Upside Versus Downside Risk: Gender, Stakes, and Skewness *

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Abstract:

This paper investigates the effects of financial risk, both "upside" (low probability of a high payoff) and "downside" (low probability of a low payoff). Subjects in the single-choice experiment exhibit more aversion to downside risk and more attraction to risky prospects with a small chance of a high payoff. Females tend to be more averse to downside risk, and this gender difference is sharper in a high-stakes treatment. In contrast, there is no clear gender difference for upside risk with positive skewness. These differences are evaluated by deconstructing utility curvature and probability weighting components of risk preferences.

Keywords: risk aversion, skewness, payoff scale, probability weighting, rank-dependent utility, gender differences, experiments

JEL Codes: C92, G20

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I. Introduction

Major economic decisions regarding investments, insurance, or pension plans are typically characterized by a "safer" option with low variance, and a "riskier" option with a high spread between best and worst outcomes. Risk preferences over such alternatives may be influenced by a bundle of emotions, motivations, and perceptions, which can vary from person to person, and over time for the same person. Despite this variability, previous research has provided important insights on demographic factors, such as gender, that seem to have persistent effects on risk preferences.[1] However, it is difficult to reconcile conclusions of studies of gender differences that examine a wide variety of risk and payoff structures.

It is important to distinguish different types of financial risks. Some risks involve very low payoffs (low portfolio valuations after a market downturn, or reduced savings after an unanticipated accident or illness), and other risks involve high payoffs, e.g. gains from speculation in housing or asset markets. This paper provides a simple, context-free experiment with a range of payoff magnitudes and risk structures, e.g. whether there is a small probability of a good outcome or a small probability of a bad outcome. One objective is to differentiate settings in which risk seeking is prevalent from those in which risk aversion prevails. The main experiment is based on a design that varies the nature of the risk ("upside" or "downside"), the subject's gender, and the magnitude of the payoff scale (low or high). Subjects only make a single decision in this experiment, with payoffs provided in cash. A second experiment involves a within-subjects design in which each person makes 20 decisions with various risk, probability, and payoff scale features, with payoff-relevant decisions selected randomly ex post. Random selection can be problematic as discussed below, but it permits the examination of a broader range of decisions in order to disentangle the probability-weighting and utility-curvature components of risk attitudes.

[1] See Eckel and Grossman (2008), Harrison and Rutström (2008), Croson and Gneezy (2009), Charness and Gneezy (2012), Charness et al. (2013), and Holt and Laury (2014) for surveys that cover the rapidly expanding literature on gender and risk. Gender differences are prevalent, but not uniform across measurement methods and contexts, as noted in Crosetto and Filippin (2017).

II. Motivation

One of the salient results from controlled experiments is that women are often found to be more risk averse than men. Such behavioral differences have been observed in financial decisions for which the riskier choice (e.g. not purchasing insurance) is characterized by a low probability of a very low payoff. In this case, the safer choice has less variance, but it also has a lower expected money payoff. In effect, the safer option provides less "downside risk." For example, consider the choice between two options, A and B:

(1) Downside Risk:
Option A: 2 in 3 chances of 838 and 1 in 3 chances of 125
Option B: 2 in 3 chances of 618 and 1 in 3 chances of 325

Option A has higher payoff variability associated with the relatively low payoff of 125, but the expected payoff of 600 for A is 80 higher than the expected payoff for Option B. In this case, those who are risk neutral or slightly risk averse would select Option A, the riskier option, and only those who are sufficiently risk averse would select Option B. Prior experiments indicate that females often exhibit more risk aversion in such situations.[2] There is also some evidence that gender differences would be even stronger if the "safe" option B offers a sure payoff instead of a lower-variance pair of payoffs (618 and 325 in this case).[3]

One avenue for explaining gender differences in risky choice settings is to specify a utility function for women with more curvature than for men. The amount of curvature required to explain the observed choice frequencies, however, is often quite high. Alternatively, some of the reluctance to take risks could be due to an overweighting of the low probability of a low payoff, which would tend to skew decisions away from Option A, which has the extreme low payoff in (1). It is difficult to distinguish between these two explanations, curvature and probability

[2] Fehr-Duda et al. (2006) find a similar pattern of gender differences in decisions characterized by a small probability of a low payoff. Laury et al. (2009) study real payoff insurance decisions in a laboratory experiment involving downside risk (low probabilities of a low final payoff due to a significant loss of a part of the subject's earned endowment for the session). Insurance was purchased at high rates, even with actuarially unfair premium prices used for some of the decisions in the experiment, but gender differences did not show up in an econometric analysis of purchase patterns, which could be due to low sample sizes.

[3] Crosetto, and Filippin (2017) have noted that the types of gender differences observed in investment task menus (Eckel/Grossman) are not generally observed BRET (bomb) or structured choice menus (Holt/Laury). They provide evidence that these differences can be explained by the presence of a safe option in the investment tasks and its absence in the other procedures.

weighting, using decision problems in which the risky choice involves a low probability of a very low payoff. If, however, the low probability outcome involves *high* payoffs instead of low payoffs, then an overweighting of low probabilities could imply *preference* for risky choices instead of aversion. For example, consider the decision in (2), for which the expected payoff difference for A over B is again 80, but the high-variance Option A offers an "upside risk" of a high payoff:

(2) **Upside Risk:**
Option A: 2 in 3 chances of 425 and 1 in 3 chances of 950
Option B: 2 in 3 chances of 485 and 1 in 3 chances of 590

The idea behind a comparison of (1) and (2) is that if probability weighting is important, then the one-third probability would tend to be overweighted in each case. This would generate a pattern of risk avoidance in the downside risk environment (with a low probability of a low payoff), but it would result in an attraction to risky choices in the upside risk environment (with a low probability of a high payoff). This observation would be consistent with some prior work and with casual observation.[4] Probability weighting is a key component of prospect theory, and experimental tests of that theory provide some mixed evidence that low probabilities are overweighted.[5]

An alternative perspective might be based on threshold effects, which imply that risky choice is influenced by target or desired payoff levels. Even though the riskier option A in (2) offers the lowest of the four possible payoffs, that payoff exceeds $4, which participants might

[4] Cohen, Jaffray, and Said (1985), for example, use a choice menu with a lottery on the left side, e.g. 1000 FF. if a "Diamond" is drawn from a deck of cards, and various sure money amounts on the right side ranging from 0 to 1000 F.F. The crossover "price" in such a menu determines a certainty equivalent. Risk aversion is indicated if the certainty equivalent is less than the expected payoff for the lottery. The payoff probability was small, however, since only one of the 134 subjects would be selected for a money payoff determined by one of the 10 choice menus that the subject completed. Payoffs were either positive or 0 for all choice menus in a "gain domain," with the probability of a gain being changed from one menu to another. A key result is that subjects switched from being risk averse to risk seeking as the probability of a high payoff decreased. To summarize, there was generally risk aversion for low probabilities of a 0 payoff, and risk seeking for low probabilities of high payoffs. The opposite pattern was observed for losses, and there was no evidence in favor of reflection effects. Gender differences were not discussed.

