger, 1976).

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 overweighting the probability of attaining favorable outcomes due to optimism, pleasure from gambling, and/or anticipatory feelings.¹ 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 skew as a decision variable.

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 re-

¹See Hey (1984), Conlisk (1993), and Caplin and Leahy (2001).

spect to this characteristic we are able to rule out explanations related to pleasure. In addition, the fact that the probabilities associated with success are objectively determined and known rules out explanations that rely on overconfidence about skill.

We offer individuals three sets of ten pairwise choices between a safe and a risky lottery. Across the three sets we vary the skew of the risky lotteries while keeping the skew of the safe lotteries constant. For each pairwise choice the mean and variance are kept constant across the three skew treatments. This design allows us to test simultaneously for risk, skew, and expected utility preferences. We perform the three sets of choices under two monetary stakes conditions—low and high stakes (20 times higher than low stakes)—on a sample of 148 Canadian students and 131 experienced French executives.

We find that the average number of safe choices decreases monotonically with an increase in skew indicating skew seeking choices. The result holds in both stakes conditions and across both students and executives. All these effects are statistically significant.

Using our within-subject skew treatments we can further classify subjects as making choices that are either a) consistent or inconsistent with Expected Utility (EU); b) skew seeking, neutral or skew averse, and c) risk seeking, neutral or risk averse. This classification is non-parametric and does not require complex estimation procedures. The classification reveals that approximately 50% of the subjects make skew seeking choices. Under low stakes 45% of the students and 52% of the executives make choices which are inconsistent with EU. Skew seeking choices come in slightly greater proportions from the EU group than from the non-EU group. Finally, increasing the monetary stakes raises the percentage of skew seeking choices, the percentage of choices that can be explained by EU, and the percentage of EU risk averse choices. These results are consistent with prior studies using other methods, but also go beyond them.

Structural estimation of decision models for the sub-samples defined by our non-parametric classification method broadly confirms the non-parametric classifications. In particular, the probability weighting parameter increases monotonically in size with the classified degree of skew aversion. However, our approach also reveals preference patterns that are not possible to uncover systematically by traditional parametric estimation. Combining structural estimation with the non-parametric classification method, we find that highly skew seeking choices are driven by an interaction between concave utility and inverse s-shape probability weighting whereas highly skew averse choices

are driven by an interaction between convex utility and s-shape probability weighting.

2 Experimental Design

A risk averse individual rejects any mean preserving increase in risk. Within the EU framework, risk aversion is equivalent to concave utility of wealth. In addition, if people prefer a higher third moment for two random variables having equal mean and variance, this is indicative of a preference for skew. The EU trade-off between risk aversion and skew preference is given a choice-theoretical characterization by Chiu (2005). As a manifestation of the preference for skew a EU 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 skew to the right.

Outside the EU framework, individuals can make “skew seeking” choices due to probability weighting. Many individuals have a tendency to overweight small probabilities and underweight large ones. This is called inverse s-shape probability weighting and is one of the major deviations from EU.² The pattern implies that individuals pay more attention to the best and worst outcomes, and less attention to intermediate ones. An individual with these preferences can make simultaneously “risk seeking” choices in positively skewed gambles (lotteries that yield large gains with small probabilities) such as in public lotteries and “risk averse” choices in negatively skewed gambles (lotteries that yield large losses with small probabilities).

In this paper we use a controlled laboratory environment to examine the degree to which people make skew seeking choices. Additionally, we want to find out if skew seeking choices are explained mainly within the EU framework—due to the shape of the utility of wealth function—or outside it—due to inverse s-shape probability weighting.

To do this we offer subjects a task with three sets of choices. Each set of choices was designed in price-list style with 10 decision rows. Each decision row was a choice between a safe and a risky lottery. 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.

²This type of behavior can be captured by rank dependent utility models which assume that individuals distort probabilities via a probability weighting function (see Kahneman and Tversky, 1979; Quiggin, 1982; Schmeidler, 1989; Tversky and Kahneman, 1992).

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.³ 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, the cross-over point indicating the preference for risk.

We generalize Holt and Laury’s method to test simultaneously for risk, skew, and expected utility preferences by departing from HL’s design in one key aspect. We consider three skew treatments of the risky lotteries. In the first treatment – the “zero skew” condition – the risky lotteries have a zero third moment (symmetric prize distributions). In the second treatment – the “intermediate skew” condition – all the risky lotteries have a standardized third moment equal to 1.69 and in the third treatment – the “maximum skew” condition – the standardized third moment is equal to 2.67 (the maximum possible skew in our framework). However, across all skew treatments the safe lotteries have symmetric prize distributions.

The difference between the mean of the safe and of the risky lottery in each decision row is decreasing over decision rows, positive in the first four rows, and negative in the last six rows. Hence, subjects should begin each set of choices by preferring the safe lottery and then switching to the risky lottery.

