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# Gender, Financial Risk, and Probability Weights\*

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## Abstract

Women are commonly stereotyped as more risk averse than men in financial decision making. In this paper we examine whether this stereotype reflects actual differences in risk taking behavior by means of a laboratory experiment with monetary incentives.

Gender differences in risk taking may be due to differences in subjects' valuations of outcomes or to the way probabilities are processed. The results of our experiment indicate that men and women differ in their probability weighting schemes; however, we do not find a significant difference in the value functions. Women tend to be less sensitive to probability changes and also tend to underestimate large probabilities of gains to a higher degree than do men, i.e. women are more pessimistic in the gain domain. The combination of both effects results in significant gender differences in average probability weights in lotteries framed as investment decisions. Women's relative insensitivity to probabilities combined with pessimism may indeed lead to higher risk aversion.

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# 1. Introduction

It is often assumed that women are more risk averse than men, and numerous questionnaire studies have confirmed this common stereotype. Psychologists and sociologists find strong gender-specific differences in responses to non-financial risk which are particularly pronounced when it comes to physical or life-threatening risks (Byrnes et al. 1999). Surprisingly, little work has been done on gender-specific differences in financial decision making. Only a few laboratory experiments and studies based on field data have tried to shed light on the question of whether women are more risk averse than men when financial risks are concerned. The studies based on field data conclude that women are relatively more risk averse than men, whereas the laboratory experiments render inconclusive results (see the survey by Eckel & Grossman 2003).

The experimental studies yield a diversity of findings: When experimental subjects are confronted with lotteries in the gain domain, two outcomes prevail: either the female sex exhibits relatively higher risk aversion or there is no clear difference between the sexes. “Everything seems possible” in the loss domain, depending on the study considered: either the female, neither sex, or even the male sex is relatively more risk averse. The latter result is based on a small number of subjects. Since the studies differ in the structure of the gambles, potential payoffs, variance of payoffs, choice task, and other dimensions, one might argue that they lack comparability and, therefore, it is not surprising that results do not coincide. However, we even find divergent results in studies with quite similar experimental designs.

We surmise that the diversity in the findings may be caused by the way men and women weight probabilities in their decisions. To our knowledge, hardly any work has been done on the question of whether women process information on probabilities differently than do men. If there are systematic gender differences in the way probabilities influence the decision process, laboratory results may depend on the mix of lotteries used in the experiment. Suppose, for the sake of the argument, that women place a much higher weight on small probabilities than do men, and that their behavior does not differ otherwise. If the experimental design comprises winning lotteries with mostly medium and large probabilities (of the largest outcome) the researcher will not find any gender differences. If, on the other hand, the design relies heavily on gambles with small probabilities, she will most likely find

women to be the relatively more risk-seeking gender. We conjecture, therefore, that some of the contradictory results of the experiments done so far may be caused by the differing ranges of probabilities used in the experiments.

In order to explore the issue of gender-specific probability weighting, we conducted a laboratory experiment based on a wide range of probabilities. To be able to infer gender-specific average behavior, we recruited a large number of subjects, allowing us to generate data on certainty equivalents for winning and losing gambles in an abstract and in a contextual environment. The certainty equivalents were used to estimate the parameters of a decision model in the tradition of prospect theory, enabling us to check value and probability weighting functions for systematic gender differences. We estimated these functions for each single individual as well as for the female and the male median person.

Our findings on relative risk premiums demonstrate that gender differences, if they do exist, systematically depend on the size of the probabilities of the gambles' larger outcomes. Furthermore, we unequivocally show that women weight probabilities differently than do men. On average, female probability weighting schemes are flatter than the males' and, in the gain domain, more depressed. Women appear to be more pessimistic about medium and large probabilities of a gain. Since these gender effects are strongest for winning gambles in the context treatment, differences in risk-taking behavior are most likely to be observed for contextual gains with probabilities exceeding approximately 0.5. Value functions, however, do not differ significantly between the sexes.

Our results are confirmed by Harbaugh et al. (2002), the only other work addressing the question of gender specific probability weights. The experimental design in this study includes only abstract gambles, with probabilities evenly spread out over the (0,1) interval. Consistent with our findings on abstract gains, neither probability weights nor risk taking behavior differ by sex in the Harbaugh experiment. Whereas most of the laboratory experiments done in a contextual gains framework (Eckel and Grossman 2002, Moore & Eckel 2003, Schubert et al. 2000 among others) conclude that women are the relatively more risk averse sex, Gysler et al. (2002) do not find a significant gender effect. This seemingly contradictory result can be explained in light of our findings: Gysler et al. use only small probabilities for which our estimates suggest no significant differences in the gender specific weights.

The paper is organized as follows. In section 2 we describe the design and procedure of our experiment. In section 3 we briefly introduce the decision model and specify the functional forms for the individual value and probability weighting functions, the parameters of which are estimated by a nonlinear maximum likelihood procedure. We present the results of our experiment and their implications for gender specific risk behavior in section 4. Finally, explanations for our findings are discussed in section 5. Section 6 concludes the paper.