[5] Harbaugh et al. (2010) summarize this literature, noting that tests supporting the predictions of prospect theory often involve using hypothetical payoffs as in Kahneman and Tversky (1979), or giving subjects hundreds of decision problems with one to be selected at random, as in Hey and Orme (1994). In contrast, Harbaugh et al. (2010) find no support for the notion that subjects are more risk seeking for small probability gains, a finding that is roughly consistent with their 2002 paper that considered behavior of both children and adults. Conducting incentivized experiments with losses is always a challenge, but the Harbaugh et al. failure to find risk seeking for low probability gains is perplexing in view of the more supportive results and the estimated probability weighting functions reported by others. For example, Fehr-Duda et al. (2006) use a price menu to elicit certainty equivalents of lotteries for high and low probability gains and losses, and they find evidence of risk seeking with low probability gains, e.g. the certainty equivalents tend to exceed expected values.

view as meeting earnings expectations, whereas the low payoff of $1.25 in (1) might not be perceived as meeting expectations. In this manner, threshold effects could explain the tendency for subjects to take more risk in the upside risk setting.

On an intuitive level, downside risk indicates the extent to which a payoff may fall below an anticipated value, in the same manner that a stock which might fall in value is subject to downside risk, unless a put option is used to mitigate this risk. Conversely, upside risk indicates the extent to which a payoff might rise above an expected value. This intuitive difference is illustrated in Figure 1, where the riskier option in each panel has a greater payoff spread, as indicated by the dark bars that bracket the light bars for the safer option. Note that the penny payoffs in (1) and (2) have been converted to dollars in Figure 1. The heights indicate probabilities, so the riskier option on the left side offers a 0.33 chance of a very low payoff of $1.25, whereas the riskier option on the right side offers a 0.33 chance of a relative high payoff of $9.50, which represents greater upside risk.

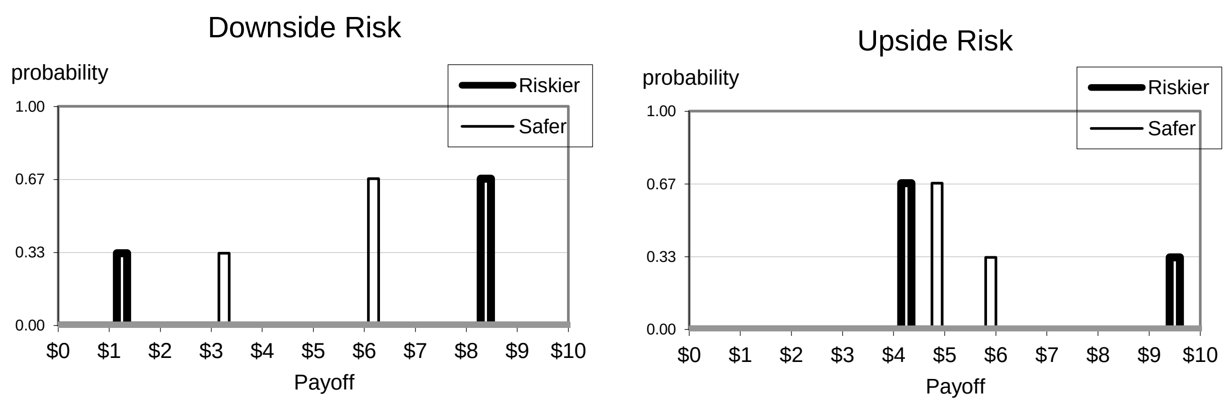

Figure 1. Downside Risk with Negative Skewness on the Left, Upside Risk with Positive Skewness on the Right

To summarize, the risky option (dark bars) in each panel of Figure 1 has a higher standard deviation, and the difference in standard deviations (1.98) between risky and safe options is the same in each panel. Also, each option in Figure 1 has a skewed distribution, with negative skewness (a "tail" to the left) in the downside risk panel and with positive skewness (a "tail" to the right) in the upside risk panel. In fact, the standard measure of skewness is negative (−0.723) for both safer and riskier options in the left panel, and is positive (0.723) for both safer and riskier options in the right panel. This figure suggests that any tendency to overweight low probabilities might produce risk aversion for downside risk (where the probability of a low payoff is overweighted) and risk seeking for upside risk where it is the low probability of the high payoff that is overweighted.

In contrast, the classic Friedman and Savage (1948) explanation for the simultaneous purchase of insurance and lottery tickets is based on risk seeking (convex utility) for very high payoffs. In other words, it is possible that any risk seeking observed in the upside risk setting might be due to utility curvature rather than to a tendency to overweight the low probability of a very high payoff with upside risk. Therefore, we decided to include a set of decisions for which all payoffs (for both upside and downside risk treatments) were scaled up by a factor of 5. Since probabilities are unaffected by such payoff scaling, any observed behavioral changes would have to be due to curvature aspects of utility instead of nonlinear probability perceptions. So the idea behind a switch from downside to upside risk is to isolate effects of probability weighting that cannot be explained by utility curvature. Then a scaling up of all payoffs by a factor of 5 in a second treatment variation (holding probabilities fixed) is used to isolate the effect of utility curvature that cannot be explained by probability perceptions.

III. Procedures for the Single-Choice Experiment

The 2x2x2 design for this experiment involved 256 subjects making a single decision, with variations in gender (half male), payoff scale (half with 5X payoffs), and risk skewness (half with downside risk and half with upside risk). The two risk decisions used are those given in (1) and (2) above, so the 5X scale would raise the low payoff in (1) from \$1.25 to \$6.25, and would raise the high payoff in (2) from \$9.50 to \$47.50. The 2x2x2 design has 8 "bins" with 32 subjects in each, for a total of 256 subjects (128 men and 128 women).