The switch points in the three skew treatments allow us to determine subjects’ risk types. For example, a EU risk neutral subject is expected to switch from option S to R when the expected value of R dominates. So, he prefers the safe lotteries in the first four decisions and the risky lotteries

³An earlier study using a different design is Cohen, Jaffray, and Said (1987). For surveys on measuring utility under risk and uncertainty, please see Seidl and Traub (1999) and Starmer, (2000).

in the last six decisions. However, a subject who switches from the safe to the risky lottery in rows 7, 4 and 2 in the zero, intermediate, and maximum skew conditions, respectively, is classified as a non-EU individual with love for skew. Section 4 explains in detail how we use choices to classify subjects.

We also differ from HL by varying prizes rather than probabilities to allow for violations of EU due to probability weighting.⁴ Lotteries are further presented in a graphical display rather than in a table. Each lottery is represented as a 10 bar diagram, each bar having an equal probability. The graphical display may reduce the cognitive effort required of subjects to make lottery choices in comparison with the tabular display.⁵ Finally, while HL uses only paper-and-pencil, we conduct the experiment using paper-and-pencil (executives) and computer (students) implementations. Subjects are presented with 10 choices under one skew in sequence and in the computer implemented version are also provided with a review section where any decision may be revisited.

Figures 1 through 3 show the first in a sequence of the ten choices between options S and R for each of three skew treatments. For this choice, the mean, variance and skew of option S are the same. The skew of option S is always zero. For the same choice, the mean and variance of option R are different, but constant across the three different levels of skew. As in Table 1, for the second choice, the mean of the safe choice increases, but the mean of the risky choice increases even more.

insert Figures 1 to 3 here

If the expected payoffs in HL's experiment were to be maintained the higher levels of skew would lead to some negative payoffs. We therefore add \$1 (€1) to HLs payoffs. We test whether there is any effect of adding \$1 (€1) and any difference between choices for graphical and tabular display. We also introduce lotteries with 20 times the payoffs to study the impact of

⁴Abdellaoui, Driouchi and L'Haridon (2009) discuss the advantages of using the outcome scale rather than the probability scale.

⁵Researchers have found graphical display of data sometimes to be superior to tabular display in terms of decision accuracy. The advantage depends 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. Speier (2006), Meyer, Shamo, and Gopher (1999), Schauenbroeck and Muralidhar (1991) and Hwang and Wu (1990).

skew under large stakes. We randomize subjects' allocation to treatments and also the order of treatments. Table 2 presents the different treatments.

insert Table 2 here

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 (T5L-T7L) and then draw a prize from one of the 4 sets; ii) Subjects perform 3 sets of high stakes choices with 3 different skews (T5H-T6H) 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. The method in sequence iii) is designed to eliminate potential wealth effects (see Laury, 2005). Subjects were randomly allocated across 10 treatments in six pre-determined treatment sequences, except executives whom did not have treatment sequence iii) as they performed the experiment with pencil and paper.

Instructions were kept identical to those in HL, with some necessary revisions to account for the difference in presentation formats and the fact that students conducted the task on the computer. Students also took a knowledge test on their understanding of the instructions and had to pass to move forward to the experiment. A random lottery incentive system was applied.⁶ Subjects were awarded lottery prizes plus a Cdn. \$5 (€5) participation fee.

Using posters we recruited 148 students at the University of Waterloo, Canada. We also recruited 131 experienced French executives which were attending HEC Paris for a one-week executive education program. Subjects in our samples are briefly described in Table 3. There are several obvious differences between the student and executive samples. The executives are, on average, 17 years older, 71% having more than 10 years of work experience, many (16%) have a Ph.D. degree, and are more likely than the students to be the decision-maker in the family (0.80 versus 0.53), and more likely to be

⁶This commonly employed technique was explained to subjects before they began the experiment. Laury (2005) demonstrates that subjects do not discount the payoffs by the probability of the task being selected.

married (0.80 versus 0.08). Sixty-five percent of the executives earn more than €90,000, while, among the students, 77% earn less than €44,000.

insert Table 3 here

The subjects could work at their own speed. For the computer implemented experiment, on average subjects took 17.2 minutes to read the instructions and complete the experimental tasks as well as the socio-economic questionnaire (the median time was 16.5 minutes, minimum 8.5, and maximum 37.3). At the end of the experiment subjects were paid in private. 99 students (82 executives) were offered low stakes only and made on average Cdn. \$3.08 (€3.35). 24 students (49 executives) were offered high stakes only and made on average Cdn. \$63.13 (€69.47). 25 students were offered low stakes first and high stakes later, in the first stage they made on average Cdn. \$3.35. Of those 25, 2 decided to retain those earnings and the remaining 23 went through the second round. In this second round they made Cdn. \$75.26 on average.