## 2. The Experiment

We designed a computerized experiment to elicit subjects' certainty equivalents; the latter serve as base for estimating value and probability weighting functions. The experiment is characterized by a (2 environments) x (2 domains) design. The environmental treatment conditions differ in the way the lotteries are framed: subjects are confronted with abstract gamble choices in the abstract environment, while the same lotteries are framed as investment and insurance decisions in the contextual environment. Each subject participates in only one of the environments. Instructions for the contextual environment are included in appendix C<sup>1</sup>.

The second dimension of the design concerns the domains of gains and losses. In both environmental treatments, each subject has to consider the same 50 two-outcome lotteries, 25 of which offer potential gains. The remaining 25 lotteries are framed as losses. Each one of the losing lotteries is equivalent to a winning lottery as it is assigned a lottery specific initial endowment such that total payoff is equal to the corresponding winning lottery's.

Since our objective is the estimation of value and probability weighting functions, we need a relatively wide range of probabilities and outcomes to obtain reliable estimates. However, subjects' attention spans are limited. A pretest confirmed that subjects can handle 50 lotteries comfortably. We use probabilities of 5, 10, 25, 50, 75, 90, and 95%. Outcomes range from zero to 150 Swiss Francs<sup>2</sup>. The lottery design is summarized in Tables 1a and 1b. The expected payoff per participant amounts to 31 Swiss Francs.

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<sup>1</sup> Instructions for the abstract treatment are available upon request. Note that the original instructions are in German.

<sup>2</sup> One Swiss Franc equals about 0.80 U.S. Dollars.

The experiment is programmed using “Z-Tree”, a special software package for conducting economic experiments (Fischbacher 1999). The 50 lotteries appear in random order for each subject. The participants fill out a separate decision form on the computer for each one of these lotteries. The computer screen displays the respective lottery (option A) and a list of 20 guaranteed amounts (options B; see Figure 1). These guaranteed amounts are arranged in algebraically descending order<sup>3</sup>, starting with the larger gamble outcome and descending in equal steps towards the smaller gamble outcome. Going down the list, the subjects have to decide on each line of the decision sheet whether they prefer the (fixed) lottery (option A) or the respective guaranteed payment (option B) by clicking on the box next to the preferred option. If subjects change from preferring guaranteed payments to preferring the lottery and switch back again, a message appears on the computer screen informing them that they have switched between A and B more than once. In this case, subjects can either reconsider their choices or stick to their previous entries. A lottery’s certainty equivalent is determined as the arithmetic mean of the minimum guaranteed payment which is preferred to the lottery and the following smaller guaranteed payment on the list (see Figure 1).

At the end of the experiment, subjects are asked to fill out a questionnaire eliciting information on a number of socioeconomic variables. When the subjects have completed the questionnaire, one of their lottery choices is randomly selected for payment by rolling dice. Their total payoffs include a show-up fee of 10 Swiss Francs. Average actual payoffs amounted to 40.61 Swiss Francs. The experimental sessions lasted about one hour in total. Financial incentives are salient considering the local student assistant’s hourly wage of 22.50 Swiss Francs.

The experiments took place at the computer lab of the Institute of Empirical Economic Research, University of Zurich, in June and August 2003. We recruited 204 students of various faculties of the Swiss Federal Institute of Technology and the University of Zurich. We had five sessions with abstract choices and five sessions with contextual choices. Since the calculation of certainty equivalents requires subjects to switch from option B to option A (or vice versa) just once, we can only use decisions that meet this condition. Since we estimate the parameters of the value and the probability weighting functions for each individual, this means that we should not exclude too many decisions from a person’s data

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<sup>3</sup> Guaranteed losses are arranged in ascending order in the loss domain (absolute).

set. Therefore, we use the following rule: if a subject exhibits inconsistent choices, i.e. if she switches back and forth between guaranteed and risky outcomes for more than two lotteries, all her decisions are excluded from the data set. Subjects' data with two or fewer inconsistent decision sheets are still considered; the erroneous decision sheets are deleted. This procedure leaves 181 subjects' data for analysis. An overview of the number of subjects according to sex and environment is presented in Table 2.

### 3. The Model

A large body of evidence supports the hypothesis of nonlinear probability weighting. Observed behavior depends on two factors then: how outcomes are valued and how probabilities are weighted. Since we surmise that men and women use probabilities differently in their decision process, we need to specify a model that allows us to estimate individual value and probability weighting functions to test our hypothesis. For this purpose we invoke the concepts of prospect theory (Tversky & Kahneman 1992).

