Dealing with Risk: Gender, Stakes, and Probability Effects

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Abstract:

This paper investigates how subjects deal with financial risk, both "upside" (with a small chance of a high payoff) and "downside" (with a small chance of a low payoff). We find that the same people who avoid risk in the downside setting tend to make more risky choices in the upside one. The experiment is designed to disentangle the probability-weighting and utility-curvature components of risk attitudes, and to differentiate settings in which gender differences arise from those in which they do not. Women are more risk averse for downside risks, but gender differences are diminished for upside risks.

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

JEL Codes: C91 G020

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I. Introduction

Major economic decisions regarding investments, insurance, or pension plans typically include a "safer" option with low payoff 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, different studies of gender differences in risk preferences examine such a variety of risk and payoff structures that is difficult to reconcile conclusions. This paper provides a context-free canonical form 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. The objective is twofold: (i) to differentiate settings in which gender differences arise from those in which no such effects are observed, and (ii)

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[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. For example, Booth and Nolen (2012) report that girls in single-sex schools are more willing to choose a risky option than is the case for girls in coeducational schools. See Nelson (2012) for a skeptical view of systematic gender effects, based on a reevaluation of empirical work on gender and risk, with particular attention to magnitudes and significance levels of reported tests in both laboratory and field studies. She concludes that gender differences in risk preferences have been overstated in both the primary and secondary (survey) literatures.

to help disentangle the probability-weighting and utility-curvature components of risk attitudes.

II. Motivation

One of the salient results from controlled experiments is that women are often found to be more risk averse than men. Some of this work is motivated by financial decisions in which the riskier choice, e.g. not purchasing insurance, is characterized by a low probability of a low payoff, and the safer choice has less variance, but it also has a low probability of a low payoff. In this setting, the safer option provides less "downside risk." In our own previous work, for example, this gender effect shows up clearly in paired decisions of the form shown:

Table 1. Moderate Downside Risk

Option A:	Option B:
2 in 3 chances of 838	2 in 3 chances of 618
1 in 3 chances of 125	1 in 3 chances of 325

Option A in Table 1 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. An even more extreme difference in variability is shown in Table 2, for which the riskier option has a low payoff of only 25, but it also yields an expected payoff that is 80 higher than for the safer option that offers a lower spread between high and low payoffs. In order to maintain the expected payoff difference constant at 80, the probability of the low payoff has been reduced from 0.33 to 0.10, which will be referred to as a switch from "moderate" to "extreme" risk.

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Table 2. Extreme Downside Risk

Option A: 9 in 10 chances of 664 1 in 10 chances of 25	Option B: 9 in 10 chances of 547 1 in 10 chances of 275

In each 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 the Option B. The observed choice pattern for these paired choices was for women to select the riskier option much less frequently than men. The percentage of riskier choices for the decision shown in Table 1 was 39% for women and 68% for men. Similarly, the percentage of riskier choices for the more extreme risks in Table 2 was 18% for women and 55% for men.[2] Thus the gender difference persists, even though the incidence of riskier decisions can be affected by the extremeness of the risk. A similar pattern of greater risk aversion for women is reported in Comeig et al. (2013) in a laboratory experiment motivated by credit market borrowing and lending decisions. The risky decisions used in that experiment were also characterized by downside risk, i.e. a small probability of a low payoff. Fehr-Duda et al. (2006, 2011) also 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

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[2] The decisions in Tables 1 and 2 were two of the eight decisions presented to subjects in Comeig, Holt, and Jaramillo (2012), where payoffs were in pennies and probabilities were expressed as chances in 100. Each decision was presented once with the safer decision on the left side and once on the right side (the presentation order did not matter). Problems were presented in a random order across subjects, with one problem selected at random in each presentation order to be used for payment. The data reported in the text are for the "simple" payment frame. In addition, each problem was translated into deviations from 300, in an attempt to trigger loss aversion. Data for this "deviations" frame did not differ from the simple payoff data in any systematic manner. Gender differences were pervasive for most of the choice problems.

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.

