Skewness Seeking: Risk Loving, Optimism or Overweighting of Small Probabilities?[⋆]

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Abstract

In a controlled laboratory experiment we use one sample of college students and one of mature executives to investigate how positive skew influences risky choices. In reduced-form regressions we find that both students and executives make riskier choices when lotteries display positive skew. We estimate decision models to explore three explanations for skew seeking choices: risk-loving (convex utility), optimism (concave probability weighting), and likelihood insensitivity (inverse s-shape probability weighting). We find no role for love for risk as neither students nor executives have convex utility. Both optimism and likelihood insensitivity play a part in skew seeking choices. Likelihood insensitivity is larger for students than for executives. Executives have more concave utility and are more optimistic than students, but this is found to be largely due to them being older.

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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).

How can one explain these choices favoring options with positive skew, high-risk and low expected return? Within the context of the classical expected utility theory (EUT from now on) such choices may be explained by love for risk due to convex utility of wealth. EUT also allows risk averse individuals to have a preference for positive skew and, indeed, Ebert (2013) shows that all commonly used risk averse utility functions exhibit skewness preference. However, because EUT's preference for positive skew is a third order effect, it cannot lead to choices of alternatives that have lower expected value and higher risk (Chiu 2010). Choices such as those discussed above can also be determined by pleasure from gambling (Conlisk 1993) or anticipatory feelings (Caplin and Leahy 2001). The choice of entrepreneurship over wage work may also be a result of a preference for being one's own boss (Benz and Frey 2008) or of overconfidence about skill (Wu and Knott 2006) Another alternative is that these choices result from overweighting the probability of attaining favorable outcomes due to optimism or likelihood insensitivity. Optimism refers to overweighting the probability of getting larger prizes and underweighting the probability of getting lower prizes regardless of the probabilities of the prizes. Likelihood insensitivity refers to the tendency to overweight small probabilities and underweight large ones regardless of the magnitude of the prizes (see Wakker 2010).

Field data are not practical to distinguish between these alternative explanations, since risk and skew are typically positively correlated. Both risk loving and optimistic persons respond similarly to increases in skew. The risk lover will favor greater skew because greater skew is associated with greater risk. The optimist will favor the same option because he will overweigh the probability of favorable outcomes. To evaluate the role of love for risk, optimism, and likelihood insensitivity as explanations for favoring positive skew we therefore use a laboratory experiment. In this experiment we ask subjects to make choices between pairs of lotteries for which we manipulate the expected value, risk and skew. Comparing choices between pairs of lotteries allow us to rule out explanations related to the pleasure of gambling. In addition, our design rules out explanations that rely on overconfidence about skill since the probabilities associated with success are objectively determined, known in advance, and do not depend on one's actions.

Our experimental design, inspired by Holt and Laury (2002), offers individuals sets of 10 choices between a safe and a risky lottery, constructed in such a way that the number of times the safe lottery is chosen is indicative of either risk averse, risk neutral or risk seeking choices. We depart from Holt and Laury's (2002) design in one critical aspect. We consider three skew conditions for the risky lotteries. In the first, second and third skew conditions the risky lotteries have zero, intermediate, and maximum skew, respectively. In all three conditions the safe lotteries are kept fixed as well as the mean and variance of the risky lotteries. Observed changes in the number of safe choices across the three skew conditions thus reveal the impact of positive skew upon decisions. Making fewer safe choices when the skew is higher is an indication that subjects make skew seeking choices, that is, that they are willing to take more risk in exchange for positive skew.

While laboratory experiments typically use college students as they are cheap and conveniently available, it has been argued that studying real decision makers with significant incentives is more relevant for testing theory (Larrick 2004). We therefore perform the experiment on a sample of 131 experienced French executive education participants (hereon "executives"). For comparison, the same experiment was performed on a standard sample of 148 Canadian college students. In both cases, the experiment was performed under both low and high stakes (20 times higher than low stakes).