3 Findings

3.1 Skew and Incentive Effects

Table 4 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 and for both samples. Thus, on average, subjects make skew seeking choices. We also find that increasing the stakes increases the average number of safe choices for all skew conditions. We cannot reject that there is no difference between the mean safe choices between the students and executives ($F = 2.44$, $p = 0.12$). Moreover, students and executives react the same to changes in skew ($F = 0.27$, $p = 0.77$) and changes in stakes ($F = 0.12$, $p = 0.73$).

insert Table 4 here

Table 5 displays the results of regressing the number of safe choices on dummies for the skew treatments and for high stakes. Columns (i) and (ii)

are for the sample of students, while columns (iii) and (iv) are for executives. Column (i) and (iii) report our basic results. The coefficients for the constant in these columns imply that under low stakes and no skew both students and executives make on average 3.9 safe choices. For students, we further find that the number of safe choices decreases by 0.34 from zero skew to intermediate skew and by 0.67 from zero skew to maximum skew. When confronted with high stakes lotteries subjects make significantly less risky choices.⁷ Regression results were similar for the executive sample, although the reaction to skew seems be slightly larger (Table 5, columns iii and iv).

insert Table 5 here

In addition to the skew and stakes dummies, in the estimations reported in columns (ii) and (iv) a number of subject demographic characteristics were included as well. As, by design, all subjects perform choices under all skew conditions, skew conditions are orthogonal to subjects' characteristics and including socio-demographic characteristics should not change the estimates of the impact of skew. The minor differences that we observe when including the demographics are due to the fact that observations are not exactly the same, as we do not observe all characteristics for all subjects.

The results for socio-demographic characteristics (see the Appendix Table 9) reveal that males and non-white students make more risky choices than females and whites, respectively. All other characteristics, except those related to income, are non-significant once controlling for everything else in the model.⁸ Regression results were of similar nature for the executive sample (Appendix Table 10) except that we do not find a gender effect in that sample.

⁷The least squares regression provides easy interpretation of estimated coefficients. 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 present changes from those reported.

⁸A 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.

Since all subjects make repeated decisions under different conditions, panel random and fixed effects models can also be estimated. Again, because skew conditions are orthogonal to individual effects, the estimates of the effect of skew do not change. If anything, the effects are slightly more precisely estimated (squared brackets in Table 5).

Overall, all of our results indicate a robust effect of skew upon choices both in the students and in the executive samples.

3.2 Robustness

Our subjects perform their choices in different sequences. 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. Dummies indicating which initial treatment (if any) the students had performed has a p-value of 0.113, while the p-value for order dummies is 0.099. Thus, we conclude that there is no meaningful order effect. The same conclusion applies to the executive sample.

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 32% of the students switched back and forth when data was presented in the tabular display, while only 6% did so in the graphical display. For the executives we find 5% (2/38) switching back and forth in the tabular display, and 22% (13/60) switching more than once in the graphical display. The first difference in proportions is significant ($z = 5.41$, $p < 0.001$) as is the second, although with reversed sign ($z = -2.20$, $p < 0.05$)⁹ We checked whether our main regression results were sensitive to whether subject switched between the safe and risky choice more than once and found no remarkable differences.¹⁰

There is some weak indication in our data that the tabular display leads

⁹We leave for future research to explain this interesting result.

¹⁰We 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.

subjects to make a larger number of safe choices. The observed average number of safe choices for students 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 the executives the observed average number of safe choices is 3.9, 3.1, 4.3 and 3.4 for T1 to T4. For the executives we cannot reject that the mean number of safe choices in T1, T2, T3 and T4 are all equal. All possible tests of equality across T1-T4 are not rejected.

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.

4 Subject Classification

In this section we explain how our task allow us to distinguish subjects who make choices consistent with EU from those who do not, and to uncover heterogeneity in risk and skew attitudes among individuals. For presenting the criteria that classifies subjects into groups, let x_j denote the number of safe choices of a subject in skew treatment $j \in \{Z, I, M\}$, where Z represents the zero skew treatment (T5), I the intermediate skew treatment (T6), and M the maximum skew treatment (T7).

The choices of an EU risk neutral and skew neutral subject satisfy (A1) $x_Z = x_I = x_M = 4$. That is, he makes 4 safe choices in all skew treatments.

The choices of an EU risk averse and skew averse subject satisfy (A2) $4 \leq x_Z \leq x_I < x_M$ or $4 \leq x_Z < x_I \leq x_M$. That is, the number of safe choices in Z is greater than or equal to 4 and either (i) the number of safe choices in Z is less than or equal to that in I and the number of safe choices in I is less than in Z , or (ii) the number of safe choices in Z is less than in I and the number of safe choices in I is less than or equal to that in Z .

The choices of an EU risk averse and skew neutral subject satisfy (A3) $4 < x_Z = x_I = x_M$. That is, he makes more than 4 safe choices in all treatments and the same number of safe choices in all treatments.

The choices of an EU risk averse and skew seeker subject satisfy (A4) $4 \leq x_M \leq x_I < x_Z$ or $4 \leq x_M < x_I \leq x_Z$. That is, the number of safe choices in Z is greater than or equal to 4 and either (i) the number of safe choices in Z is greater than in I and the number of safe choices in I is greater than or equal than in M , or (ii) the number of safe choices in Z is greater

than or equal than that in I and the number of safe choices in I is greater than in M .

The choices of an EU risk seeker and skew averse subject satisfy (A5) $x_Z \leq x_I < x_M \leq 4$ or $x_Z < x_I \leq x_M \leq 4$. That is, the number of safe choices in M is less than or equal to 4 and either (i) the number of safe choices in Z is less than or equal to that in I and the number of safe choices in I is less than in M , or (ii) the number of safe choices in Z is less than in I and the number of safe choices in I is less than or equal to that in M .