One avenue for explaining these gender differences would be 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 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 (with extreme low payoffs) in Tables 1 and 2. Therefore, it is difficult to distinguish between these two explanations, curvature and probability 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 Table 3, for which the expected payoff difference for A over B is again 80, but the high-variance risky Option A offers an "upside risk" of a high payoff:

Table 3. Extreme Upside Risk

Option A:	Option B:
9 in 10 chances of 389	9 in 10 chances of 511
1 in 10 chances of 2500	1 in 10 chances of 600

The idea behind this upside risk setting is that if probability weighting is important, then a pattern of risk avoidance in the downside risk environment would be replaced by an attraction to risky choices in the upside risk environment. This observation would be consistent with some prior work and with casual observation.[3]

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[3] 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

Probability weighting is a key component of prospect theory, and experimental tests of that theory are also relevant since a tendency to overweight the low probability of a high payoff will increase the attractiveness of a risky prospect with upside risk. 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. We will discuss these results further in section V below.

On an intuitive level, downside risk indicates the extent to which a payoff may fall below an expected value, in the same manner that a stock which might

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 for the gain domain were either positive or 0 for all choice menus, 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.

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. 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.[4] This figure also suggests that any tendency to overweight low probabilities might produce risk aversion for downside risk and risk seeking for upside risk where it is the low probability of the high payoff that is overweighted.
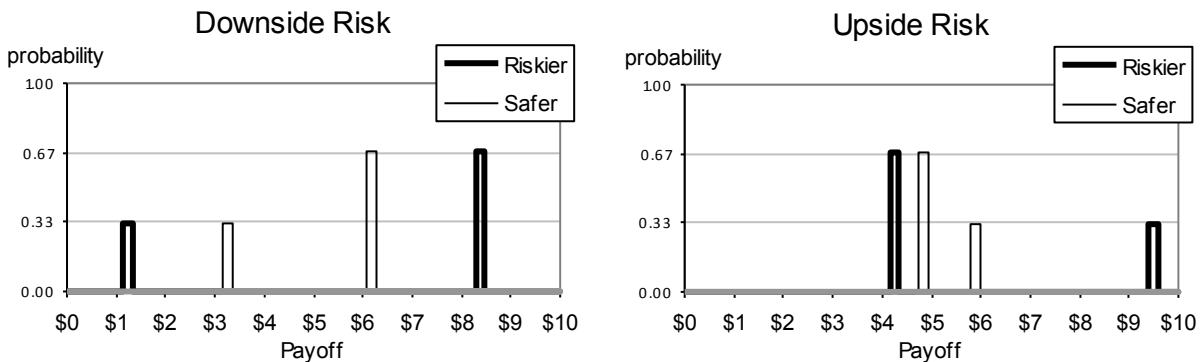

Figure 1. Downside Risk with Negative Skewness on the Left, Upside Risk with Positive Skewness on the Right

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

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[4] Note that each option has a skewed distribution, with negative skewness (a "tail" to the left) in the downside risk panel and with positive skeweness (a "tail" to the right) in the upside risk panel. In fact, the standard measure of skewness is negative for both safer and riskier options in the left panel, and is positive for both safer and riskier options in the right panel.

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 experimental idea is to switch from downside to upside risk in order to isolate effects of probability weighting that cannot be explained by utility curvature, and to scale up all payoffs holding probabilities fixed in order to isolate some effects of utility curvature that cannot be explained by probability perceptions. The goal of the paper is to promote a deeper understanding of how risk preferences depend on the underlying structure of risky choices, so as to better understand why risk preferences in one setting may be reversed in another.

III. Procedures

The ten decisions used in the experiment are shown in Table 4. Notice that there are two decisions 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 bottom two rows show the paired choices for the case of balanced (0.5, 0.5) risk. In particular, the bottom row of the table is the equal-probability row of a standard choice menu from Holt and Laury (2002). The difference in expected payoffs in favor of the risky option A is $0.80 for the first 9 decisions and is $0.35 for the final decision. Therefore, this option would be preferred by anyone who is risk neutral or only slightly risk averse, and those who are sufficiently risk averse should prefer the safer option B (in the absence of nonlinear probability weighting). In addition to low payoff decisions in Table 4, there was a high payoff treatment in which payoffs for all 10 decisions were scaled up by a factor

of 5. Therefore, the primary treatments involve: downside risk with low payoffs, downside risk with high payoffs, upside risk with low payoffs, and upside risk with high payoffs.