We find that, in both samples, subjects make riskier choices when the choice task includes positively skewed lotteries. We estimate structural decision models that allow for utility curvature, optimism, and likelihood insensitivity. We find no evidence of love for risk (convex utility) and we find that both optimism and likelihood insensitivity contribute to skew seeking choices. Students display linear utility of wealth and executives concave utility of wealth. Students display more likelihood insensitivity and are less optimistic than executives. Differences in optimism and utility curvature between executives and students disappear when we control for differences in age.

2 Experimental Design

Two broad sets of theories have been proposed to explain the attractiveness of positive skew, high-risk and low expected return options. First, within classical EUT individuals may only make such skew seeking choices due to risk-loving utility functions.[1] Within this framework, a risk loving individual accepts any mean preserving increase in risk and can accept a lower expected return for a riskier distribution of payoffs. Conversely, a risk averse individual rejects any mean preserving increase in risk regardless of a change in skew. Within EUT, no preference for skewness can ever lead an individual to favor positive skew, high-risk and low expected return options (Chiu 2010).

Alternatively, behavioral theories suggest that cognitive errors and misperceptions of probabilities play a role behind skew seeking choices. According to these theories individuals can make skew seeking choices due to two kinds of probability weighting: optimism and likelihood insensitivity. These

[1] Risk preferences under EUT are not only determined by risk aversion but also by high-order risk preferences such as prudence and temperance. Under differentiable EUT, risk aversion, prudence and temperance are equivalent to $u'' < 0$, $u''' < 0$, and $u'''' < 0$, respectively. Menezes et al. (1980) characterize prudence as downside risk aversion and show that prudence relates to measures of skewness, in particular the third central moment. Chiu (2005) links prudence to a strong measure of skewness due to van Zwet (1964). Chiu (2010) establishes a skewness-comparability condition on probability distributions that is necessary and sufficient far any decision maker's preferences over distributions to depend on their means, variances, and third moments only. Ebert (2013) shows that prudence implies a preference for skewness, but it also requires this preference to be robust towards variations in kurtosis.

ideas form an important foundation of non-expected utility models.

Many individuals are optimistic, i.e., they overweight the probability of favorable outcomes and underweight the probability of unfavorable outcomes (e.g. Scheier et al. 1994 and 2001). An optimistic individual will be overly attracted to positive skew gambles such as public lotteries since he will systematically overweight the probability of getting larger prizes and underweight the probability of getting lower prizes.

Many individuals also have a tendency to overweight small probabilities and underweight large ones. This is termed likelihood insensitivity (Wakker 2010). Likelihood insensitivity implies that individuals pay more attention to the best and worst outcomes, and less attention to intermediate ones. Such individuals exhibit equal overweighting of the lower and upper tails of probability distributions. An individual with these preferences can make simultaneously risk seeking choices in positively skewed gambles (lotteries that yield large gains with small probabilities) and risk averse choices in negatively skewed gambles (lotteries that yield large losses with small probabilities).

Optimism and likelihood insensitivity can be captured by non-expected utility models such as rank-dependent utility and prospect theory which assume that individuals transform objective probabilities into subjective ones via a probability weighting function (see Kahneman and Tversky 1979, Quiggin 1982, Schmeidler 1989, and Tversky and Kahneman 1992). A concave probability weighting function represents optimism. An inverse s-shape probability weighting function represents likelihood insensitivity.

To see how love for risk, optimism and likelihood insensitivity are alternative explanations for skew seeking choices consider a decision maker with a constant relative risk aversion utility of wealth given by $u(x) = x^{1-\alpha}/(1-\alpha)$, if $\alpha \neq 1$ and $u(x) = \ln x$, if $\alpha = 1$. Suppose this decision maker must choose between the sure amount 22 and the positive skew lottery $(\frac{1}{3}, 50; \frac{1}{3}, 10; \frac{1}{3}, 0)$, which has expected value equal to 20. One can think of this decision maker as someone who is making 22 as a wage earner and who is considering a business opportunity in which he can make 50, 10 or 0 with equal probabilities. Alternatively, one can also think of someone who is considering to spend 22 to buy a lottery ticket which pays the prizes above, or trading a bond with expected return of 22 for a stock that will pay 50, 10 or 0 with equal probabilities.