The idea behind the "odd" penny amounts for most of the payoffs in (1) and (2) was to trigger reliance on intuition instead of mathematical calculations that would have been simpler with integer dollar amounts. Decisions were simply labeled as "Option A" or "Option B," and the probabilities were presented in terms of "chances in 100."[6] Since we wanted subjects to be fully

[6] The use of 0.67 and 0.33 probabilities in the experiment instead of 2/3 and 1/3 caused some of the expected payoff differences to be slightly different from the difference of 80 for the other decisions. This change was made because of the way that probabilities were explained to subjects in terms of "chances in 100" instead in terms of probabilities. The truncated 0.67 and 0.33 probabilities that were used in the experiment are used for the econometric estimation in section VI.

aware of payoff scale, the payoffs were labeled in dollars and cents, instead of using higher numbers of points that could have been converted to cash subsequently.

The experiment was run with web-based software, and the instructions are presented in the Appendix.[7] The instructions are the same for all treatments, with a couple of common examples that were used "for illustrative purposes only," so subjects did not encounter the actual payoffs and probabilities until they reached the submit-decision page, which was followed by a confirm/re-choose page. Results were not available until everyone had finished. The results page had a link to a short demographic survey that included age, gender, major, etc. Subjects were recruited from the University of Virginia. The experiment lasted 30-45 minutes, and earnings ranged from $10-$54, including a $6 show-up payment.

IV. Single-Choice Results

Recall that each subject made a single decision between two options, with the expected payoff for the risky decision (A) being 80 higher than for the safe decision (B), regardless of whether the decision involved downside or upside risk. With the 5X scale, this expected payoff difference is 400 ($4) in the experiment. The variance, however, is higher for the risky option, with the difference in standard deviations for the risky and safe options being the same for both upside and downside risk. The key difference between these settings is that skewness is negative for each option in the downside case (a "tail" to the left) and positive for each option in the upside case (a "tail" to the right).

Gender Effects

The choice counts and percentages shown in Table 1 support several insights about how people deal with risk according to differences in gender, payoff scale, and risk structure. First, consider the top row (Downside, 1X scale). The 32 men chose the risky option 25 times, whereas the women only chose risky 19 times. Thus the risky choice percentage was 78% for men and 59% for women, for a treatment difference of 19 percentage points.

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[7] The Pairwise Lottery Choice program that was used can be found on the Decisions menu of the V*e*conlab site: http://veconlab.econ.virginia.edu/admin.php This web-based software is written and maintained by one of the coauthors (Holt) and is freely available for instructional and research use.

Table 1. Choices by Treatment for the Between Subjects (Single Choice) Experiment

		Men Choosing Risky (A)	Women Choosing Risky (A)
Downside 1X	32 male, 32 female	25/32 78%	19/32 59%
Downside 5X	32 male, 32 female	17/32 53%	4/32 13%

		Men Choosing Risky (A)	Women Choosing Risky (A)
Upside 1X	32 male, 32 female	30/32 94%	29/32 91%
Upside 5X	32 male, 32 female	28/32 88%	27/32 84%

A Pearson exact-probability test is based on the idea that there is no gender effect under the null hypothesis, so random switches in gender labels should not matter. In other words, each possible assignment of the 32 male and 32 female gender labels to the observed decisions would be equally likely ex ante. In this case, the observation of an extreme outcome (e.g. males making most of the observed risky choices) would suggest that the null can be rejected. For 1X scale in the top row of the table, the test statistic can be constructed by randomly permuting the gender labels assigned to each of the 64 observed A or B decisions, keeping 32 male labels and 32 female labels. The *p* value for such a test is the proportion of such permutations that yield a treatment difference that exceeds the 19% observed difference. Since there are “64 take 32” ways that gender labels can be permuted (a number in the thousands of trillions), we used 100,000 simulations in which the gender labels (32 men and 32 women) are randomly reassigned to decisions in each simulation. The *p* value (proportion of simulations that yield a treatment difference exceeding 19 percentage points) is about 0.09 for a 1-tailed test, which provides only modest support for a gender difference.

Notice that the treatment difference is much sharper (40 percentage points) in the second row of Table 1, with high (5X) payoff stakes, which yields a *p* value of 0.0012 for a 2-tailed test.[8] One way to avoid the dangers of relying on multiple statistical tests is to use a *joint* test of the gender effect for downside risk. Such a joint test can be constructed by *simultaneously* permuting the gender labels in each of the top two rows of Table 1, while holding the total number of risky decisions constant in each row. This “stratified” permutation test controls for payoff-scale effects

[8] More precisely, 61 of 100,000 simulations yielded a treatment difference greater than +40.06 ($p = 0.0006$), and 121 of 100,000 simulations yielded a treatment difference greater than 40.06 in absolute value.

by permuting the 64 gender labels *separately* for each payoff-scale row or "strata." The result of this joint test provides strong evidence that women are more risk averse in the downside risk treatment, with a p value of 0.0002 (128 observations, 2-tailed test, 2 strata). In contrast, there is no significant gender difference with upside risk, as would be expected given the behavioral similarities shown in the bottom two rows of Table 1. The main insight here is that gender differences in risk taking are context specific.

Gender Effects: *Women are more risk averse than men in the downside risk treatment, especially with high (5X) payoff stakes, but there is no gender difference in the upside risk treatment, irrespective of payoff scale.*

Skewness Effects

The most salient feature of the results in Table 1 is that subjects are much more willing to take the high-variance upside risks than is the case for the high-variance downside risks. This risk effect can be seen clearly by comparing the proportions of risky choices for the top and bottom panels for each combination of gender and payoff stakes, as shown in Figure 2.

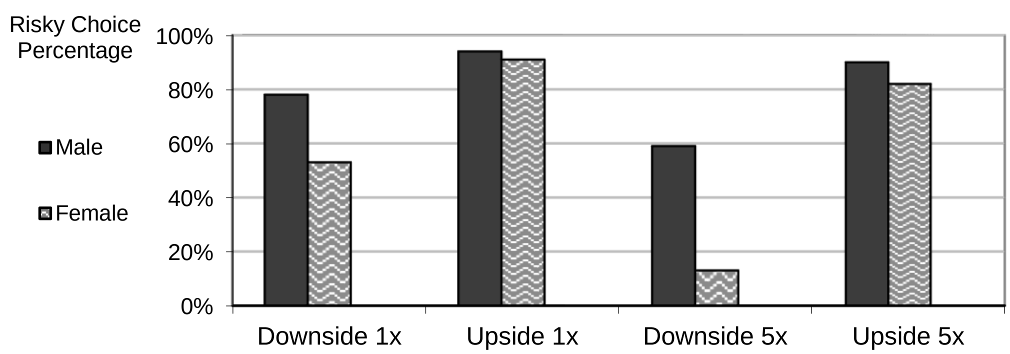

Figure 2. Male Versus Female Percentage of Risky Choices by Risk Type (Upside or Downside) Payoff Scale (1x or 5x)