Table 4. 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

Decisions were simply labeled as "Option A" or "Option B," and the probabilities were presented in terms of "chances in 100."[5] Since we wanted subjects to be fully 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. Finally, the purpose of using the "odd" penny amounts for most of the payoffs in Table 4 was to trigger reliance on intuition instead of

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[5] 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 V.

mathematical calculations that would have been simpler with integer dollar amounts.

Half of the subjects (half of the men and half of the women) did the 10 high payoff decisions first and half did them last. Within a treatment, decisions were presented in random order, so different subjects faced different decision sequences.[6] Results from each decision were not released until all decisions were made. One randomly selected decision from each treatment was used for payment. This random selection procedure is commonly used to control for wealth effects while generating more data and avoiding the high monetary payoffs that would result if all decisions were used. This approach, however, may not work properly if subjects fail to view each decision in isolation. We discuss this issue in more detail in section VI below, where we report a follow-up experiment that does not use random selection payment.

The experiment was run with the Veconlab software, and the instructions are presented in the Appendix.[7] Each decision was made only once.[8] The experiment lasted 45 minutes, and earnings averaged about $30 plus a $6 show-up payment. There were 64 subjects, recruited from the University of Virginia student pool. Half of the subjects (32) were women. Additional 64 subjects were used in the follow-experiment (without random selection payments) that is discussed later in section VI.

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[6] Recent research indicates that estimates of risk preference can be influenced by the procedure being used and by presentation effects, e.g. Loomes and Pogrebna, 2014. Therefore, we avoided structured choice menus or sets of alternative decisions.

[7] The administrator site can be found with a Google search for "Veconlab admin" (the Pairwise Lottery Choice program on the Decisions menu). The subject login page can be found by a Google search for "Veconlab login." This web-based software is written and maintained by one of the coauthors (Holt) and is freely available for instructional and research use.

[8] There was no left-right reordering of decisions, since this reordering did not have an effect in Comeig, Holt and Jaramillo (2012), and avoiding the reordering enabled us to reduce the number of decisions by half, thereby enhancing the salience of each one. The risky option A was always listed on the left, so changes in the percentages of risky choices across treatments cannot be attributed to changes in the presentation order.

IV. Results

This section presents the main qualitative patterns in the data, which are supported by standard nonparametric tests, without reference to specific theoretical perspectives on risk preferences. The results are organized around three dimensions: risk structure (upside versus downside), payoff scale (low versus high), and gender. The following section presents econometric estimates of a model, estimated separately for men and women, that permits risk aversion measures to be affected by payoff scale and permits probability perceptions to depend on probability magnitudes.

Downside Versus Upside Risk

Figure 2 shows the proportion of riskier (Option A) choices for categories of decisions sorted by payoff scale and risk intensity. This figure indicates strong support for the idea that subjects tend to be more risk averse for downside risk than for upside risk. Subjects select the riskier choice about twice as often with upside risk (dark bars) than with downside risk (light bars), 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 at the individual level, as indicated by our first result:
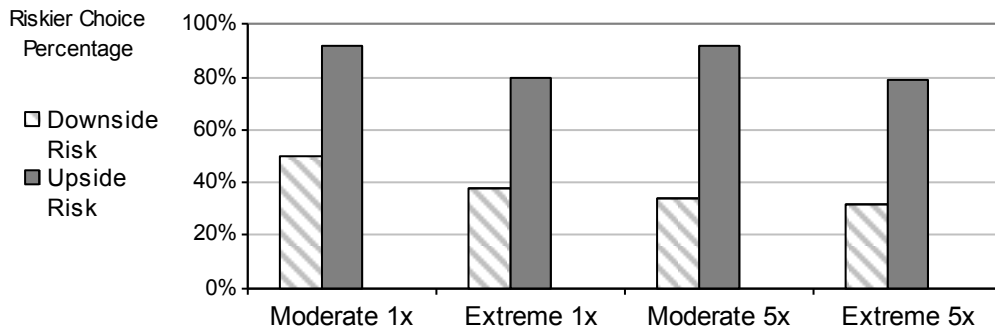