If these probabilities are properly taken into account and the agent has a linear utility of wealth ($\alpha = 0$) this person would, of course, prefer the safer option, since his gain is greater than what he can expect if he chooses the riskier option. If the agent has a concave utility of wealth ($\alpha > 0$) the preference for the safer option is even greater since the agent dislikes risk. However, if the agent has a convex utility of wealth ($\alpha < 0$) he might prefer the risky option. This happens when risk-loving is sufficiently strong; in this example when $\alpha < -0.164$.

Consider now that rather than the objective probabilities $\left(\frac{1}{3}, \frac{1}{3}, \frac{1}{3}\right)$, our agent uses subjective decision weights (π_1, π_2, π_3) to weight the different possible outcomes of the lottery. Assume that these decision weights are determined as $\pi_1 = w(\frac{1}{3}) - w(0)$, $\pi_2 = w(\frac{2}{3}) - w(\frac{1}{3})$, $\pi_3 = w(1) - w(\frac{2}{3})$, where $w(p)$ is the probability weighting function with $w(0) = 0$ and $w(1) = 1$. The rank-dependent utility of the lottery is given by $\sum_{i=1}^{3} \pi_i \frac{x_i^{1-\alpha}}{1-\alpha}$. Furthermore, suppose from now on that the agent has a linear utility of wealth ($\alpha = 0$) and that $w(p)$ is the Goldstein and Einhorn (1987) probability weighting function $w(p) = \beta p^{\eta}/(\beta p^{\eta} + (1-p)^{\eta})$, where $\beta > 0$ and $\eta > 0$ and consider what happens for different parameter values.[2] Note that $\beta = \eta = 1$ corresponds to the case where the agent properly evaluates the probabilities ($w(p) = p$).)

For $\beta = 1.5$ and $\eta = 1$ the decision maker is optimistic ($w(p)$ is concave). In this case, his evaluation of the lottery value is based on subjective decision weights (0.43, 0.32, 0.25) and the value of the lottery is 24.6. Hence, optimism may lead our agent to choose the positive skew risky option since this option seems to be worth more than the safe alternative. When $\eta = 0.5$ and $\beta = 1$ the decision maker displays likelihood insensitivity. Here $w(p)$ has an inverse s-shape, i.e., it is concave for $p \in [0, 1/2]$ and convex for $p \in [1/2, 1]$. In this case, the decision weights are (0.41, 0.17, 0.41) and the value of the risky alternative is 22.4. Hence, likelihood insensitivity can also lead our agent into choosing the risky alternative. Of course, the interaction of optimism and likelihood insensitivity can magnify the effect of positive skew on choices. If the agent has $\beta = 1.5$ and $\eta = 0.5$ the decision weights are $(0.51, 0.16, 0.32)$, the value of the risky alternative is 27.4 and it will look really attractive.

Our experimental design allows us to generate the data needed to estimate the parameters α, β and η in order to infer utility curvature, optimism and likelihood insensitivity, respectively. 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

[2] We here use Goldstein and Einhorn's weighting function simply for illustrative purposes. In the empirical section we estimate two popular alternate weighting functions.

the subject's preferred lottery is then played out to determine 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.[3] In HL, subjects are given the choice between the pairs of lotteries displayed in ten ordered decision rows in Table 1. It is expected that subjects start by choosing the safe lottery (S) in the top decision row as it has both higher expected value and lower variance. As one proceeds down the table, the expected values of both lotteries increase, 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.

insert Table 1 here

We depart from HL's design in one key aspect. We consider three skew conditions 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 switch points in the three skew treatments allow us to determine if subjects take more risk in exchange for positive skew. Section 3.2 explains in detail how we relate these choices to convex utility, optimism, and likelihood insensitivity.