For a two-outcome lottery

$$L[x_1, p; x_2], \quad |x_1| > |x_2|, \quad x_1, x_2 \geq 0 \quad \text{or} \quad x_1, x_2 \leq 0,$$

where  $x_i$  ( $i=1, 2$ ) denotes outcomes, and  $p$  denotes the probability of  $x_1$  occurring, the certainty equivalent CE is defined by

$$v(\text{CE}) = \pi_1 v(x_1) + \pi_2 v(x_2).$$

The decision weights are denoted by  $\pi_i$  ( $i=1, 2$ ),  $v$  is the value function defined on the monetary outcomes  $x$ . Both value function and decision weights are assumed to depend on the sign of the outcomes. The decision weights depend on the subject's domain specific probability weighting function  $w(p)$ . Decision weights in cumulative prospect theory are assumed to be a function of the cumulative distribution of the probabilities depending on the rank of the corresponding outcomes. In our two-outcome case, rank order does not play a role and the decision weights can be represented as

$$\pi_1 = w(p)$$

$$\pi_2 = 1 - w(p).$$

We have to choose functional forms for  $w$  and  $v$  to make the model operational. One of the functional forms most frequently used for the probability weighting function  $w$  is a one-parameter version introduced by Quiggin (1991) and Kahneman & Tversky (1979). Lattimore et al. (1992) propose the following two-parameter functional:

$$w(p) = \delta p^\gamma / [\delta p^\gamma + (1-p)^\gamma]; \quad \delta \geq 0, \quad \gamma \geq 0,$$

which we tested against the Quiggin version on the basis of the Akaike information criterion. It turns out that the Akaike criterion favors the Lattimore functional for the majority of our participants. This result holds across both environments and domains. Therefore, we present parameter estimates for the Lattimore version only. Note that the parameters  $\gamma$  and  $\delta$  are domain specific, i.e. they may take on different values for winning and losing gambles.

Elevation and slope of this functional cannot be varied totally independently from each other since  $w(p)$  is fixed “at both ends” ( $w(0) = 0$ ,  $w(1) = 1$ ). However, parameter  $\delta$  largely governs the elevation of the curve, while  $\gamma$  largely determines its slope: the greater the value of  $\gamma$ , the steeper the  $w(p)$  curve, and the greater the value of  $\delta$ , the more elevated the curve, *ceteris paribus*. Linear weighting is characterized by  $\gamma = \delta = 1$ .

The parameters have a neat psychological interpretation (Wu & Gonzalez 1996):  $\gamma$  reflects a subject’s responsiveness to changes in probability,  $\delta$  can be viewed as a winning gamble’s attractiveness. The more elevated the probability weighting curve, the greater are the weights placed on the probabilities. In this sense, a person finds a gamble more attractive than does another person if she puts more weight on the (larger outcome’s) probability than does the other person. The elevation of the curve also determines where the curve intersects the diagonal, i.e. the linear probability weighting line in  $(p, w(p))$  space. Therefore, for the typical inverted S-shape of the curve, the higher the point of intersection with the diagonal, the larger the range of probabilities where the subject displays optimism ( $w(p) > p$ ). It works the other way round for losing gambles: the more elevated the curve, the less attractive a gamble is judged to be, and the more pessimistic the person views the probabilities.



The value function  $v$  is modeled in the tradition of Kahneman & Tversky (1979) by the following power functional:

$$v(x) = \begin{cases} x^\alpha & x \geq 0 \\ -\lambda(-x)^\beta & x < 0 \end{cases}$$

Based on the aforementioned assumptions, we estimate the parameters  $(\alpha, \gamma, \delta)$  for the gain domain and  $(\beta, \gamma, \delta)$  for the loss domain for each single individual using the maximum likelihood method<sup>4</sup>. Moreover, we also estimate the parameters for the median probability weights. The latter estimates are based on the median certainty equivalents for each lottery. The parameter for loss aversion  $\lambda$  is not identifiable, since our lottery design does not include any mixed gambles, i.e. gambles with both positive and negative outcomes. For the model to be economically meaningful, the value function parameters  $\alpha$  and  $\beta$  need to differ significantly from zero. This does not necessarily apply to  $\gamma$  and  $\delta$ , however. When  $\gamma = 0$ , the subject exhibits a flat probability weighting curve, i.e. probabilities are totally neglected in the decision. When  $\delta = 0$ , the decision model reduces to  $x_2$  being the only relevant input. Both cases may be reflections of specific heuristics that are being used. Judged by the significance of  $\alpha$  and  $\beta$ , our model works well for 93% of the subjects. If we require all six parameters to be significantly different from zero, 80% of our participants meet this standard.

## 4. Results

Our results are based on three levels of analysis: subjects' direct responses to the experimental lotteries, individual parameter estimates, and estimates of the median functions. We first present a descriptive overview of female and male risk-taking behavior in Tables 1a and 1b. These tables comprise information on the lottery design and average risk taking behavior by sex and environmental condition.

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<sup>4</sup> To correct for heteroscedasticity the intervals  $[x_2, x_1]$  are transformed to uniform length.