Figure 2. Percentages of Riskier Choices for Downside Versus Upside Risk,

by Risk Intensity (Moderate 0.33 or Extreme 0.10) and Payoff Scale (1x or 5x)

Downside versus Upside Risk Results: *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) 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) made more of the riskier choices 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.

Payoff Scale

One perspective on risky choice is that people are influenced by target or desired payoff levels. For example, Table 5 shows the 5x scale payoffs for decision 7 for upside risk.[9] Even though the riskier option in Table 5 offers the lowest of the four possible payoffs, that payoff exceeds $19, which participants might view as meeting earnings expectations.

Table 5. Extreme Upside Risk (Decision 7, 5x scale)

Option A:	Option B:
9 in 10 chances of $19.45	9 in 10 chances of $25.55
1 in 10 chances of $125.00	1 in 10 chances of $30.00

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[9] This is the same decision that was presented previously in Table 3 for 1x payoffs, with payoffs expressed in pennies instead of dollars.

In this case, the person might be more willing to take on an upside risk of getting a very high payoff. In other words, the effect of a threshold for desired payoffs might diminish a previously documented tendency to be more risk averse when the stakes are high.[10] Alternatively, the tendency to be attracted to high upside payoffs might be consistent with decreasing absolute risk aversion that is activated by high payoffs. Either way, the next result provides some evidence that payoff scale effects are different for upside and downside risk.

Payoff Scale Results: *With downside risk, a five-fold increase in payoff scale results in significantly fewer riskier choices; the 44% rate of riskier choices for low payoffs falls to 33% for high payoffs. This scale effect is significant with downside risk, but not with upside risk.*

Support: With low payoffs and downside risk, subjects make four choices, two with moderate and two with extreme risk. The number of risky choices in these choices is compared with the corresponding number for the case of high payoffs and downside risk, using a Wilcoxon matched-pairs test ($p < 0.02$). A comparison of low and high payoff scales for upside risk is not significant at conventional levels. These effects can be seen in Figure 2 above, where the two light bars for downside risk on the left side (1x scale) are higher than the than the two light bars on the right (5x scale). In contrast, the dark bars for upside risk in Figure 2 do not show a declining pattern from left to right.

Gender Effects

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

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[10] The presence of a reference point payoff is, of course, a major element in prospect theory, but the typical view is that risk aversion is pervasive for payoffs above the reference point, which would be different from a tendency to seek risk if the low payoff meets a target expectation.

overall effects of gender in the present study. This seems to be because gender differences for low-stakes downside risk documented previously tend to be diminished for high stakes and upside risk treatments reported in this paper. This result is indicated by a comparison of the percentages of risky choices for males (dark bars) and females (textured bars) in Figure 3, where the only significant difference is for downside risk with low stakes, on the left side.
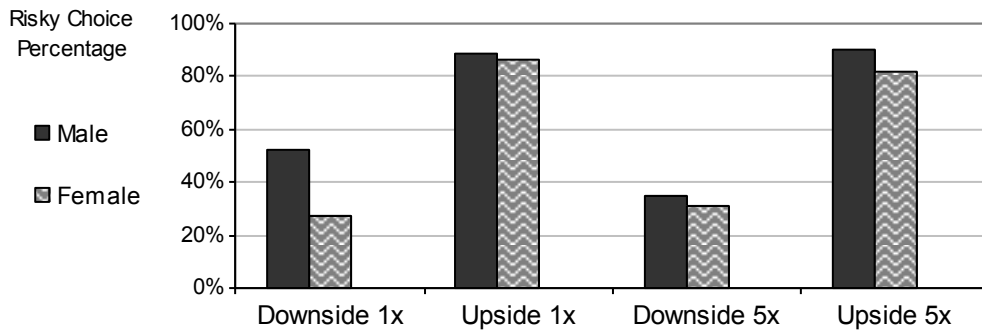