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

[3]Seidl and Traub (1999) and Starmer, (2000) offer surveys on measuring utility under risk and uncertainty. See also Cohen, Jaffray, and Said (1987) for an early study using a related design.

[4]Abdellaoui, Driouchi and L'Haridon (2011) discuss the advantages of using the outcome scale rather than the probability scale.

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 4 show the first in a sequence of ten choices between options S and R for each of HL's lotteries and for each of our three skew treatments. Option S is to the right, option R to the left. Each lottery contains ten prizes represented by ten bars, the height of each bar is proportional to the prize and the prize is given above the bar. Figure 1 is equivalent to the first row in Table 1. Figures 2 to 4 represent the first choices in each of our three skew treatments. For these first choices, the mean, variance and skew of option S are the same. The skew of option S is always zero for the different choices. 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, and so on for choice three, four, etc.

insert Figures 1 to 4 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 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

[5]Researchers 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), Schaubroeck and Muralidhar (1991) and Hwang and Wu (1990).

There are three basic treatment sequences: i) subjects perform one set of HL prize distribution choices (T1-T4) followed by three sets of low stakes choices with three skews (T5L-T7L) and then draw a prize from one of the four sets; ii) Subjects perform three sets of high stakes choices with three different skews (T5H-T7H) and then draw a prize from one of the three sets; iii) Subjects perform three sets of low stakes choices with three different skews. These 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 three 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.

We recruited 131 experienced French executive education participants (executives) from HEC's five different European programs which came together for a three-day on-campus summer institute. Participation in the experiment was voluntary. We also randomly recruited 148 students at the University of Waterloo, Canada. Subjects in our samples are briefly described in Table 3. There are several obvious differences between the executive and student 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 married (0.80 versus 0.08). Sixty-five percent of the executives earn more than €90,000, while, among the college students, 98% earn less than €48,000. Nevertheless, only nine students report annual income of less than Cdn \$5,000 and 69% report paying for at

[6]This 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.

least part of tuition and living expenses. The high self-reliance on own income by these students is due to that Waterloo has one of the world's largest co-op program where students work for one trimester a year. These students are thus likely to have a good grasp of money matters.

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 socioeconomic 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.[7]

3 Results

3.1 Tabulations and Regressions

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 on average react the same to changes in skew ($F = 0.27$, $p = 0.77$) and changes in stakes ($F = 0.12$, $p = 0.73$).

[7] The full set of lotteries and the experimental instructions are available online at http://www.hec.unil.ch/lspinto/.

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. Column (i) reports our basic results. The coefficient for the constant in these column imply that under low stakes and no skew subjects make on average 3.9 safe choices. We further find that the number of safe choices decreases by 0.46 from zero skew to intermediate skew and by 0.72 from zero skew to maximum skew. When confronted with high stakes lotteries subjects make significantly less risky choices.[8]

insert Table 5 here

These results were obtained by ordinary least squares regression, as OLS provides an easy interpretation of estimated coefficients.[9] In addition to the skew and stakes dummies, the estimations reported in column (ii) include a number of subject demographic characteristics. As, by design, all subjects perform choices under all skew conditions, skew conditions are orthogonal to subjects' characteristics and including sociodemographics 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.

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. In the fixed effects regression, the effect of high stakes is almost the same as the corresponding OLS estimate in column (i) (both are around 0.54). Yet, the fixed effect estimate is slightly less precisely estimated, as it relies only on the student's sample, being significant

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

[9] As a robustness check, in preliminary regressions 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.

only at the 5% level. In the random effects regression corresponding to column (ii), the effect of high stakes is estimated to be 0.54 rather than 0.58 as in OLS, and the estimate is significant at the 1% level.