Downside versus Upside Risk: *Subjects are more likely to select the risky option when it involves the upside risk of a high payoff than when it involves the downside risk of a low payoff, despite the fact that the expected payoff and variance differences between the safe and risky options are the same in each case.*

Support: The proportion of upside risky choices is higher for all four categories (male/1X, male/5X, female/1X, and female/5X). In other words, all four choice proportions in the bottom part of Table 1 are higher than the corresponding choice proportions in the top part. Under the null hypothesis that the type of risk (upside or downside) has no effect, the risk labels do not matter and could be randomly switched for each person. The statistical test involves randomly switching the risk label for each of the 256 choices of A or B, but keeping permutations separate for males and females and for 1X scale and 5X scale. In other words, the test "holds constant" both the gender and payoff scale dimensions in order to calculate the proportion of risky decisions for each risk treatment for each permutation. Then the p value is determined from the tails of the distribution of the difference between the proportion of risky choices under upside risk and that under downside risk. This p value is the proportion of differences (resulting from random permutation of upside/downside labels) that are at least as extreme as the difference observed in Table 1. As before, we use 100,000 simulations to determine the proportions of "as or more extreme" treatment differences, and the resulting p value is less than 0.001 (256 observations, 2-tailed test, with 4 data clusters based on gender and payoff scale).

Payoff Scale

The third result pertains to payoff scale, which can be evaluated by comparing the heights of the risky choice bars on the right (5X) side of Figure 2 with the corresponding bars (for the same risk structure) on the left (1X):

Payoff Scale: *An increase in payoff scale tends to increase risk aversion, especially in the case of downside risk.*

Support: Restricting attention to downside risk, the null of no scale effect can be rejected with p = 0.006 (2-tailed test, 128 subjects for downside risk, stratified by gender). Running the same test with all 256 subjects and stratifying by gender and risk structure yields the same p value. Similarly, it can be verified that the effect of payoff scale is not significant for the upside risk data alone.

V. A Within-Subjects Experiment with Random Selection

Our results for upside risk are consistent with those of Eckel and Grossman (2015), who document the tendency for subjects to "love the long shot" of a high payoff. They offer a conjecture and some indirect evidence that this behavior is due to nonlinear probability weighting, which typically results in overweighting low probabilities and underweighting high probabilities.

In order to evaluate probability weighting in our design, we ran a within-subjects experiment with a wider range of payoffs of probabilities that included 0.1, 0.33 0.5, 0.67, and 0.9. Subjects made 10 decisions with low (1X) scale and another ten decisions with high (5X) scale. The decisions included four paired options with upside risk and four paired options with downside risk, all of which generated an expected payoff difference of 80 in favor of the risky option in the pair. These decisions are listed in Table A1 in the online appendix, with decisions D1 and D3 corresponding to the Downside and Upside Risk decisions in (1) and (2), as shown in Figure 1. There are two decisions in Table A1 with moderate (0.67, 0.33) downside risk, two decisions with moderate (0.67, 0.33) upside risk, two decisions with extreme (0.90, 0.10) downside risk, and two decisions with extreme (0.90, 0.10) upside risk. The remaining two decisions had 0.5 probabilities, one of which was taken from the standard Holt and Laury (2002) menu.

In order to accommodate this wide range of decisions, we had to use a within-subjects design in which each subject made all 10 decisions with low stakes and all 10 decisions with high stakes, with the low stakes encountered first in half of the sessions. The order in which decisions were made was randomized within payoff-scale treatment. This experiment had two objectives: to generate enough data to estimate probability weighting and stakes-sensitive risk aversion parameters, and to determine whether the *same* subjects exhibit risk aversion with downside risk and risk seeking with upside risk.

The justification often given for using random selection among a number of decisions is that subjects tend to "isolate" their attention to the currently observed choice problem and make a decision that is, therefore, unaffected by the range of other possible decision problems that might be used to determine payoffs. Random selection is the most commonly used procedure for controlling for wealth effects. Although it has been defended by Starmer and Sugden (1991), Hey and Lee (2005), and others, some researchers have suggested caution in using random selection (e.g. Holt, 1986, Davis and Holt, 1993, and more recently and forcefully Cox et al. 2013).[9] In particular, this approach may not work properly if subjects fail to view each decision in isolation. We discuss this issue in more detail by considering a comparison of differences in choice

[9] Harrison and Swarthout (2012) find that experiments with a single decision (a between-subjects design with carefully modeled heterogeneity) provide different econometric estimates of probability weighting and risk preference parameters than are obtained by using the random selection and estimation that incorporates multiple decisions per subject.

proportions for the basic downside and upside risk decisions that were used in both the single choice experiment and in the between-subjects experiments with random selection.

As was the case for each of the rows in Table 1, this experiment involved 64 subjects, half men, who were recruited from the University of Virginia student pool. Each person was paid for one randomly selected low scale (1X) decision and for one randomly selected (5X) decision. The within-subjects results shown in Table 2 are generally similar to those obtained in the single-choice experiment: an increase in payoff scale reduces the tendency to choose the risky option with downside risk, and subjects select the riskier choice about twice as often with upside risk than with downside risk, for both payoff scales and for risks that are moderate (0.33 probability) or extreme (0.10 probability). This pattern in the aggregate data also shows up clearly for the two decisions used previously in the single-choice experiment:

Table 2. Choice Percentages for Selected Decisions in the Within-Subjects Experiment[a]

		Men Choosing Risky (A)		Women Choosing Risky (A)	
Downside 1X	32 male, 32 female	19/32	59%	13/32	41%
Downside 5X	32 male, 32 female	9/32	28%	9/32	28%

		Men Choosing Risky (A)		Women Choosing Risky (A)	
Upside 1X	32 male, 32 female	30/32	94%	31/32	97%
Upside 5X	32 male, 32 female	30/32	94%	28/32	88%

[a] The two decisions listed here are labeled D1 and D3 in the Appendix table A1.

Downside versus Upside Risk (Between Subjects): *The same subjects who tend to select the safer option when faced with the downside risk of a low payoff also tend to select the riskier option when faced with the upside risk of a high payoff, despite the fact that the expected payoff differences between the options are the same in each case.*

Support: Each subject made four choices with downside risk (decisions 1, 2, 5, and 6 in Table A1) and we summed the number of riskier choices to obtain individual measures of downside risk taking. Similarly, each subject made four choices with upside risk (decisions 3, 4, 7, and 8), and we constructed a measure of upside risk taking in the same manner. Most subjects (51 out of 64) chose the risky option more often with upside risk. This result is highly significant ($p < 0.001$) for both the low payoff scale and the high payoff scale using a Wilcoxon matched-pairs test.