The choices of an EU risk seeker and skew neutral subject satisfy (A6) $x_Z = x_I = x_M < 4$. That is, he makes less than 4 safe choices in all treatments and the same number of safe choices in all treatments.

Finally, the choices of an EU risk seeker and skew seeker subject satisfy (A7) $x_M \leq x_I < x_Z \leq 4$ or $x_M < x_I \leq x_Z \leq 4$. That is, the number of safe choices in Z is less than or equal to 4 and either (i) the number of safe choices in M is less than or equal to that in I and the number of safe choices in I is less than in Z , or (ii) the number of safe choices in M is less than in I and the number of safe choices in I is less than or equal to that in Z .

A subject whose choices do not satisfy any of the conditions (A1)-(A7) has non-EU preferences since he violates EU's assumptions that risk and skew attitudes are independent of probabilities. We classify non-EU subjects into three different groups according to behavior towards skew: (i) skew seeking, (ii) skew neutral, and (iii) skew averse.

The choices of a non-EU skew seeking subject do not satisfy any of the conditions (A1)-(A7) and satisfy (B1) $x_Z > x_M$, that is, he makes more safe choices in Z than in M . Several violations of EU fit into this category. For example, $x_Z > x_I \geq 4 > x_M$, that is, risk averse choices in Z and I but risk seeking choices in M , which violate EU's assumption that risk attitudes are independent of probabilities. Another example is $x_I > x_Z > x_M > 4$, that is, more safe choices in I than in either Z or M , which violate EU's assumption that skew attitudes are independent of probabilities.

The choices of a non-EU skew neutral subject do not satisfy any of the conditions (A1)-(A7) and satisfy (B2) $x_Z = x_M$, that is, he makes the same number of safe choices in Z and in M . Several violations of EU also fit this category. For example, $x_Z = x_M > 4 > x_I$, that is risk averse choices in Z and M but risk seeking choices in I , which violates EU's assumption that risk attitudes are independent of probabilities. Or, $x_Z = x_M = 5 < x_I$, that is, more risk averse choices in Z and M than in I , which violates EU's assumption that skew attitudes are independent of probabilities.

Finally, the choices of a non-EU skew averse subject do not satisfy any of the conditions (A1)-(A7) and satisfy (B3) $x_M > x_Z$, that is, he makes more safe choices in M than in Z . For example, $x_M > 4 \geq x_I > x_Z$, that is, risk averse choices in M but risk seeking choices in I and Z , which violate EU's assumption that risk attitudes are independent of probabilities. Or, $4 > x_M > x_Z > x_I$, that is, less safe choices in I than in either M or Z , which violate EU's assumption that skew attitudes are independent of probabilities.

Table 6 displays the classification of the student (executive) subjects in each of the stakes conditions. When stakes are low 55% (48%) of subjects make choices consistent with EU and 45% (52%) make choices inconsistent with EU. We also see that 50% (46%) of subjects are skew seekers, 31% (26%) are indifferent to skew, and 19% (28%) are averse to skew. Among the skew seekers, 42% (45%) are non-EU and 58% (55%) are EU.

insert Table 6 here

When stakes are high 68% (59%) of subjects make choices consistent with EU and 32% (41%) make choices inconsistent with EU. We also see that 68% (49%) of subjects are skew seekers, 15% (27%) are indifferent to skew, and 17% (24%) are averse to skew. Among the skew seekers, 72% (58%) are EU individuals and 28% (42%) are non-EU individuals.

Overall, raising the stakes leads to higher percentages of: i) skew seeking choices, ii) choices that are consistent with EU, and iii) EU risk averse choices. This applies both to students and executives. Indeed, we find no significant differences in classification frequencies between the two samples in Table 6.¹¹

5 Estimation of Decision Models

In this section we show that the method of allocating subjects to preference groups in the non-parametric approach used in Section 4 produces results consistent with more traditional parametric estimation of utility functions.

¹¹This comparison was made using six classes (skew averse, skew neutral and skew seeking for EU and non-EU individuals) and leads to χ^2 statistics of 3.59, and 4.71 for low and high stakes, respectively. Given the low incidence of the skew averse and skew seeking in the high stakes case, for the comparison in this case these two classes were aggregated.

To model probability weighting we use the one-parameter probability weighting function in Prelec (1998): $w(p) = \exp(-(-\ln(p))^\eta)$, where $0 < p \leq 1$ and $0 < \eta$. The parameter η determines the degree of distortion of probabilities. When $\eta = 1$ there is no probability weighting and we are back to EU. The further away η is from 1 the higher the degree of probability weighting. If $\eta \in (0, 1)$, then the function captures the inverse s-shape pattern where small probabilities are overweighted and large probabilities are underweighted. If $\eta > 1$, we have an s-shaped pattern where small probabilities are underweighted and large probabilities are overweighted.

To model the utility function we use power utility, the benchmark approach in most empirical work on risk attitudes: $u(x) = x^{1-\beta}/(1-\beta)$, if $\beta \neq 1$ and $u(x) = \ln x$, if $\beta = 1$. The parameter β determines the curvature of the utility function. When $\beta > 0$ there is risk aversion, when $\beta = 0$ risk neutrality, and when $\beta < 0$ there is love for risk.