Figure 3. Male Versus Female Percentage of Risky Choices
by Risk Type (Upside or Downside) Payoff Scale (1x or 5x)

Gender Results: With downside risk, male subjects tend to select the riskier option more often than females with low stakes, but this difference disappears with high stakes. With upside risk, there is no significant difference between male and female proportions of riskier choices, regardless of payoff scale.

Support: Each subject makes four choices for each of the four categories shown in Figure 3, and the sum of riskier choices is used in a Mann Whitney two-sample signed ranks test. The difference for downside risk with low stakes is significant at the 10% level, two tailed test (p = 0.07), but the gender comparisons for the other three categories are not significant at conventional levels.

Previous work, often motivated by insurance or bankruptcy, tends to focus on the 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 and payoffs below $10, but this "bravado" goes away with high-stakes downside risk decisions. There is no significant gender difference for upside risk, irrespective of payoff scale.

Recall that the decision problems in Table 4 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 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. For the problems used in the experiment, the cutoff value of constant relative risk aversion (CRRA) that equates expected utility for the safer and riskier prospects varies from one problem to another. However, it turns out to be the case that the risk aversion cutoffs are quite close for problems 2 and 5 with downside risk and for problem 8 for upside risk (the cutoff values of r are about 0.82 or 0.83 in those problems). In particular, any

individual whose risk preferences are represented by utility $U(x) = x^{1-r}/(1-r)$ should choose the safer option when $r > 0.83$ and not otherwise. Since the same people made decisions for all problems, the riskier choice proportions for these problems should be the same on average if utility were characterized by constant relative risk aversion. This is clearly not the case. The riskier choice proportions for decision 8 with upside risk are 0.94 and 0.75 for men and women respectively, which is about twice as high as the average of the decisions for the downside risk problems with the same CRRA cutoff (these risky choice proportions for men and women are 0.59 and 0.41 for problem 2 and 0.44 and 0.34 for problem 5). The same comparison is relevant for the 5x scale, because scale does not affect comparisons made with constant relative risk aversion. For the 5x scale, the average proportions of riskier choices for problem 8 with upside risk are 0.84 and 0.78, which are again about twice as high as the averages of the corresponding proportions for problem 2 (0.38 and 0.44) and problem 5 (0.38 and 0.19). The implication is that the expected utility framework with constant relative risk aversion cannot explain these differences, because it does not distinguish between downside and upside risk, and it is insensitive to payoff scale. The next section provides a more general econometric model that is sensitive to these differences and that includes CRRA expected utility as a limiting case.

V. Estimation

In this section 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.

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The utility function to be used is the "power-expo" function:

$$(1) \qquad U(x) = \frac{1 - \exp(-\alpha x^{1-r})}{\alpha},$$

for $r \neq 1$. This function exhibits constant absolute risk aversion in the limit as $r \rightarrow 0$ and constant relative risk aversion as $\alpha \rightarrow 0$. 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.

The probability weighting function popularized by Kahneman and Tversky (1979) is:

$$(2) \qquad w(p) = \frac{p^{\gamma}}{(p^{\gamma} + (1-p)^{\gamma})^{1/\gamma}} \quad for \ \gamma > 0.$$

If the weighting parameter γ is equal to 1, then $w(p) = p$ and there is no distortion. When $\gamma < 1$, low probabilities (below about a third) tend to be over-weighted, and higher probabilities tend to be under-weighted. A number of prior studies have reported probability weighting parameters that are between 0.5 and 1.0, with an estimate of 0.7 being typical. The weighting function is applied to the inverse cumulative distribution in order to avoid violations of stochastic dominance.[12] With only two payoffs in each choice, with $L \leq H$, this means applying the weight to the probability of the high payoff and using the residual for the low

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[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] 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 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).