Average behavior is captured by the median relative risk premium<sup>5</sup>. The relative risk premium (RRP hereafter) is defined as

$$\text{RRP} = (\text{expected payoff} - \text{certainty equivalent}) / |\text{expected payoff}|.$$

$\text{RRP} > 0$  indicates risk aversion,  $\text{RRP} = 0$  risk neutrality, and  $\text{RRP} < 0$  risk seeking. Tables 1a and 1b reveal a four-fold pattern of risk attitudes in our data: men and women in both environments are risk averse for medium and large probabilities of a gain, and risk seeking for small probabilities. They are also risk seeking for large probabilities of a loss, and risk averse for small and medium probabilities. This pattern of behavior has been found in many empirical investigations and fostered the idea that subjects weight probabilities nonlinearly. We also detect a regularity in gender differences: women are either equally risk averse or even more risk averse than men for the range of lotteries for which both sexes tend to be risk averse. The opposite holds for the lotteries with predominantly risk seeking behavior: women tend, with a few exceptions, to be either as risk seeking as men or even more so.

We now turn to our estimates of probability weights and value function parameters. As far as the individual parameter estimates are concerned, we find that subjects' probability weighting schemes differ vastly. Some of our participants weight probabilities linearly, but the majority under- and overweight them to some extent, with some people being optimistic or pessimistic over practically the whole range of probabilities. We find subjects with flat weighting functions as well. Median behavior, however, is characterized by the typical inverted S-shape of the probability weighting function (for both sexes and all treatment conditions) consistent with earlier estimates (Abdellaoui 2000, Bleichrodt & Pinter 2000, Gonzalez & Wu 1999, Lattimore et al. 1992, Kahneman & Tversky 1979 among others).

Individual variety in probability weights contrasts starkly with homogeneity in value function parameters: the estimated individual values for  $\alpha$  and  $\beta$  do not differ significantly from one for 76% of the subjects (70% of the women and 81% of the men; at the 5% level of significance), i.e. the value functions are practically linear for the vast majority of subjects. The linearity of the value functions is not surprising: the range of outcomes typically used in experiments with real financial incentives is rather limited. Therefore, decreasing marginal utility may not play a role.

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<sup>5</sup> Since the experimental design includes lotteries with varying ranges of probabilities and outcomes, we report relative risk premiums rather than CEs.

Finally, we address the focal point of our paper: are there trends in the female data that distinguishes it from that of the males? Results 1 through 6 present our findings on gender effects, Result 7 presents the effects of contextual framing.

### **Result 1:**

*Women are typically more risk averse than men in those lotteries where we find significant gender differences in risk taking. The existence of gender differences systematically depends on the size of the probabilities ( $p$ ) for the lotteries' larger outcomes  $x_1$ . While women exhibit greater risk aversion than do men for winning gambles with large probabilities, they display this trait for losing gambles with small and median probabilities.*

Table 3 summarizes the Mann-Whitney tests for the equality of the gender specific distributions of the relative risk premiums (RRP). The first results we present are those for the gain domain comprising a total of 25 lotteries. The experimental design includes 9 lotteries with large probabilities and 16 lotteries with small and medium probabilities of the larger outcome. We find women to be more risk averse with respect to 5 contextual decisions and 2 abstract ones involving large probabilities (0.75 to 0.95) whereas men are relatively more risk averse in just one case characterized by a small probability ( $p = 0.1$ ). If the proportion of significant gender differences is calculated on the basis of the number of lotteries in the relevant probability range, we find significant effects in 5 cases out of 9 (= 55.6%) for contextual gains and 2 out of 9 (= 22.2%) for abstract gains where women are more risk averse than men.

The loss domain also comprises 25 lotteries. The larger loss is assigned a small or medium probability in 15 lotteries, while 10 lotteries feature large probabilities. 5 cases of significant gender differences are identified in each environment. Women are more risk averse here in the probability range of 0.05 to 0.5 and more risk seeking in the case of just one losing gamble with  $p = 0.95$ . Relating the cases of significant differences to the relevant number of lotteries, we find a gender effect in 5 cases (= 33.3%) for abstract losses and 4 (= 26.7%) for contextual losses where women are more risk averse.

Summing up, there is a clear pattern of gender-specific behavior depending on the size of the probabilities of the larger gamble outcome. Women are more risk averse only in decisions with large probabilities in the gain domain and in decisions with small and medium

probabilities in the loss domain. We find just one case (out of 16 and 10 relevant lotteries) in the contextual environment in both domains where women are more risk seeking than men.

Gender differences in risk taking behavior may result from differences in the way monetary outcomes are valued or from differences in probability weights or both. The following result provides a first indication as to the source of gender-specific behavior.

## **Result 2:**

*Women are significantly less responsive to changes in probability in all four treatments, i.e. women's probability weighting functions are, on average, flatter than are men's.*

Two groups of findings back gender differences in probability weights: the distributions of the individual parameter estimates and the estimates of the median parameters. A bootstrapped<sup>6</sup> Mann-Whitney test assesses differences in the distributions of the individual parameter estimates. The female sensitivity to changes in probability, expressed by the parameter  $\gamma$ , tends to be significantly smaller (at the 1%-level of significance) across both domains and environments. The same characteristic can be seen in the estimates for the median probability weighting functions. Table 4 summarizes the estimated parameter values for all treatment conditions. Focusing on the estimates for  $\gamma$ , one can discern the following regularities: the estimate for the female responsiveness to probabilities is consistently smaller (by 0.09 or more) across all treatment conditions. Moreover, the parameter estimates for both the females and the males are strikingly stable across treatments. The gender differences in responsiveness are also highly significant as Table 5 reveals. The numbers in Table 5 are calculated as female coefficients relative to the male coefficients. We see significant differences in  $\gamma$  across all treatment conditions which implies that the median female curve is significantly flatter. The largest relative gender difference is observed for contextual gains ( $\Delta = -27\%$ ; see the small box in Table 5).