The parameters of interest are estimated by maximum likelihood (see Harrison and Rutström, 2008). In order to account for the possibility that choices made by the same individual are correlated, standard errors are clustered at the individual level. Furthermore, we allow choices to be contaminated by errors made when the utilities of the two lotteries are compared by using Luce's (1959) decision error specification: $\Pr(\text{Choice} = S) = RDU_S^{1/\mu} / (RDU_S^{1/\mu} + RDU_R^{1/\mu})$, where μ is the parameter that represents the errors.¹²

We split our sample into groups according to the prior classification scheme and estimate a decision model for groups containing at least five subjects.¹³ Results are reported in Table 7.

insert Table 7 here

To save space we only report results for the student sample in this section. Results for the executives are very similar and are available in Ta-

¹²As $\mu \rightarrow 0$ Luce's specification collapses to the conventional RDU model where the choice is strictly determined by the utility of the two lotteries. As μ gets very large the choice becomes completely random.

¹³In the high stakes treatment there were only four groups with five or more subjects. Except in one case where the estimated β is greater than one (although not significantly so) the results, not reported here, were very similar to the corresponding groups in the low stakes case.

ble 8. The parametric estimation results are broadly consistent with our non-parametric classification.¹⁴ First, for those classified as not making EU-consistent choices, the estimates of the probability weighting parameter η increase monotonically with the increase in the degree of skew aversion. The estimates of η are smaller than one for the skew seeking groups, not different from one for the skew neutral group and greater than one for the skew averse groups. Values of η smaller than unity mean that the probability of extreme prizes are overweighted and the probability of middle prizes is underweighted, while values of η greater than unity mean that the probability of extreme prizes are underweighted and the probability of middle prizes is overweighted. Of course, with positive skew the probability weighting of the highest prize has a disproportionate impact upon the evaluation of the lotteries.¹⁵ Finally, note that subjects in the non-EU skew seeking group have a concave power utility function since the estimate of β is 0.130 whereas subjects in the non-EU skew averse group have a convex power utility since the estimate of β is -0.697 . This means that highly skew seeking choices are actually driven by an interaction between concave utility and inverse s-shape probability weighting. In contrast, highly skew averse choices are driven by an interaction between convex utility and s-shape probability weighting.

For those classified as making choices consistent with EU, the estimated β is significantly negative for the groups classified as making risk seeking choices, not significantly different from 0 for the group classified as making risk neutral choices and significantly positive for the group classified as making risk averse choices. That is, our non-parametric classification of preferences for risk is consistent with standard parametric estimation of preferences for risk.

More importantly, for three out of the five EU-consistent groups, η is sig-

¹⁴The error parameter is almost always statistically different from zero, which indicates that people make decision errors.

¹⁵To provide a sense of the degree of probability weighting, we report the estimated probabilities for the first and last prizes. Subjects in the non-EU skew seeking group display inverse s-shape probability weighting since the estimate of η is 0.687. This estimate implies that subjects in this group consider the probabilities of getting the highest and the lowest prize to be 0.17 and 0.192, respectively. In contrast, subjects in the non-EU skew averse group display s-shaped probability weighting since the estimate of η is 1.331. This estimate implies that subjects in this group consider the highest and lowest prizes to have probability 0.048 and 0.049, respectively. For the non-EU skew neutral group the indication is that on average subjects make no probability weighting since the estimate of η is not significantly different from unity.

nificantly different from unity (economically irrelevantly different from unity in one additional case). The pattern of deviations from unity for η follows the same pattern as for the non-EU groups: skew seekers overweight the probabilities of the first and the last prize and skew averse do the opposite. This casts some doubts on the likelihood that these subjects are EU-consistent. Of course, it may be the case that these subjects are indeed EU-consistent, but the power is not a sufficiently general utility function to replicate their choices. It is possible that other utility functions might be able to rationalize the choices of these subjects within the context of EU.

For executives, we were hampered in our estimations by smaller group sizes, but for the groups where we could perform structural estimations, we find very similar patterns to the corresponding student groups. The main difference between the executive and the student structural estimations is that we obtain higher levels of probability weighting for executives than for students across all groups, except the non-EU skew neutral.

6 Relation to Prior Results on Risk and Skew

We find that 50% (46%) of our students (executives) exhibit skew seeking behavior in low stakes. Under high stakes the numbers increase to [68%, (49%)]. These percentages are somewhat higher than what has been found in previous laboratory experiments using lottery choices, and which analyze data within the context of the EU framework. Brunner, Levinsky and Qiu (2007) as well as Tarazona-Gomez (2004) find roughly 40% skew seekers. However, studies that, as us, do not impose EU also arrive at higher percentages. Both Deck and Schlesinger (2008) and Ebert and Wiesen (2009) find approximately 60% to be skew seekers.

In addition, we find that at least 45% (52%) of students (executives) are EU-inconsistent in low stakes. These percentages are consistent with prior studies, across which there is some considerable variation.¹⁶ Under high stakes the numbers decrease to [32%, (41%)]. Further, we find that when subjects face higher stakes they tend to make a larger number of safe choices. This is in agreement with most (but not all) of the results in the literature that has examined the impact of stake size on attitudes towards risk. See for

¹⁶Percentages of non-EUT subjects are as follows across various studies: Harrison and Rutström (2009), 45%; Harrison et al. (2005), 54%; Hey and Orme (1994), 61%; Lattimore et al. (1992), 80%; Bruhin et al. (2010), 80%.

example Holt and Laury (2002, 2005) and Fehr-Duda et al. (2010).