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.[13]

$$(3) \qquad \qquad \Pr(A) = \frac{(U_A)^{1/\mu}}{(U_A)^{1/\mu} + (U_B)^{1/\mu}},$$

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 on the right side of (3) 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 in (1) and (2) 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 (3).

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

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[13] The power function stochastic choice model in (3) 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 in (3) 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.

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 6, where standard errors have been adjusted for clustering of individual decisions.

Table 6. Maximum Likelihood Estimates

Parameter	Gender	Coefficient[a]	Robust Standard Error
Risk Aversion (r)	Men	0.18 **	0.07, $z = 2.52$
	Women	0.39 ***	0.08, $z = 4.99$
Risk Aversion (α)	Men	0.02 ***	0.01, $z = 2.79$
	Women	0.04 ***	0.02, $z = 2.63$
Probability Weighting (γ)	Men	0.66 ***	0.04, $z = 17.08$ [b]
	Women	0.67 ***	0.03, $z = 22.70$ [b]
Error Parameter(μ)	Men	0.07 ***	0.01, $z = 7.23$
	Women	0.06 ***	0.00, $z = 5.10$

[a] Note: ** indicates that $p < 0.05$, and *** indicates that $p < 0.01$.
[b] The z value for the probability weighting parameter is for testing the difference between the coefficient estimate and a value of 1 (no weighting).

The parameter estimates in the table are significant and of plausible magnitudes.[14] 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.[15] The difference between the

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[14] 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.

[15] Gender differences in probability weighting have been reported by others. For example, Comeig, Jaramillo-Gutierrez, and Ramirez (2013) do report that women exhibit more nonlinear probability weighting than men, in a low-payoff downside risk setting motivated by borrowing and insurance. In contrast, we estimate single probability weighting parameters for men and women for the four settings: low payoff downside risk, low payoff upside risk, high payoff downside risk, and high payoff upside risk. It may be more difficult to distinguish the separate effects of utility curvature and probability weighting in a single setting in which both of these factors lead to more safe decisions. One possible interpretation of our results is that the use of

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.[16]

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 4 shows 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.

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four different settings enabled us to isolate the separate effects of utility curvature and probability perception for men and women. Alternatively, it could be the case that gender differences in probability weighting would be apparent with alternative econometric specifications. We believe that this is an important area for future research.

[16] 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.
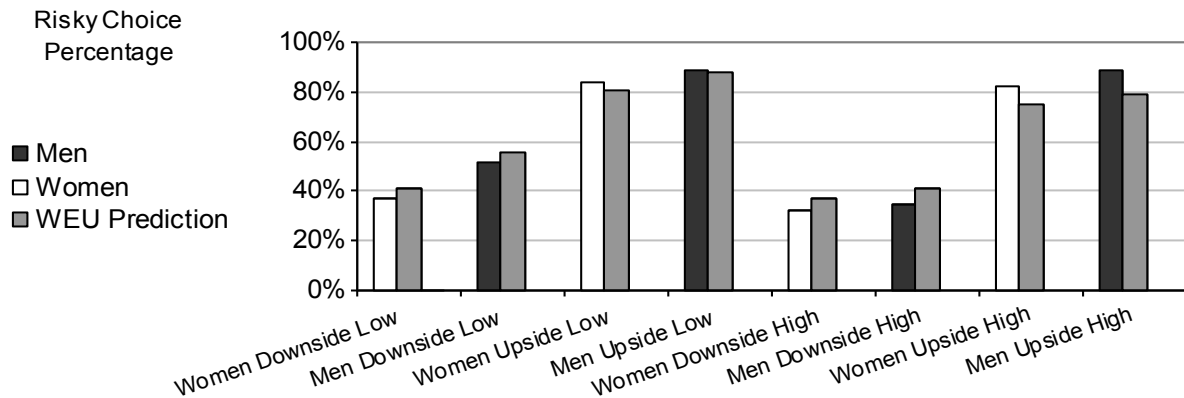
Figure 4. Percentages of Risky Choices
for Men (Dark Bars) and Women (Light Bars),
Together with Weighted Expected Utility Predictions (Gray Bars)

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):

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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 6 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.