The sociodemographics variables were not significant, with the possible exception of gender. The coefficient on being male is estimated to be -0.44 in OLS and -0.40 in the random effects model, the effect being significant at the 5% level.[10]

We also tested whether there are differences between executives and students by including a dummy variable for executives and interactions between this dummy and our skew and high stakes variables. These variables were never (individually or jointly) significant indicating no statistically significant differences in behavior. We run separate regression for executives and students using also the variables that are available in one sample but not in the other. The results for executive sociodemographics (see the Appendix Table 8) reveal that only having a graduate degree is significantly correlated with making more risky choices. All other characteristics, except those related to income, are non-significant once controlling for everything else in the model. Regressions with student sociodemographics were of similar nature (Appendix Table 9) except that here males and non-white students make more risky choices than females and whites, respectively. The effect of gender which appeared in the pooled sample thus comes only from our sample of students.

3.2 Further robustness checks

Our subjects perform their choices in different sequences. Moreover, some of them went through the initial round (containing one of T1-T4) 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.

[10] 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, etc.). In all cases we cannot reject the null that the effects are identical.

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 ($z = -2.20$, $p < 0.05$).[11] 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.[12]

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

3.3 Estimation of Decision Models

Having established that both students and executives make skew seeking choices we estimate structural models of decision making to find out what drives these choices. Using this modeling technique we may address whether it is utility curvature or subjective probability assessments that drive the observed choices. Further, earlier we found that there were no differences

[11] We leave for future research to explain this interesting result.

[12] 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.

between students and executives in their average attitudes towards skew. However, even if averages may be the same, there might be countervailing effects from these three alternative explanations that may be hidden when studying simple group averages. For example, it is a truism that risk attitudes differ between males and females, and in the regressions we find such differences as well (for college students). Many argue that this reflects differences in risk aversion, while others that it reflects differences in optimism (e.g. Jacobsen et al. 2010). Estimating decisions models will more precisely address this concern.

To model the utility function we use power utility, the benchmark approach in most empirical work on risk attitudes (see Harrison and Rutström 2008): $u(x) = x^{1-\alpha}/(1-\alpha)$, if $\alpha \neq 1$ and $u(x) = \ln x$, if $\alpha = 1$. The parameter α determines the curvature of the utility function. When $\alpha > 0$ there is risk aversion, when $\alpha = 0$ risk neutrality, and when $\alpha < 0$ there is love for risk.

To model probability weighting we use the two-parameter probability weighting function in Prelec (1998): $w(p) = \exp(-(-\beta \ln(p))^{\eta})$, where $0 < p \leq 1$, $\beta > 0$ and $\eta > 0$. While we report the results using Prelec's model, qualitatively similar results were obtained with the two-parameter weighting model due to Goldstein and Einhorn (1987). In Prelec's model, the parameter β measures the degree of optimism / pessimism of the decision maker. If $\beta \in (0,1)$ the probability weighting function captures optimism. If $\beta > 1$ the probability weighting function captures pessimism. The parameter η determines likelihood sensitivity. If $\eta \in (0,1)$, then the function reflects inverse s-shape pattern where small probabilities are overweighted and large probabilities are underweighted (likelihood insensitivity). If $\eta > 1$, we have an s-shaped pattern where small probabilities are underweighted and large probabilities are overweighted (likelihood oversensitiveness). When $\beta = 1$ and $\eta = 1$ there is no probability weighting.

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: $\Pr(Choice = S) = RDU_S^{1/\mu}/(RDU_S^{1/\mu} + RDU_R^{1/\mu})$, where μ is the parameter that represents the errors.[13]

There are four parameters: α, β, η, and μ. We report the results of estimating the model pooling the student and executive samples under high and low stakes. (Results estimated on four separate subsamples: students / executives and high / low stakes were consistent with pooled estimations reported here, but each model had higher standard errors due to lower degrees of freedom.) We include dummy variables for students / executives and high / low stakes to control for potential differences across stakes and samples. Our basic specification therefore has twelve parameters to be estimated. The results of this specification are reported in Table 6 column 1, where we chose to report explicit values for students and executives (not differences) and the effect of making choices under high stakes as differences from the omitted category of low stakes. Therefore, the estimate in the top row for students, $\alpha = 0.107$, refers to students' choices under low stakes and the second estimate $\alpha = 0.478$ refers to executives also under low stakes.