The overall pattern of results shown in Table 2 with random selection is similar to that shown in Table 1 with a single decision data (between subjects). In addition to the strong increase in risk taking with upside risk documented above, there is modest evidence that men are more risk averse than women (with downside risk only), and there are strong and highly significant payoff scale effects. With downside risk, for example, a stratified permutation test with 2 strata for gender supports a payoff scale effect (p =0.18, 128 observations, stratified by gender, 2-tailed test). Despite these similarities in the overall patterns of risk taking, a comparison of the top rows of Tables 1 and 2 suggests that men and women take more downside risk with 1X scale in the single-choice setting, as compared with the random selection setting. This observation is supported by a stratified permutation test p = 0.043 (128 observations, stratified by gender, 2-tailed test).[10]

Recall that all of the decision problems were structured so that the expected payoff advantage in favor of the riskier option is $0.80 for the low payoff scale in all cases (with the exception of decision 10 in the within subjects experiment, which was taken from a standard risk assessment choice menu to serve as a benchmark). Instead of using expected payoff maximization as the basis for the design, we could have used the parametric version of another perspective, e.g. expected utility with constant relative risk aversion (CRRA). But the strong payoff scale effects that we observe cannot be explained by a constant relative risk aversion utility function, which is insensitive to payoff scale. The estimation reported in the Appendix provides a more general "expo-power" utility function, $U(x) = \dfrac{1-\exp(-a x^{1-r})}{a}$, for $r \neq 1$, which exhibits increasing relative risk aversion (more aversion at high payoff scales) that than reduces to CRRA expected the α parameter goes to 0 in the limit. In addition, we use a nonlinear probability weighting function, $w(p) = \dfrac{p^{\gamma}}{(p^{\gamma}+(1-p)^{\gamma})^{1/\gamma}}$ *for* $\gamma > 0$. This function, which was popularized by Kahneman and Tversky (1979), reduces to $w(p) = p$ with no weighting as the weighting parameter γ goes to 1. This function will overweight low probabilities when $0 < \gamma < 1$. A number of prior

[10] Here it is not permissible to stratify by gender and payoff scale, since each person in the random selection treatment made decisions for both scales, so observations are not independent.

studies have reported probability weighting parameters that are between 0.5 and 1.0, with an estimate of 0.7 being typical. To summarize, we specified a two-parameter expo-power utility function to allow for payoff scale effects, and we specify a nonlinear probability weighting function to permit overweighting of low probabilities (of a low payoff with downside risk and of a high payoff with upside risk). The maximum likelihood estimates (and robust standard errors) of the weighting parameters were 0.66 (0.04) for men and 0.67 (0.03) for women. Both weighting parameters were significantly different from 1, which implies overweighting of low probabilities. The risk aversion parameter estimates for α and r were significantly different from zero, suggesting risk aversion for both genders, with slightly more risk aversion for women (details provided in the appendix). Finally, the parameter estimates are used to predict choice proportions for the risk option that follow the general patterns observed in the data in Table 2: more risk seeking with upside risk, clear payoff scale effects and modest gender effects with downside risk.

VII. Conclusion

Having seen large gender differences in some prior work with downside risk (Comeig et al., 2012; Comeig et al., 2013), we were surprised to find smaller overall effects of gender in the present study, with both a single decision and with random selection for payment among multiple decisions. This seems to be because gender differences for downside risk documented previously tend to be diminished in the upside risk treatments reported in this paper. For example, the previous work was often motivated by insurance or bankruptcy, which tends to generate a downside risk of a very low payoff. The main qualitative patterns in the data highlight the importance of distinguishing between upside and downside risk and between high-stakes and low-stakes decisions:

1) People tend to be more risk averse for downside risk than for upside risk. The same people choose the riskier option about twice as often when it involves upside risk instead of downside risk, even though the expected payoff advantage of the riskier option is the same for all of these decision pairs.
2) A five-fold increase in all payoffs results in a lower incidence of riskier choices for downside risk, but this effect is not present with upside risk.
3) Male subjects exhibit less risk aversion than females in the baseline case of downside risk, but there is no significant gender difference for upside risk, irrespective of payoff scale.

Laboratory experiments are well suited for deconstructing separate components of complex decision theories, since key aspects of incentives and probabilities can be varied independently. The second (within-subjects) experiment was designed to evaluate the utility curvature and probability weighting components of risk aversion. The experiment used a within-subjects design to reproduce risk aversion tendencies (with gender effects) for the downside risk setting. Notably the same subjects tended to choose the riskier option much more frequently in the upside risk setting. Maximum likelihood estimates reveal significant curvature in the probability weighting function, comparable for men and women, but with greater utility curvature for women. Finally, a scaling up of payoffs by a factor of five tended to result in a little more risk aversion, and gender differences in some choice problems evaporated as the men behaved more cautiously (more like the women) in the high-stakes environment. We estimated a probabilistic choice model with a standard specification of probability weighting and a two-parameter "power-expo" utility function. The estimated model explains the salient features of the data in terms of gender, scale, and upside versus downside risk effects.

The distinction between different types of risk, upside versus downside, can be important in understanding apparent instabilities in risk preferences across domains. In models of "directed search," for example, a worker who decides to concentrate efforts on obtaining a high-paid position must keep in mind the possibility that others may also direct their search towards that position. The alternative is to apply for a position with a moderate salary, knowing that more of those positions are available. In equilibrium, the probability of obtaining the high paid job may be somewhat low, but a tendency to overweight that probability may attract search efforts in that direction, more than would be otherwise expected. In particular, people who appear risk averse in terms of insurance and savings decisions may target search in the risky direction of the high paid position. This tendency to seek out upside risk could cause the expected payoff to be lower for search in that direction, even though the payoff variance could be higher due to congestion in the applications for those jobs.

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Appendix: Experiment 2 with Random Selection

The ten decisions used in the second, within-subjects experiment are shown in Table A1. The expected payoff for the risky option A is 80 cents higher for each of the decisions with unequal probabilities, D1 – D8.