VI. A Follow-up Experiment without Random Selection

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).[17] Therefore, we conducted a second experiment without random selection among 10 decisions in each treatment. The purpose of this follow-up experiment is not to provide a complete test of random selection and alternative approaches, but to determine whether the main treatment effects that we observe with random selection are present without it.

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[17] In particular, 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.

As before, we used 64 subjects with gender balance across treatments, but with only a single decision in each treatment. Payment was made for both treatments, but results were not announced until after the final decision had been made. Subjects were told in advance that there would only be two decisions, which would differ, but they were not shown the second decision until the first had been made. Each person faced one decision with downside risk and one with upside risk (decisions D1 and D3 from Table 4). Recall that these decisions have the same expected payoff difference of $0.80 in favor of the riskier choice ($4.00 in the 5x scale). In addition, both of these decision problems have the same difference between the variances of the riskier and safer options; this difference is $1.98 in both cases. As with the previous experiment, the payoff scale changed from the first part to the second, in order to maintain a comparable level of earnings across subjects. Thus there were 4 sessions, each with 8 men and 8 women, using the four possible sequences: Downside 1x followed by Upside 5x; Downside 5x followed by Upside 1x; Upside 1x followed by Downside 5x, and Upside 5x followed by Downside 1x.

Even though there is only a tenth as much data and less variation in decision structure (using only decisions D1 and D3), the overall pattern of risky choice percentages in Figure 5 is quite similar to that provided earlier in Figure 3. As before, the dark bars for men are higher, especially with downside risk and low payoff scale. Moreover, proportions of risky choices are lower for downside risk than for upside risk for each of the two payoff scales.[18]

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[18] To evaluate payoff scale effects, a between subjects approach is required since nobody made the same choice (downside or upside) for two different payoff scales. The effects of payoff scale cannot be determined with this limited amount of data, although the higher payoff scale results in marginally fewer risky choices for both downside risk (from 16/32 to 15/32) and with upside risk (from 31/32 to 29/32).
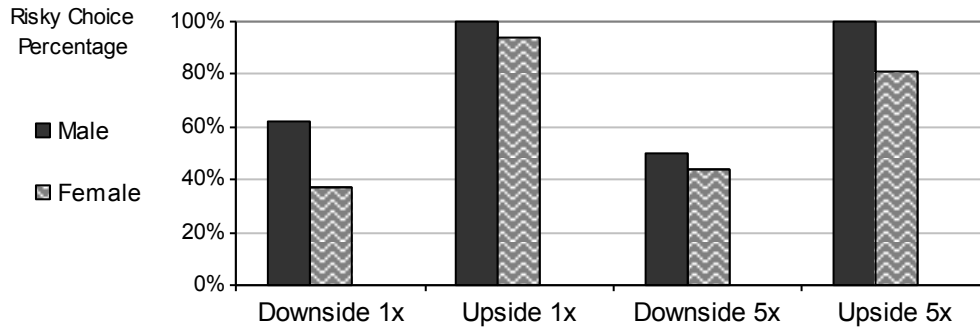
Figure 5. Data without Random Selection for Decisions D1 and D3 Only
Male Versus Female Percentage of Risky Choices
by Risk Type (Downside D1 or Upside D3) Payoff Scale (1x or 5x)

First, we consider the extent to which choice proportions with random selection differ from the choice proportions for the follow-up experiment without it. These proportions are shown in Table 7. Consider the two rows labeled "Difference," which show differences in observed choice proportions between the non-random and random selection procedures. The only significant difference is for the Downside risk 5x scale (all subjects), as indicated by the asterisk (*). In general, the differences in risky choice proportions are small in magnitude for other treatments.