One of the goals of the experiment was to find out if skew seeking choices are explained mainly within the EU framework or outside it. We discover that among subjects who make skew seeking choices 42% (45%) of students (executives) violate EU. These percentages drop to 28% (42%) under high stakes. Among subjects who make EU-inconsistent choices, 46% (40%) make skew seeking choices whereas 21% (30%) make skew averse choices, the rest being skew neutral. We find no comparable studies on these results.

Outside the lab, our results suggest that heterogeneity in preferences for risk and skew might explain the favorite-longshot gambling bias. Empirical work examining the favorite-longshot bias has used a representative agent framework and found that probability weighting seems to explain the behavior of the average bettor better than risk loving preferences [Jullien and Salanié (2000), Snowberg and Wolfers (2007)]. In contrast, if bettors have similar preferences towards risk and skew as the ones found in our sample, the favorite-longshot bias is likely to be driven by the behavior of a subset of bettors who distort probabilities.

Another example of a field application of our results is entry into entrepreneurship. A commonly held assumption is that entrepreneurs are individuals which are significantly less risk averse than the average individual in the population (see e.g. Kihlstrom and Laffont, 1979). Our findings instead suggest that a small fraction of individuals with very distinct risk profiles may decide to enter entrepreneurship as they are likely to significantly distort the assessment of the likelihood of success. Many other individuals may have very different (no) subjective evaluations of probabilities and may thus remain employees.

7 Conclusion

This paper use a new laboratory experiment to examine the impact of positive skew in the distribution of payoffs on choices under risk. We find that subjects make riskier choices when lotteries display greater positive skew. The design of the experiment stipulates that subjects make decisions in all skew conditions. Thus, we can rule out unobserved variation across subjects as a potential explanation for skew loving choices. In addition, using our within-subject skew treatments, we are able to classify subjects as making choices that are either a) consistent or inconsistent with Expected Utility

Theory (EU); b) skew seeking, neutral or skew averse, and c) risk seeking, neutral or risk averse. Two additional benefits from our study are that we can identify non-EU subjects without assuming a specific functional form of the utility of prizes or probability weighting and that we demand a reduced number of choices from the subjects (we need 30 while for example Hey and Orme (1994) use over 500).

Our classification results are generally consistent with prior work; half of the subjects make skew seeking choices and slightly less than half of these come from the non-EU group. In addition, more than one half of the subjects in our sample make choices that are not consistent with EU. We also find that raising the stakes increases the percentage of skew seeking choices but decreases the number of choices that violate EUT.

Parametric estimations confirm the results from our non-parametric classification method. When individuals classified as exhibiting increasing (decreasing) preference for skew, inverse-s-shaped (s-shaped) probability weighting increases. Similarly, when individuals classified as exhibiting increasing (decreasing) preference for risk, the convexity (concavity) of the utility function increases. However, our approach also reveals preference patterns that are not possible to uncover systematically by traditional parametric estimation. For example, for the non-EU individuals we find an interaction between the shape of the utility function and the degree of probability weighting across the skew-preference groups. Had we instead been uninformed about skew preferences and estimated a single utility function for the non-EU individuals this would have averaged to no probability weighting (results suppressed, available from the corresponding author).

We include two distinct samples in this study: students and high-paid executives. There are significant differences in earnings, experience, and most other background characteristics between the two groups. While an a-priori judgment might have been that students are less able to analyze risk rationally, our results reveal no significant differences between these samples in their response to our stimuli.

Our experiment is conducted by asking subjects to choose between lotteries. An obvious application of our findings is gambling and, indeed, our results can help explain the favorite-longshot gambling bias. However, knowing how individuals simultaneously 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.

8 References

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9 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 intermediate skew
T6H	Graphical display intermediate skew 20x (high payoff)
T7L	Graphical display maximum skew
T7H	Graphical display maximum skew 20x (high payoff)

Table 3: Average characteristics in the samples of students and executives.

	Students	Executives
Age	22.95	39.89
Standard Deviation of Age	3.96	4.89
Male	0.67	0.78
Non main decision maker in house	0.47	0.20
Non married	0.92	0.20
Non full time student	0.07	0.96
Education		
Currently graduate student	0.23	
Holds a graduate degree		0.85
Income		
Cad 15,000 (\approx €11, 000) and under	0.36	
Cad 15,001 – Cad 60,000 (\approx €11,000 – €44,000)	0.41	
Cad 60,001 (\approx €44, 000) and over	0.23	
€90,000 and under		0.35
€90,001 – €130,000		0.40
€130,001 and over		0.25

Notes: The number of observations varies from 144 to 148 in the students' sample and from 113 to 124 in the executives' sample.

Table 4: Average Numbers of Safe Choices with Real Stakes: Effect of Skew.