Our next result refers to the elevation of the probability weighting function where we also find a significant gender difference.

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<sup>6</sup> Normally, a standard Mann-Whitney test is sufficient for discerning among distributions of two random variables. In our case, we would like to test the distributions of the true parameter values for equality. Unfortunately, these are unobservable and we only have estimates at our disposal. Therefore, we construct the

### **Result 3:**

*Women are on average more pessimistic than men in the gain domain.*

Table 4 reveals that the parameter estimates for  $\delta$ , the elevation of the probability weighting curve, differ between the sexes. This difference seems to be more pronounced in the gain domain. Whether these differences are statistically significant can be inferred from Table 5. Whereas we do not find any gender effects for losing gambles, the parameter estimates for the gain domain differ significantly between the sexes. The women's average probability weighting curve is less elevated than the men's for gains in both environments, signifying a higher degree of female pessimism, i.e.  $w(p) < p$ . This gender difference is more pronounced in the contextual environment ( $\Delta = -21\%$ ) than in the abstract one ( $\Delta = -16\%$ ). However, significant differences in single parameters do not necessarily imply significant differences in the probability weights since the shape of the probability weighting curve depends simultaneously on both  $\gamma$  and  $\delta$ . Therefore, we need to examine the combined effect of these parameters on the probability weights.

### **Result 4:**

*In general, women's probability weighting functions are different from men's. This difference, however, is only significant for contextual gains where the gender differences are greatest both in responsiveness ( $\gamma$ ) and attractiveness ( $\delta$ ).*

The main body of evidence for Result 4 is depicted in the graphs of the median probability weighting functions (Figures 2 to 5). The graph of the female median weighting function is plotted against that of the male for one of the treatment conditions in each of the Figures 2 to 5. The female curve is flatter than the male curve in all four figures and, in the gain domain, it tends to be more depressed. The largest difference between the gender specific probability weighting functions can be observed for contextual gains (Figure 3).

A first indication for Result 4 can be inferred from Table 3. At the level of the RRP's, the number of lotteries with observed significant gender differences is highest for contextual gains (6 out of 25). Moreover, the 5 cases with high probabilities where the RRP's differ significantly between the sexes constitute a high proportion of all the lotteries with large

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empirical distributions of the Mann-Whitney test statistic by a non parametric bootstrapping procedure which then serves as a basis for our tests (see Appendix A).

probabilities in the gain domain (5 out of 9). The relevant proportion of lotteries with significant differences is smaller than for contextual gains for all the other treatment conditions.

As argued above, the combined effect of the parameters drives the shape of the probability weighting function. Table 5 reveals that the gender difference in the estimates for  $\gamma$  (indicating responsiveness) is highest for contextual gains ( $\Delta = -27\%$ ) whereas the differences in the other treatment conditions are approximately of the same order of magnitude ( $\Delta = -17\%$ ,  $-18\%$ ). There are also significant effects for  $\delta$  (indicating attractiveness) in the gain domain which are much more pronounced for contextual gains ( $\Delta = -21\%$ ). Thus, the total gender difference is strongest for winning gambles in the context environment.

Finally, we turn to the statistical evidence for Result 4, i.e. the 95% confidence bands<sup>7</sup> for the median probability weighting functions. The gender-specific confidence bands diverge only for contextual gains when probabilities exceed approximately 0.5 (Figure 7). The confidence bands for men's and women's median probability weighting functions overlap over the whole range of probabilities in the other treatments (Figures 6, 8, 9).

The next result links our findings on gender-specific probability weights to women's strong reaction to framing: Women respond differently to winning and losing gambles.

### **Result 5:**

*The probability weighting functions of both sexes tend to be more elevated for losses than for gains. However, women's domain specific curves differ significantly whereas men's do not.*

There is a significant framing effect in the parameters of the individual probability weighting functions. The hypothesis of equal domain-specific distributions of the parameter estimates for  $\delta$  can be rejected at the 1% level (Mann-Whitney test, bootstrapped). The elevation of the probability weighting function tends to be higher for losses than for gains. Again, we constructed the 95% confidence bands of the median probability weighting functions to analyze the combined impact of both parameters  $\gamma$  and  $\delta$  on the domain specific curves. Figures 10 and 11 display the 95% confidence bands for the female curve in the gain domain

plotted against the female curve in the loss domain for the abstract and the contextual environment, respectively. The curves do not overlap for considerable portions of the probability range in either environment. The male curves do not exhibit such a pattern (see Figures 12 and 13) which means that the observed gender effects are, at least partly, caused by the women's strong reaction to the framing of lotteries in terms of gains and losses.