insert Table 6 here

The implications of the results reported in column 1 are the following (see Tables 6 and 7 for p-values): 1. Only executives report significant concavity of utility; α is marginally significantly higher for executives than for students indicating that executives have more concave utility than students. 2. Only executives report significant degrees of optimism; β is significantly lower for executives than for students, reflecting greater optimism. 3. There are significant rates of decision errors for students and executives; the rates are of similar magnitudes. 4. As for η, only students report significant likelihood insensitivity. 5. While none of the high stakes dummies is statistically significant on its own, the four dummies are collectively significant ($\chi^2(4) = 10.27$, $p = 0.04$). The most important changes when the estimates are evaluated at high stakes are that η becomes statistically different from unity (although only marginally for executives, $p = 0.09$), and β is no longer significantly different from unity (p-value for executive increases from less than 0.01 to 0.21.)

[13] μ will increase the greater the number of subjects which switch back and forth. We do not exclude subjects switching more than once. As $\mu \to 0$ 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.

insert Table 7 here

Since there are sociodemographic differences between the student and executive samples, we wanted to check whether these differences could account for the different estimates we obtain in α, β, and η between students and executives.[14] Age was the only characteristic that was found to be related to parameter estimates. Results including this variable are reported in the second column of Table 6. Age is significantly associated with higher degrees of risk aversion and with higher degrees of optimism (no significant relationship was found with μ or η). Once we control for differences in age between students and executives there are no remaining statistically significant differences between the parameter estimates for students and executives (see column 2 of Table 7). Note that annual income, in particular, was not a significant predictor of risky choices in our data. Including income instead of age in the estimation (Column 3), we get non-significant coefficients for income and the remaining coefficients are very similar to those in Column 1. Hence, in contrast to age, income does not explain the differences between the executives and students.

These age-dependent results are consistent with a number of disparate earlier findings showing a) a positive relationship between risk aversion and age (Morin and Suarez 1983, Pålsson 1996), b) a positive relationship between optimism and age (Puri and Robinson 2007), and c) a positive relationship between age and entry into entrepreneurship (Parker 2004). The relationship between age and entry has often been interpreted as reflecting that age allows people to accumulate experience and alleviate cash constraints (Cabral and Mata 2003). Our findings suggest that mature individuals seek out positive skew choices because they significantly overestimate the likelihood of success due to higher degree of optimism, although this tendency is partially tempered by increasing risk aversion with age. It is reasonable that decision making changes over the life of an individual as she becomes more experienced. Still, the finding that age is the only difference between students and executives that matter for their decision process is somewhat unexpected, as is the finding that increasing age (experience) makes people more optimistic.

[14] We explored differences across all comparable background characteristics in our samples, that is, age, gender, education, marital status, who's in charge of household budget, who's responsible for paying tuition and expenses, current and past employment status, and personal income.

It is also worth noting that changes in optimism comes along with changes in risk preference. In our samples, executives are both more optimistic and more risk averse and both seem to be related to age. These two differences cancel somewhat and in the reduced-form regressions reported in Table 5 these differences are not clearly visible.

4 Conclusion

Our paper contributes to the experimental literature on choice under risk that investigates skewness seeking behavior in a systematic way. Previous studies on this topic, both in the context of the EUT paradigm (Mao 1970, and Brünner et al. 2011) and outside this paradigm (Ebert and Wiesen 2011, Deck and Schlesinger 2010, Burke and Tobler 2011, and Wu et al. 2011), have found that most individuals are prudent and make skew seeking choices. We also find evidence on skew seeking choices, as subjects in our experiment make riskier choices when lotteries display greater positive skew. None of these previous studies, however, attempted to distinguish between competing explanations for these type of choices by estimating structural models of decision making. We estimate such models, and find that the observed choices are not driven by love for risk, but rather by optimism and likelihood insensitivity. By being optimistic, individuals overweight the probability of getting larger prizes and underweight the probability of getting lower prizes regardless of the probabilities of the prizes while, by being likelihood insensitive, they overweight small probabilities and underweight large ones regardless of the magnitude of the prizes