Number of subjects	Treatment	Low Stakes	High Stakes
Students (Executives)			(20 \times)
124 (82)	Zero skew	3.86 (3.87)	
47 (49)	Zero skew		4.62 (4.41)
124 (82)	Intermediate Skew	3.59 (3.24)	
47 (49)	Intermediate Skew		4.11 (3.80)
124 (82)	Maximum Skew	3.25 (3.12)	
47 (49)	Maximum Skew		3.79 (3.57)

Table 5: Regression results: Effect of Skew and Stakes.

	Students		Executives	
	(i)	(ii)	(iii)	(iv)
Constant	3.904 (0.128)	3.633 (1.032)	3.876 (0.189)	3.687 (1.266)
Intermediate Skew	-0.339 ^{b,a} (0.171) [0.111]	-0.316 ^{b,a} (0.156) [0.122]	-0.618 ^{b,a} (0.242) [0.173]	-0.609 ^{b,a} (0.254) [0.189]
High Skew	-0.673 ^{a,a} (0.171) [0.111]	-0.677 ^{a,a} (0.156) [0.122]	-0.779 ^{a,a} (0.254) [0.173]	-0.727 ^{a,a} (0.271) [0.221]
High Stakes	0.603 ^{a,a} (0.156) [0.175]	0.458 ^{a,a} [0.153] [0.153]	0.515 ^b (0.205) —	0.573 ^b (0.232) [0.334]
R^2/\bar{R}^2	0.03/0.03	0.06/0.05	0.04/0.03	0.12/0.07
Subjects/observations	148/513	135/474	124/393	113/330

Note: Robust standard errors in parenthesis. Standard errors in square brackets are for fixed (columns i, iii) and random effects (columns ii, iv) respectively. Superscripts a, b and c indicate significance at the 1% and 5% level, respectively. First superscript refers to OLS, the second to panel estimation. Estimation in columns (ii) and (iv) also includes controls for age, gender, non main decision maker status, marital status, and income level. For the students sample (column ii), additional controls were student status, major in Economics or Business, race, source of income and responsible for tuition. For the executive sample (column iv), additional controls were employment status, business ownership experience, education, and job market experience.

Table 6: Percent of Subjects in Each Class in the Student and Executive Samples

	Consistent with EUT						Non-EUT		Total	
	Risk Seeker		Risk Neutral		Risk Averse				st	ex
	st	ex	st	ex	st	ex	st	ex	st	ex
Skew seeker										
Low Stakes	16	16	0	0	13	10	21	21	50	46
High Stakes	15	10	0	0	34	18	19	20	68	49
Skew neutral										
Low Stakes	6	5	9	1	2	4	15	16	31	26
High Stakes	6	6	4	2	0	8	4	10	15	27
Skew averse										
Low Stakes	9	6	0	0	1	6	10	16	19	28
High Stakes	4	8	0	0	4	6	9	10	17	24
Total										
Low Stakes			55	48			45	52		
High Stakes			68	59			32	41		

Note: Figures in each cell are the percent of subjects in each class relative to the total in the corresponding sample. The first(second) figure in each cell is for the student (executive) samples. Sample sizes are 124 (students low stake), 47 (students high stake), 82 (executive low stake), and 49 (executive high stake).

Table 7: Estimation of Decision Model with Prelec Weighting Function, Power Utility, and Luce Errors in the Student Sample

		Choices Consistent with EUT			Non-EUT	
		Risk Seeker	Risk Neutral	Risk Averse		
Skew Seeker						
β	-0.766 ^a	(0.166)		1	-	0.130 ^c (0.075)
μ	0.188 ^a	(0.033)		0.010 ^a	(0.001)	0.088 ^a (0.018)
η	0.573 ^a	(0.052)		0.791 ^a	(0.047)	0.687 ^a (0.030)
LL	-141.87			-64.33		-206.52
Subj.	20		0	16		26
Skew Neutral						
β	-1.408 ^c	(0.638)	-0.007	(0.006)		-0.697 ^a (0.229)
μ	0.217	(0.118)	0.021 ^a	(0.008)		0.119 ^a (0.022)
η	1.042	(0.100)	1.008 ^a	(0.003)		0.969 (0.031)
LL	-45.64		-14.36			-162.63
Subj.	7		11		2	18
Skew Averse						
β	-0.809 ^a	(0.270)				-0.697 ^a (0.229)
μ	0.116 ^b	(0.053)				0.217 ^a (0.061)
η	1.159 ^a	(0.033)				1.331 ^a (0.092)
LL	-59.77					-127.41
Subj.	11		0		1	12

Note: Clustered standard errors in parentheses. Superscripts *a*, *b*, and *c* indicate significance at the 1%, 5%, and 10% levels, respectively. For β and μ relative to 0. For η relative to 1.