So far we have seen gender differences in probability weighting. We next examine whether we find any gender effects in the valuations of outcomes.

### **Result 6:**

*The vast majority of women and men value monetary outcomes linearly. Hence, there are no significant gender differences in the parameters of the individuals' value functions.*

As already mentioned above, we cannot reject the hypothesis of linear value functions for 76% of our subjects. Furthermore, a bootstrapped Mann-Whitney test yields no significant gender differences in the distributions of  $\alpha$  and  $\beta$  at the 5% level of significance.

Finally, we turn to the question whether context makes a difference, i.e. whether subjects respond differently to gambles presented as abstract or contextual decisions.

### **Result 7:**

*Men and women value abstract gains more highly than contextual gains. Probability weights, however, do not depend on context.*

Turning to the individual value functions, we find that only the estimates for  $\alpha$  show a context effect (bootstrapped Mann-Whitney test at the 5% level of significance). There is no context effect in the loss domain. Men and women value monetary gains more highly when they result from abstract gambles rather than contextual ones, i.e. the parameter  $\alpha$  is larger for abstract gains than for contextual gains. We interpret this difference as the additional utility subjects derive from gambling. This pattern of differences is repeated in the estimates of the median parameters: In Table 4 the estimates for  $\alpha$  in the abstract environment amount to approximately 1.1 whereas the corresponding values in the context treatment are much

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<sup>7</sup> Due to the nonlinearity of the model, standard deviations estimated by the usual delta method may not be trustworthy. Instead, we estimated combined empirical confidence intervals for  $\gamma$  and  $\delta$  based on a non

smaller (0.9). As Table 6 shows, these differences are also significant for both sexes. Again, men and women value outcomes more highly when confronted with abstract winning gambles, but we also find a significant, albeit smaller, effect for men in the loss domain. Moreover, both women's and men's probability weighting functions seem to react to contextual framing to some degree. It turns out, though, that the curves of the median probability weighting functions do not differ significantly by environment when judged by the respective confidence bands, nor do we find a significant context effect at the level of the individual parameter estimates for the probability weighting functions (by a bootstrapped Mann-Whitney test).

## 5. Discussion

Are women relatively more risk averse than men in financial decision making? It depends. We can safely conclude that women and men do not strongly differ in their valuations of outcomes, but there is convincing evidence that the sexes process information on probabilities differently. Women are less sensitive to changes in probability than men. Whether this gender difference is strong enough to have an impact on actual observed risk taking behavior seems to depend on context and domain. Women tend to be especially pessimistic when responding to risky contextual gains with large probabilities of realization. Therefore, we observe women to be the significantly more risk averse sex in the domain of investment decisions.

In the following we discuss different hypotheses regarding the sources of gender differences in probability weights. First of all, how can we explain women's stronger pessimism? Pessimism could be a manifestation of female underconfidence. When important investment decisions have to be made, women might have doubts about their judgment and underestimate probabilities more strongly than do men. We do have evidence on men's overconfidence in investment decisions (see e.g. Barber & Odean 2001); however, we have not yet come across any evidence on female underconfidence in financial decision making.

Loewenstein et al. (2001) put forward a hypothesis which mainly relates to responsiveness to probabilities. The authors argue that both cognitive and emotional processes influence a

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parametric bootstrap procedure with 9999 repetitions (see Appendix B for details).



decision. Their risk-as-feelings hypothesis claims that, first, emotions respond to outcomes and probabilities in a fashion that is different from cognitive evaluations. Second, these emotions are influenced by variables that play only a minor role in cognitive evaluations, such as vividness of imagery associated with the outcomes of the risky decision, the background mood state of the decision maker, and the time-course of the decision. These anticipatory feelings may conflict with the cognitive assessment of the situation and even overrule it. One consequence of these intervening feelings could be that information about probabilities is discounted to some degree. Consistent with the risk-as-feelings hypothesis, we would predict probability weighting functions to be flatter as the importance of the influence of anticipatory feelings increases.

Applying this line of reasoning, gender differences in vividness might explain gender differences in risk taking behavior. Vividness is likely to depend both on individual mental imagery ability and on situational factors, such as how vividly an outcome is described. As far as imagery is concerned, several studies have shown that women report more and better imagery than men. They seem to experience emotions more intensely than do men and they report experiencing nervousness and fear more intensely (see the references in Loewenstein et al. 2001). Consequently, females might be relatively more inclined to neglect probabilities in their decision making, i.e. to exhibit rather flat probability weighting curves. Moreover, women's stronger feelings of nervousness could manifest themselves as pessimism in a risky decision, which could explain the relatively more depressed female median weighting function.