Table A1. Payoff Structure for Riskier and Safer Options (1x Payoffs)

Decision	Option A	Option B
D1: Moderate Downside Risk	0.67 of $**8.38**, 0.33 of $1.25	0.67 of $**6.18**, 0.33 of $3.25
D2: Moderate Downside Risk	0.67 of $**8.13**, 0.33 of $1.75	0.67 of $**5.93**, 0.33 of $3.75
D3: Moderate Upside Risk:	0.33 of $**9.50**, 0.67 of $4.25	0.33 of $**5.90**, 0.67 of $4.85
D4: Moderate Upside Risk	0.33 of $**8.55**, 0.67 of $4.73	0.33 of $**5.75**, 0.67 of $4.93
D5: Extreme Downside Risk	0.9 of $**6.64**, 0.1 of $0.25	0.9 of $**5.47**, 0.1 of $2.75
D6: Extreme Downside Risk	0.9 of $**6.58**, 0.1 of $0.75	0.9 of $**5.53**, 0.1 of $2.25
D7: Extreme Upside Risk:	0.1 of $**25.00**, 0.9 of $3.89	0.1 of $**6.00**, 0.9 of $5.11
D8: Extreme Upside Risk	0.1 of $**21.00**, 0.9 of $4.33	0.1 of $**6.80**, 0.9 of $5.02
D9: Balanced Risk:	0.5 of $**8.25**, 0.5 of $3.75	0.5 of $**5.60**, 0.5 of $4.80
D10: Balanced Risk	0.5 of $**7.70**, 0.5 of $0.20	0.5 of $**4.00**, 0.5 of $3.20

Table A2 shows the proportions of risky choices for each of the 10 decisions, D1 – D10, organized by gender and payoff scale. The general pattern of results matches shown in Table 2 above for decisions D1 and D3 tends to hold for the other decisions, with more risk seeking for upside risk, and with gender differences and payoff scale effects for downside risk but not for upside risk.

Next, we evaluate the extent to which the rich data patterns summarized at the end of the previous section can be explained by a unified theoretical perspective. To do this, we estimate a rank-dependent expected utility model, using a standard probability weighting function and a two-parameter utility function that is well adapted for examining effects of payoff scale. The third component is a "Luce" probabilistic choice function, used to generate choice probability predictions that can be used in the estimation. The utility function to be used is the "power-expo" function presented in section VI of the paper. This function exhibits constant absolute risk aversion in the limit as r →0 and constant relative risk aversion as α→0. When both parameters are positive, the function exhibits increasing relative risk aversion (more risk aversion as payoffs are all scaled up) and decreasing absolute risk aversion (less risk aversion as an additive constant is added to all payoffs).[11] The payoffs to be used are the money payoffs in each choice problem.

Table A2: Proportions of Risky Choices with Random Selection[12]

Decision Number	**Structure (Chances for High Payoff)**	**1x Payoffs Men**	**1x Payoffs Women**	**5x Payoffs Men**	**5x Payoffs Women**
D1	downside risk (33)	0.59	0.41	0.28	0.28
D2	downside risk (33)	0.59	0.41	0.38	0.44
D3	upside risk (33)	0.94	0.97	0.94	0.88
D4	upside risk (33)	0.91	0.88	0.97	0.91
D5	downside risk (10)	0.44	0.34	0.38	0.19
D6	downside risk (10)	0.44	0.31	0.38	0.34
D7	upside risk (10)	0.78	0.75	0.81	0.72
D8	upside risk (10)	0.94	0.75	0.84	0.78
D9	balanced risk (50)	0.81	0.75	0.69	0.78
D10	balanced risk (50)	0.19	0.09	0.09	0.06
	All Problems	**0.66**	**0.57**	**0.61**	**0.54**

The Kahnemen and Tversky probability weighting function was also used in the estimation. The weighting function is applied to the inverse cumulative distribution in order to avoid violations of stochastic dominance.[13] With only two payoffs in each choice, with $L \leq H$, this means applying

[11] This function was proposed by Saha (1993). Holt and Laury (2002) provide maximum likelihood estimates of the two parameters of this function and use those parameters to show that the function offers a reasonably good explanation of the payoff scale effects, ranging from 1x to 90x, for the choice menus used in their experiments.

[12] There are 64 observed choices, safer or riskier, for each decision in each payoff treatment, half of which pertain to men and half to women. Note that the decision number refers to the number in Table A1 and does not indicate the order in which it was encountered, since the 10 decisions for each payoff treatment block were randomly shuffled.

[13] Applying the weighting directly to all probabilities is known to imply violations of stochastic dominance Handa (1977). In particular, for any nonlinear weighting function it is possible to find two probability distribution functions

the weight to the probability of the high payoff and using the residual for the low payoff: $w(p)U(H) + (1-w(p)U(L)$. This "weighted expected utility" expression is then used to derive choice predictions.

For any specific weighting and utility parameters, the implication would be that choice probabilities are either 0 or 1, so we introduce a probabilistic choice function to capture unobserved factors that produce "noise" in the data[14]: $\Pr(A) = \dfrac{(U_A)^{1/\mu}}{(U_A)^{1/\mu} + (U_B)^{1/\mu}}$, where μ is a positive "noise" parameter and the weighted expected utilities for options *A* and *B* are represented by U_A and U_B respectively. As $\mu \to \infty$, the noise dominates and choice probabilities go to 0.5 as each of the utility terms are raised to the power 0 in the limit. In contrast, it can be shown that as $\mu \to 0$ the choice probability converges to 1 for the option with the higher weighted expected utility. For each decision, the utility and probability weighting functions are used to compute the weighted expected utilities of U_A and U_B for options *A* and *B* in the choice pair, and the associated choice probability prediction is determined from the probabilistic choice function.

The likelihood function to be maximized is the product of these probabilities, each raised to a power determined by the number of *A* choices for that problem. Thus maximum likelihood estimation essentially involves finding the parameters for utility (α and *r*), probability weighting (γ), and noise parameter (μ) that maximize the probability of seeing what was observed in the data. The maximum likelihood estimates are provided in Table A3, where standard errors have been adjusted for clustering of individual decisions.

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for which inverse cumulative function $(1 - F(x))$ of one is higher, but this dominating function has a lower weighted expected utility. The theoretical fix is to apply the weighting function directly to the inverse cumulative distribution (Quiggin, 1982).

[14] The power function stochastic choice model can be derived by assuming that positive payoffs are perturbed by multiplicative errors, which implies that "noise" does not diminish as payoffs are scaled up. In contrast, scaling up payoffs in a standard logit model tends to diminish the effects of additive errors, and subjects' responses to incentives are predicted to be "sharper" at high payoff scales. Since we do not observe sharper response functions in experiments with high payoff scales (Holt and Laury, 2002), it is desirable to use a stochastic formulation for which noise does not diminish with high payoffs. The Luce formulation that we use is one way to accomplish this. To see the intuition, suppose for simplicity that the subject is risk neutral, and hence, the U_A and U_B terms in the equation are expected payoffs. In this case, a 5x increase in payoff scale would increase all expected payoffs up by 5, and this multiplicative constant would factor out of both the numerator and the denominator, having no effect. We prefer to use the Luce error structure when there is a wide range of payoff scales, since otherwise, the estimation would gravitate toward utility parameters that flatten utility differences at high payoff treatments, in order to be consistent with any observed absence of sharp responses in those treatments.