Table 8: Estimation of Decision Model with Prelec Weighting Function, Power Utility, and Luce Errors in the Executive Sample

		Choices Consistent with EUT			Non-EUT	
		Risk Seeker	Risk Neutral	Risk Averse		
Skew Seeker						
β	-0.840 ^a	(0.228)		1	-	0.051 (0.117)
μ	0.262 ^a	(0.067)		0.012 ^a	(0.004)	0.146 ^a (0.041)
η	0.278 ^a	(0.140)		0.710 ^a	(0.032)	0.327 ^a (0.087)
LL	-105.06			-37.23		-178.71
Subj.	13	0		8		17
Skew Neutral						
β						-0.230 (0.286)
μ						0.208 ^a (0.066)
η						0.929 (0.046)
LL						-169.72
Subj.	4	1		3		13
Skew Averse						
β	-2.047 ^c	(1.117)		0.795	(0.742)	-1.175 ^a (0.448)
μ	0.298	(0.177)		0.026	(0.082)	0.350 ^a (0.140)
η	1.418 ^b	(0.191)		1.677	(0.450)	1.562 ^a (0.108)
LL	-39.56			-45.46		-163.28
Subj.	5	0		5		13

Note: Clustered standard errors in parentheses. Superscripts *a*, *b*, and *c* indicate significance at the 1%, 5%, and 10% levels, respectively. For β and μ relative to 0. For η relative to 1.

Table 9: Appendix. - Regression results for the Student Sample.

Constant	3.633 (1.032)
Intermediate Skew	-0.316 ^b (0.156)
High Skew	-0.677 ^a (0.156)
High Stakes	0.458 ^a (0.153)
Age	-0.005 (0.033)
Male	-0.488 ^a (0.156)
Non white	-0.559 ^a (0.177)
Raised in Canada	-0.168 (0.167)
Major in Economics or Business	-0.072 (0.176)
People in house	0.065 (0.064)
Non main decision maker in the house	0.651 (0.229)
Non married	0.396 (0.338)
Non full time student	-0.530 (0.364)
Graduate student	0.190 (0.263)
R^2/\bar{R}^2	0.06/0.05
Subjects/observations	135/474

Note: Robust standard errors in parenthesis. Superscripts a and b indicate significance at the 1% and 5% level, respectively. Estimation also includes controls for income level, source of income and responsible for tuition.

Table 10: Appendix. - Regression results for the Executive Sample.

Constant	3.687
	(1.266)
Intermediate Skew	-0.609 ^b
	(0.254)
High Skew	-0.727 ^a
	(0.271)
High Stakes	0.573 ^a
	(0.232)
Age	0.034
	(0.028)
Male	0.243
	(0.290)
Non main decision maker in the house	0.113
	(0.288)
Non married	0.252
	(0.319)
Full time employee	-0.277
	(0.452)
Currently self-employed	0.294
	(0.551)
Ever self-employed	0.064
	(0.297)
Graduate degree	0.487
	(0.343)
Ph.D. degree	0.348
	(0.436)
R^2/\bar{R}^2	0.12/0.06
Subjects/observations	110/330

Note: Robust standard errors in parenthesis for col (i) and (ii). Superscripts a, b, and c indicate significance at the 1%, 5% and 10% level, respectively. Estimation also includes controls for work experience and income level.

Figure 1 - Graphical representation for the first choice between S and R in the zero skew treatment

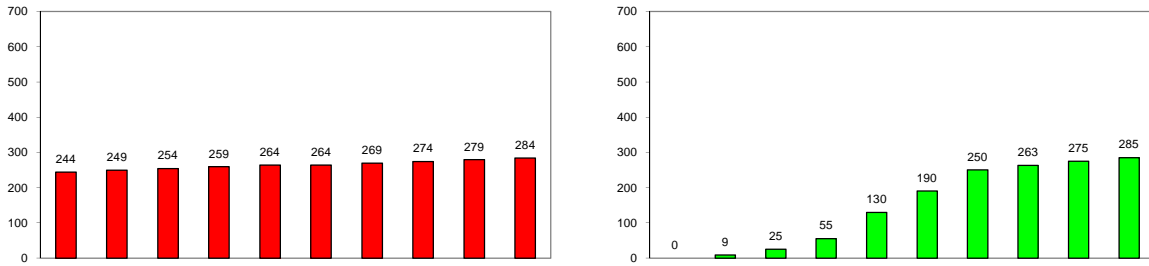


Figure 2 - Graphical representation for the first choice between S and R in the moderate skew treatment

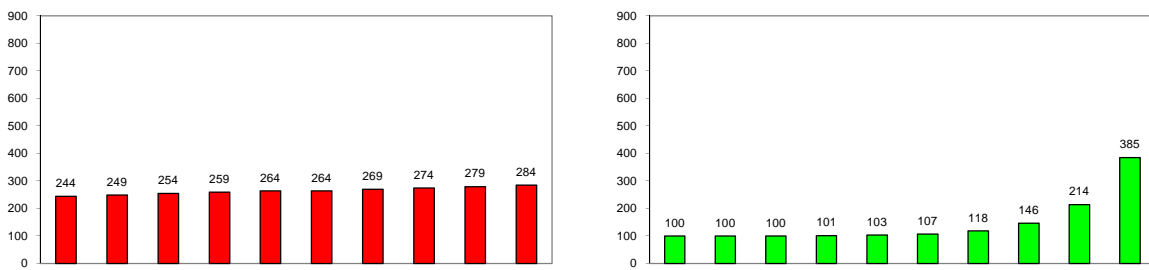


Figure 3 - Graphical representation for the first choice between S and R in the maximum skew treatment