If women react more strongly to vivid images, gender differences should be more pronounced in a contextual environment. Contextual frames may trigger more vivid images and thus stronger anticipatory feelings than the comparatively pallid monetary outcomes of abstract gambles. As a consequence, the probability weighting functions might be flatter in the contextual environment (see also Rottenstreich & Hsee 2001 for a similar experimental result). Our results are consistent with the risk-as-feelings hypothesis. However, this framework cannot explain why we do not observe a similar gender effect in the loss domain. The average female probability weighting function is still significantly flatter than that of the male, but the confidence bands for the median gender specific curves overlap over the whole range of probabilities. The female curves lie closer to the diagonal in the loss domain than in the gain domain. It seems as if women exert more effort to make the "right" decision when

losses are at stake, thereby sticking more closely to linear weighting. In this case it looks as if cognitive assessment is assigned more weight in the decision process and female anticipatory feelings become less influential.

Another hypothesis to account for gender differences in probability weighting argues that people make errors in judging probabilities and that errors may differ by sex depending on the choice task (Eckel & Grossman 2003). The general argument rests on the idea that one can hardly underweight very small probabilities, or overweight very large ones. Therefore, a pattern of errors is likely to be found which is consistent with the typical inverted S-shape of the probability weighting function. We have doubts about this interpretation. First of all, there is great diversity in the individual probability weighting schemes: many people do not distort probabilities in this particular fashion. The inverted S-shape is observed for median choices, but it is not necessarily the predominant type of curve. The average weighting curve in the gain domain usually intersects the diagonal at probabilities valuing 0.3 to 0.4. One would have to find an explanation why people, men and women alike, make asymmetric errors. Average curves are typically more elevated in the loss domain, thereby shifting the point of intersection closer to 0.5. The error hypothesis can only be applied to losing gambles, if at all. Since errors, per definition, can only be committed in a cognitive process, this conclusion is also consistent with the hypothesis of women's higher cognitive effort in the loss domain. If, on one hand, the error hypothesis makes sense only in the context of losses and, on the other hand, we do not observe significant gender differences in the loss domain, gender-specific error processes are implausible. Of course, our reasoning does not preclude that men and women make systematically different errors in other choice tasks.

The framework of bounded rationality offers yet another possible explanation for gender differences in probability weighting. People have to take many small, occasionally some big, financial decisions in everyday life which are typically not characterized by risk but rather by uncertainty: probabilities of outcomes are usually not well defined numbers but tend to be ambiguous. We speculate that people have adapted to their environment by using specific heuristics for decision making under uncertainty. Possibly, women use heuristics differing from men's since, in the course of the evolution, women have had to solve different problems. Maybe, when confronted with purely risky decisions, women tend to stick more strongly to their rules for ambiguous situations which result in a lower responsiveness to probability information and, possibly, stronger outcome orientation. To our knowledge, no work has been

done on gender specific heuristics so far. Therefore, we do not have any evidence supporting such a speculation.

## 6. Conclusion

Women are different - but it does not always show. Women's and men's valuations of financial outcomes do not deviate strongly from each other, whereas women tend to weight probabilities in a specific way. They are less responsive to changes in probabilities than men and they are more pessimistic in situations when gains are at stake. These two factors impact the observable behavior most likely in investment decisions when the probability of a gain is of medium or large size. Our analysis demonstrates that gender differences in risk taking behavior crucially depend on probabilities. Studies that do not take this relationship into account may yield flawed conclusions.

The question of whether women and men differ in loss aversion remains open, since we did not estimate  $\lambda$ , the parameter of loss aversion. Gender-specific estimates of loss aversion are an obvious candidate for future research. Moreover, research will have to be done on financial decision making under (genuine) uncertainty to check whether our results are repeated in ambiguous situations. In our view, another interesting venue for future endeavors concerns psychological explanations of gender-specific behavior. The risk-as-feelings hypothesis is one promising candidate.

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**TABLE 1a: Lotteries - Gain Domain  
Median Relative Risk Premium (RRP) by Sex and Environment**

Lottery number	Lottery design			Median RRP		Median RRP	
	Probability p of $x_1$ (%)	Outcome $x_1$ CHF	Outcome $x_2$ CHF	Abstract environment Women	Men	Context environment Women	Men
29	5	20	0	-3.50	-3.50	-2.50	-2.50
5	5	40	10	-0.46	-0.33	-0.39	-0.33
17	5	50	20	-0.17	-0.17	-0.17	-0.21
37	5	150	50	-0.23	-0.14	-0.23	-0.23
1	10	10	0	-2.25	-1.75	-1.75	-1.25
30	10	20	10	-0.16	-0.16	-0.16	-0.14
44	10	50	0	-0.75	-1.25	-0.75	-0.75
20	25	20	0	-0.50	-0.50	-0.10	-0.10
12	25	40	10	-0.13	-0.13	-0.13	-0.04
10	25	50	20	-0.08	-0.08	-0.08	-0.08
42	50	10	0	0.05	-0.05	0.05	0.05
4	50	20	10	0.02	0.02	0.02	0.00
39	50	40	10	0.03	0.03	0.15	0.03
28	50	50	0	0.05	0.05	0.10	0.05
7	50	50	20	0.11	0.04	0.09	0.02
6	50	150	0	0.25	0.25	0.25	0.25
49	75	20	0	0.17	0.03	0.37	0.10
27	75	40	10	0.21	0.09	0.14	0.09
11	75	50	20	0.16	0.07	0.12	0.07
26	90	10	0	0.08	0.08	0.19	0.08
23	90	20	10	0.12	0.07	0.14	0.07
2	90	50	0	0.19	0.14	0.31	0.14
8	95	20	0	0.18	0.08	0.24	0.14
35	95	40	10	0.14	0.10	0.18	0.08
16	95	50	20	0.11	0.11	0.17	0.11

Shaded areas indicate risk seeking behavior.