We conducted our experiments with a conventional sample of college students and another composed of mature executives. Notwithstanding the significant differences in earnings, experience, and most other background characteristics between executives and college students, the two groups behave rather similarly and differences in their behavior appear to be largely due to age differences. We estimate executives to have more concave utility and to be more optimistic than students, but these differences disappear when age is taken into account. This suggests that the common practice of using college students to analyze behavior as is done by experimental researchers may not be as restrictive as it is sometimes argued (Larrick 2004). However, our findings are consistent with earlier evidence on a positive relationship between risk aversion and age (Morin and Suarez 1983, Pålsson 1996), and optimism and age (Puri and Robinson 2007), and adjustments for college students' lower optimism and risk aversion may, however, be necessary if one wants to draw inferences for a wider population.

Our study casts new light on why individuals choose high-risk low expected return alternatives when the gains under such alternatives are significantly skewed. Given that we asked subjects to choose between lotteries in the laboratory, our results are perhaps most obviously useful for the analysis of gambling behavior. However, knowing how individuals simultaneously respond to risk and skew can also be useful in a variety of other settings such as occupational choices (such as the choice between entrepreneurship and wage work), household portfolio choices, and the design of incentives in organizations (e.g. employee stock options and prizes in rank-order tournaments).

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6 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 decison 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 (≈ €10, 000) and under	0.36	
Cad 15,001 – Cad 60,000 (≈ €10,000 – €38,000)	0.41	
Cad 60,001 (≈ €38, 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 Students	(Executives)	Treatment	Low Stakes	High Stakes (20×)
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.

	(i)	(ii)
Constant	3.900	4.439
	(0.114)	(0.980)
Intermediate Skew	-0.460[a]	-0.441[a]
	(0.100)	(0.105)
High Skew	-0.719[a]	-0.715[a]
	(0.104)	(0.109)
High Stakes	0.543[a]	0.576[a]
	(0.183)	(0.197)
R^2	0.05	0.07
Subjects/observations	279/906	248/810

Note: Clustered standard errors for subjects in parentheses. Superscripts a and b indicate significance at the 1% and 5% level, respectively. Estimation in column (ii) also includes controls for age, gender, non main decision maker status, and marital status.

Table 6: Estimation of Decision Model with Prelec Weighting Function, Power Utility, and Luce Errors in the Pooled Student and Executive Samples

	(1)	(2)	(3)
α			
Students	0.106	-0.429	0.069
	(0.180)	(0.281)	(0.197)
Executives	0.478^{a}	-0.847	0.482^{a}
	(0.181)	(0.548)	(0.201)
Age		0.028^{a}	
		(0.007)	
Income			-0.092
			(0.800)
High Stakes	-0.207	-0.313	-0.253
	(0.277)	(0.319)	(0.303)
μ			
Students	0.109^{a}	0.092^{a}	0.110^{a}
	(0.019)	(0.013)	(0.022)
Executives	0.102^{a}	0.141^{a}	0.099^{a}
	(0.032)	(0.053)	(0.034)
High Stakes	0.044	0.060	0.054
	(0.041)	(0.045)	(0.044)
η			
Students	0.904^{b}	0.933^{c}	0.890^{a}
	(0.043)	(0.035)	(0.045)
Executives	0.941	0.871	0.943
	(0.068)	(0.085)	(0.073)
High Stakes	-0.072	-0.100	-0.075
	(0.077)	(0.072)	(0.081)
β			
Students	0.858	1.218	0.889
	(0.095)	(0.210)	(0.103)
Executives	0.600^{a}	0.602^{a}	0.602^{a}
	(0.088)	(0.348)	(0.135)
Age		-0.018^{b}	
		(0.007)	
Income			-0.058
			(0.860)
High Stakes	0.227	0.290	0.244
	(0.152)	(0.172)	(0.164)
LL	-3220.29	-3184.97	-3122.04

Note: Observations = 8458, subjects = 259. Clustered standard errors for subjects in parentheses. Superscripts a, b, and c indicate significance at the 1% and 5% 10% levels, respectively. Tests are for the hypotheses that the parameters are equal to 0 (α and μ) and to 1 (η and β). The null hypotheses for the coefficients of Age, Income and High Stakes are always that the coefficients is 0.