Table A3. Maximum Likelihood Estimates

Parameter	Gender	Coefficient (Robust Standard Error)
Risk Aversion (r)	Men	0.18 (0.07)
	Women	0.39 (0.08)
Risk Aversion (α)	Men	0.02 (0.01)
	Women	0.04 (0.02)
Probability Weighting (γ)	Men	0.66 (0.04)
	Women	0.67 (0.03)
Error Parameter(μ)	Men	0.07 (0.01)
	Women	0.06 (0.00)

The parameter estimates in the table are significant and of plausible magnitudes.[15] Note that the estimated risk aversion parameters, r and α, are higher for women, indicating more curvature of the utility function that provides the best fit for their decisions. In contrast, the probability weighting parameter estimates are essentially the same for both genders.[16] The difference between the estimated probability weighting parameters and a value of 1 (no weighting) is statistically significant and in line with many prior estimates. Finally, note that the estimated error parameters in the bottom row of Table 6 are essentially the same for men and women. To summarize, the main estimation results reveal 1) significantly positive risk aversion parameters (α and r) that are higher for women than for men, and 2) estimated probability weighting parameters implying significant curvature that is comparable for men and women.[17]

Even though the parameter estimates for the weighted expected utility model appear to be reasonable, the important test is whether this model can explain the qualitative patterns that we observe in the aggregate data, e.g. risk aversion for downside risk and risk seeking for upside risk, or the presence of gender and scale effects in some settings and not in others. Figure A1 shows

[15] For example, the coefficient estimates for r in Table 6 for men and women bracket the estimate of $r = 0.27$ reported by Holt and Laury (2002) for both genders combined, using data from a structured choice menu risk elicitation task.
[16] Gender differences in probability weighting have been reported by others. For example, Fehr et al. (2011) found that women were more likely to weight probabilities of good outcomes less optimistically when they are not in a good mood, and vice versa. Men seemed to be less responsive to moods, and more prone to rely on mechanical decision rules instead of intuition. In particular, about 40 per cent of the men in their study reported using expected value as a decision criterion, whereas only a handful of women in the study reported this behavior. As noted in the procedures section above, we used “odd numbers” for many of the payoffs listed in Table 4 in an attempt to diminish any tendency for subjects to rely on simple mathematical decision rules.
[17] These two features of the estimates do not change when we estimate a two-parameter version of the Kahneman and Tversky probability weighting function or a two-parameter version of the Prelec “expo-ln” weighting function. In each case, the two risk aversion parameters are significantly positive ($p < 0.03$ in all cases) and greater for women, whereas both probability weighting parameters are quite close in value for men and women, with a significant amount of curvature in the weighting function for both genders.

the percentages of riskier choices for each of the treatment combinations, for each gender (dark bars for men and light bars for women). For comparison, the gray bars indicate the predicted proportions that are calculated from the parameter estimates for each gender. The low stakes treatments are shown on the left side and the high stakes treatments are shown on the right side. It is apparent from the figure that the fitted predictions track the major difference between risk aversion for downside risk and risk seeking for upside risk, and the gender difference for low stakes downside risk that is diminished for the other treatments.

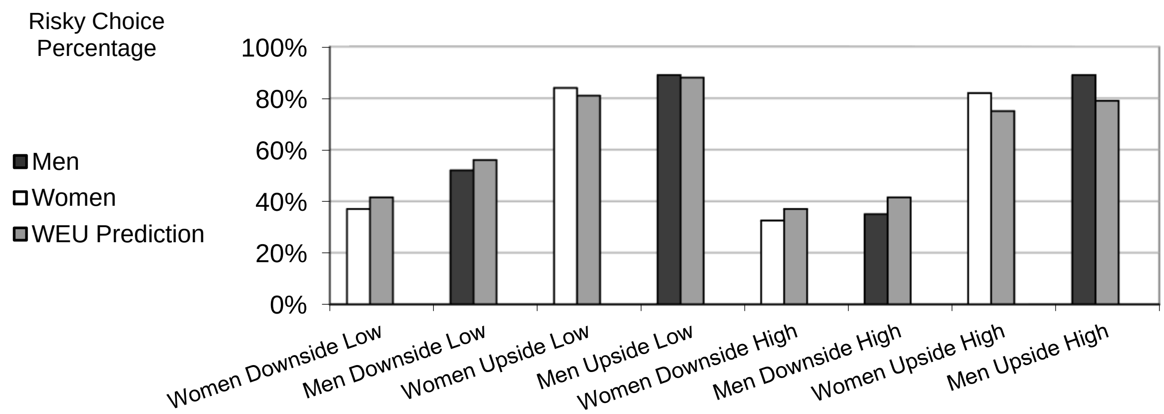

Figure A1. Percentages of Risky Choices
for Men (Dark Bars) and Women (Light Bars),
Together with Weighted Expected Utility Predictions (Gray Bars)

Although the main focus of this experiment is on differences in the structure of risk for salient low probability events, we also included a couple of decisions (9 and 10) for balanced risk. Even though the probabilities for the high payoff are 0.5 in each of these two decisions, the expected payoff difference in favor of the risky choice is lower for problem 10 (only $0.35 instead of $0.80 as was the case for the other 9 problems). Hence it is not surprising that the theoretical predictions (using fitted parameter values for low stakes) are higher for decision 9 (67% for women and 74% for men), and lower for decision 10 (2% for women and 12% for men). This sharp difference in predicted proportions of risky choices is observed in the data; risky choice percentages were 75% for women and 81% for men in decision 9, and 9% for women and 19% for men in decision 10.
In summary, the econometric estimates for the rank-dependent expected utility model provide a unified explanation of the main qualitative features of the choice data for a wide variety of settings in terms of payoff scales, risk intensity, and risk direction (upside or downside):

1) Risk directional effects are explained by probability weighting that overweights the low probability of a low payoff with downside risk and overweights the low probability of a high payoff with upside risk.
2) The payoff scale effects are explained by an estimated utility function that exhibits increasing relative risk aversion.
3) Gender differences in risk aversion, where they exist, seem to be driven by differences in utility curvature parameters, since the estimated probability weights are about the same for both genders.