Table 7. Risky Choice Proportions, With and Without Random Selection

Downside Risk	Male 1x	Female 1x	Total	Male 5x	Female 5x	Total
D1 Random	0.594	0.406	0.5	0.281	0.281	0.281
D1 Non-random	0.625	0.375	0.5	0.5	0.438	0.469
Difference	0.031	-0.031	0.0	0.219	0.151	0.188*
Upside Risk	**Male 1x**	**Female 1x**	**Total**	**Male 5x**	**Female 5x**	**Total**
D3 Random	0.938	0.969	0.953	0.9375	0.875	0.906
D3 Non-random	1.0	0.938	0.969	1.0	0.813	0.906
Difference	0.062	-0.031	0.016	0.0625	-0.063	0

Key: * indicates significance for a Chi Square test with $p < 0.10$ (two tailed).

Next, we focus attention on whether the most salient treatment patterns observed before, those for gender and upside versus downside risk, are also significant in the second experiment without randomization. Our results are summarized:

Treatment Effects without Random Selection: Men make more riskier choices than women, with the observed difference again being largest with low stakes and downside risk. The proportion of riskier choices is significantly higher with upside risk, even though the difference in expected value and variance between the riskier and safer options are the same for the upside and downside risk treatments.

Support: Recall that the main gender difference for the first experiment with random selection involved downside risk with low 1x payoffs. To see if this difference persists, consider the D1 Random and D1 Non-random rows in the upper left part of Table 7. With random selection, the difference in risky choice proportions was about 20 percentage points (59% for men and 41% for women). In the new experiment without random selection, this difference increases to about 25 percentage points (63% for men and 38% for women). Given the small amount of data, this difference is not significant. Next, consider the effects of risk structure. Each person made a single choice with downside risk and a single choice with upside risk, with balance in terms of payoff scale and treatment order. Therefore we use the number of riskier choices with downside risk (0 or 1) as a measure of risk taking in this setting, and the number of riskier choices with upside risk to be an analogous measure. Of the 64 subjects, 29 chose the riskier option in both upside and downside risk scenarios and 2 chose safer in both. Of the 33 others who exhibited a difference, 31 chose safer in the downside setting

and riskier in the upside setting. Only 2 subjects exhibited the reverse pattern (choosing the safer option with upside risk and the riskier option with downside risk). This difference is significant ($p < 0.001$) using a Chi-square test.

VII. Conclusion

Laboratory experiments are well suited for deconstructing separate components of complex decision theories, since key aspects of incentives and probabilities can be varied independently. This paper reports an experiment designed to evaluate the utility curvature and probability weighting components of risk aversion. The design is motivated by a prior experiment, in which subjects were presented with a set of paired choices between a safer lottery and a riskier lottery offering low probability of a very low payoff and a high probability of a better payoff. In this "downside risk" environment, subjects were risk averse in the sense that a significant fraction chose the safer option, even though the riskier option had a higher expected value. Women were more risk averse than men in that they tended to choose the risky option much less frequently than men. This risk aversion could be due to either utility curvature or to an overweighting of the low probability of a low payoff. But standard inverse-S probability weighing functions would also predict risk seeking in an "upside risk" treatment in which the risky option offers a low probability of a very high payoff. If this payoff were over-weighted, then risk seeking would be observed. These effects might be used to explain behavioral differences in investments with upside risk, e.g R&D, and investments with downside risk associated with bankruptcy in the event of failure.

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. It is also possible to consider models in which one type of player faces upside risk, e.g. an attacker in a game motivated by terrorism, and another player in the same game deals with downside risk, e.g. a defender faced with a small probability of a damaging attack.

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Data Appendix with Menus of 10 Decisions (Random Selection):

Proportions of Risky Choices by Gender and Payoff Scale[19]

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**

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[19] 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 4 and does not indicate the order in which it was encountered, since the 10 decisions for each payoff treatment block were randomly shuffled.

For Online Publication: Instructions Appendix

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

• **Options:** In each part of this experiment, 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

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

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

•   **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: *Additional 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**.

<div align="center">

○ **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**

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Continue with Instructions

(new page)

Summary

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- **Single Choice:** To summarize, you will begin by making a **single decision** that will determine your earnings for this part. (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.
- **Subsequent Parts:** This whole process (making a single decision 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. (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.

<div align="center">**Finished with Instructions**</div>