Table 7: p-values for the tests that the coefficients are identical for Students and Executives

	(1)	(2)
α	0.09	0.22
μ	0.00	0.32
η	0.60	0.42
β	0.03	0.32

Table 8: Appendix. - Regression results for the Executive Sample.

Constant	4.409
	(1.214)
Intermediate Skew	-0.609^b
	(0.251)
High Skew	-0.727^a
	(0.268)
High Stakes	0.483^b
	(0.229)
Age	0.028
	(0.026)
Male	0.334
	(0.281)
Non main decison maker in the house	0.134
	(0.289)
Non married	0.262
	(0.333)
Full time employee	-0.468
	(0.435)
Currently self-employed	0.086
	(0.543)
Ever self-employed	0.112
	(0.290)
Graduate degree	-1.242^a
	(0.346)
Ph.D. degree	-0.352
	(0.440)
$R^2/\bar{R}^2$	0.14/0.09
Subjects/observations	110/330

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

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 decison 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.

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

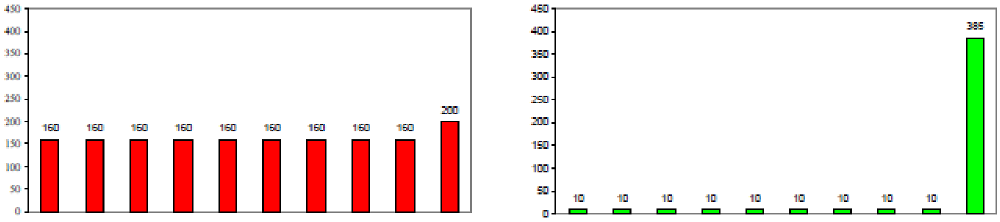

Figure 2 - Graphical representation for the first choice between S and R in the zero skew treatment

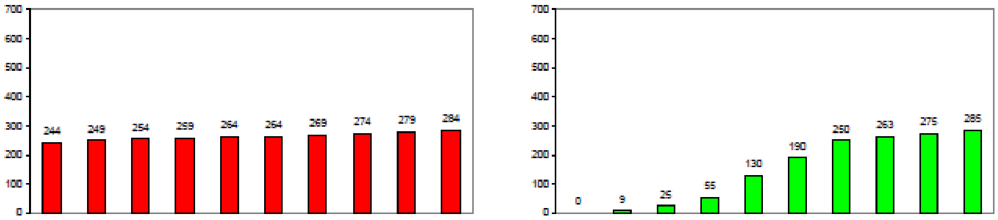

Figure 3 - Graphical representation for the first choice between S and R in the moderate skew treatment

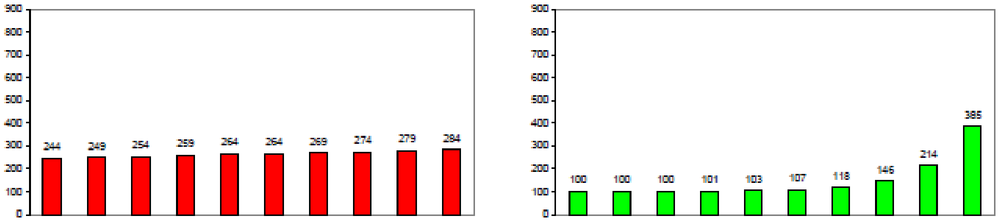

Figure 4 - Graphical representation for the first choice between S and R in the maximum skew treatment