One remaining issue is the extent to which the implications of our econometric estimates are inconsistent with the Harbaugh et al. (2010) results discussed earlier in section II. They did not report a gender breakdown for their subject pool, so as a first approximation, we took an average of the econometric estimates for men and women in Table A3 and used these to predict behavior in the Harbaugh et al. choice tasks. The three decision problems involved a lottery with a specified probability of a $20 gain, where the probabilities were varied from 0.1 to 0.4 to 0.8. The choice was between the lottery and its expected value ($2, $8, or $16 respectively). Note that the 0.1 chance of $20 is one with upside risk, and the 0.8 chance of $20, $0 otherwise, is one of downside risk. Adding in the $22 fixed payoff to each outcome and using the parameters from Table 5 (averaged between men and women), it can be shown that the predicted probability of choosing the gamble falls from 0.60 to 0.42 to 0.23 as the probability of the high payoff is raised from 0.1 to 0.4 to 0.8. The reported choice proportions for the gamble, in contrast, are 0.50, 0.39, and 0.56, which is inconsistent with the pattern that we would predict from our estimates, based on admittedly different procedures. One possibility is that the tendency for choice percentages to hover around 0.5 in the Harbaugh et al. (2010) paper is that the simple setup that they intentionally selected may facilitate a mechanical expected value calculation. In particular, they used only 6 decisions, each with a certain safe choice and a risky choice that pays either $0 or $20, so only one multiplication (e.g. 0.1 times $20 = $2) is required to see that the expected value of the risky prospect is equal to the sure payoff for the safe option for each decision. If many subjects anchor on this expected value comparison, then choice proportions may be biased towards 0.5. There is no other evidence to support this conjecture, except that the other (more complicated) Becker DeGroot Marshack pricing task that they used did indicate more risk seeking for the upside risk gamble with a win probability of 0.1 and more risk aversion for the downside risk gamble with a win probability of 0.8.

Instructions Appendix

(These instructions are for the case of a single decision.
Wording changes for sessions with random selection are indicated in italics.)

- **Options:** You will be making a **single choice** between alternative options, such as "Option A" and "Option B" below. Each option offers two (or more) possible money prizes. You must select one of these options, without knowing in advance which monetary amount will be obtained. (WITH RANDOM SELECTION: ***Options:*** *In each part of this experiment, you will be making a **series of choices** between alternative options, such as "Option A" and "Option B" below. Each option offers two (or more) possible money prizes. You must select one of these options, without knowing in advance which monetary amount will be obtained.*)
- **Monetary Prizes:** The money prize that is relevant for the option you select is determined by the computer equivalent of throwing a ten-sided die or spinning a roulette wheel with ten equally-likely stops. In the example below, if you choose Option A, the wheel would have 5 stops labeled $4.00 and 5 stops labeled $6.00, and the wheel for option B would have 5 stops labeled $0.00 and 5 stops labeled $12.00. Thus if you choose Option A, you will have a **5 in 10** chance of earning **$4.00** and a **5 in 10** chance of earning **$6.00**. Similarly, Option B offers a **5 in 10** chance of earning **$0.00** and a **5 in 10** chance of earning **$12.00**. Please Note: The numbers used in the example below are for illustrative purposes only, the actual choice that you will consider will be different from those used in this example,
- **Choice:** You will register your choice by using the mouse to click on the small circle ("radio button") for the option you select. Then you must click on the gray Submit button at the bottom. Please go ahead and make a choice for this practice round to see how this process will work.

Option A	**Option B**
5 chances in 10 of **$4.00**	**5** chances in 10 of **$0.00**
5 chances in 10 of **$6.00**	**5** chances in 10 of **$12.00**

Submit Practice Decision

(new page)

5 chances in 10 of **$12.00**

You selected Option B.
We will now use the computer to generate a random number,
which is equally likely to be any number between (and including) 1 and 10.

The payoff will be **$0.00** if the number is in the range **1 - 5**
The payoff will be **$12.00** if the number is in the range **6 - 10**.

Show Practice Results

(new page)

You selected Option B.
The payoff will be **$0.00** if the number is in the range **1 - 5**
The payoff will be **$12.00** if the number is in the range **6 - 10**.

Option B

5 chances in 10 of **$0.00**

5 chances in 10 of **$12.00**

Result: The random draw turned out to be **3**.
Thus the payoff would be **$0.00**.
Continue

(new page)

- **Additional Setup Details:** You will be making a single choice between alternative options. These options may be expressed in terms of **"chances in 100"** instead of "chances in 10" as in the previous example. (WITH RANDOM SELECTION: A*dditional Setup Details: You will be making a series of choices between alternative options. These options may be expressed in terms of "chances in 100" instead of "chances in 10" as in the previous example*.
- **Monetary Prizes:** In the example below, the money prize that is relevant for the option you select is determined by the computer equivalent of throwing a **100-sided die** or spinning a roulette wheel with **100 equally-likely stops**.
- **Options:** In particular, if you choose Option A, the wheel would have 25 stops labeled $4.00 and 75 stops labeled $6.00, and the wheel for option B would have 25 stops labeled $0.00 and 75 stops labeled $12.00.
- **Chances in 100:** Thus if you choose Option A, you will have a **25 in 100** chance of earning **$4.00** and a **75 in 100** chance of earning **$6.00**. Similarly, Option B offers a **25 in 100** chance of earning **$0.00** and a **75 in 100** chance of earning **$12.00**.

○ **Option A**	○ **Option B**
25 chances in 100 of **$4.00**	**25** chances in 100 of **$0.00**

75 chances in 100 of **$6.00** **75** chances in 100 of **$12.00**

Continue with Instructions

Summary

- **Single Choice:** To summarize, you will begin by making a **single decision** that will determine your earnings. (WITH RANDOM SELECTION: *To summarize, you will begin by making a series of **10 decisions**.*)
- **Options:** For this decision problem, you must select one of the two options, A or B. (NEW PARAGRAPHS WITH RANDOM SELECTION: ***Relevant Decision:*** *After you have made all 10, decisions, **only one of these will be selected at random** to determine your total earnings for this part. Each of the 10 decisions has an equal chance of being selected, independently of the choices you made.* ***Possible Prizes:*** *After you have made all decisions, only one of the 10 choice problems will be used. The option that you have **already** selected for that choice problem will have 2 possible money earnings amounts, each associated with the chances that it will be the actual amount obtained.*)
- **Random Number:** Then the computer will generate a random number that determines which of the money prizes for the option you selected will be the amount of money that you earn.
- WITH RANDOM SELECTION*:* ***Subsequent Parts:*** *This whole process (making 10 decisions and having one selected at random to determine your earnings) will be repeated once, with some changes in the structure of the options themselves in the second part. Earnings for each decision will not be released until you finish the final part.*)
- **Earnings Record:** The computer keeps track of your earnings, i.e. the sum of the amounts earned in each part.