**TABLE 1b: Lotteries - Loss Domain  
Median Relative Risk Premium (RRP) by Sex and Environment**

Lottery number	Lottery design			Median RRP		Median RRP	
	Probability p of $x_1$ (%)	Outcome $x_1$ CHF	Outcome $x_2$ CHF	Abstract environment Women	Abstract environment Men	Context environment Women	Context environment Men
33	5	20	0	3.50	1.50	3.50	2.50
48	5	40	10	0.33	0.26	0.59	0.33
15	5	50	20	0.24	0.17	0.24	0.17
47	10	10	0	2.25	1.25	2.25	0.75
13	10	20	10	0.23	0.16	0.16	0.16
19	10	50	0	2.25	1.25	2.00	1.25
22	25	20	0	0.50	0.30	0.80	0.30
38	25	40	10	0.21	0.17	0.39	0.13
43	25	50	20	0.25	0.08	0.14	0.14
32	50	10	0	0.05	-0.05	0.05	0.05
13	50	20	10	0.23	0.16	0.16	0.16
36	50	40	10	0.03	0.03	0.09	0.03
24	50	50	0	0.15	0.05	0.10	0.05
25	50	50	20	0.02	0.00	0.00	0.02
46	50	150	0	0.35	0.20	0.45	0.05
18	75	20	0	-0.17	-0.10	-0.07	-0.03
21	75	40	10	-0.07	-0.07	-0.07	-0.07
50	75	50	20	-0.05	-0.05	-0.02	-0.05
9	90	10	0	-0.14	-0.14	-0.17	-0.14
31	90	20	10	-0.09	-0.09	-0.09	-0.07
40	90	50	0	-0.14	-0.11	-0.08	-0.11
14	95	20	0	-0.13	-0.08	-0.13	-0.13
45	95	40	10	-0.09	-0.09	-0.09	-0.09
41	95	50	20	-0.08	-0.08	-0.06	-0.06
3	95	150	50	-0.09	-0.09	-0.17	-0.05

Shaded areas indicate risk seeking behavior.

**TABLE 2: Number of Participants by Sex and Environment**

	<b>Abstract environment</b>	<b>Contextual environment</b>	<b>Pooled environments</b>
<b>Female</b>	37	40	77
<b>Male</b>	54	50	104
<b>Both sexes</b>	91	90	181



**Table 3: Significant Gender Effects in the Relative Risk Premiums by Lottery**

Mann-Whitney test

Significant at 5%

Significant at 1%

### Gains

Lottery	p %	Abstract environment		Context environment		
		Women	Men	Women	Men	
1	10			RRP <sub>f</sub>	<	RRP <sub>m</sub>
2	90	RRP <sub>f</sub>	>	RRP <sub>m</sub>		
8	95			RRP <sub>f</sub>	>	RRP <sub>m</sub>
23	90	RRP <sub>f</sub>	>	RRP <sub>m</sub>		
35	95			RRP <sub>f</sub>	>	RRP <sub>m</sub>
49	75			RRP <sub>f</sub>	>	RRP <sub>m</sub>

### Losses

Lottery	p %	Abstract environment		Context environment			
		Women	Men	Women	Men		
3	95			RRP <sub>f</sub>	<	RRP <sub>m</sub>	
32	50	RRP <sub>f</sub>	>	RRP <sub>m</sub>			
33	5	RRP <sub>f</sub>	>	RRP <sub>m</sub>			
36	50			RRP <sub>f</sub>	>	RRP <sub>m</sub>	
38	25			RRP <sub>f</sub>	>	RRP <sub>m</sub>	
43	25	RRP <sub>f</sub>	>	RRP <sub>m</sub>			
46	50	RRP <sub>f</sub>	>	RRP <sub>m</sub>	RRP <sub>f</sub>	>	RRP <sub>m</sub>
47	10	RRP <sub>f</sub>	>	RRP <sub>m</sub>			
48	5			RRP <sub>f</sub>	>	RRP <sub>m</sub>	

**Table 4: Estimates of Median Parameters  
and Standard Deviations**

**Abstract Environment**

$\alpha, \beta$                        $\gamma$                        $\delta$

	$\alpha, \beta$		$\gamma$		$\delta$	
	Women	Men	Women	Men	Women	Men
<b>Gains</b>	<b>1.16</b>	<b>1.13</b>	<b>0.47</b>	<b>0.56</b>	<b>0.74</b>	<b>0.88</b>
	<i>0.105</i>	<i>0.096</i>	<i>0.028</i>	<i>0.028</i>	<i>0.077</i>	<i>0.081</i>
<b>Losses</b>	<b>1.09</b>	<b>1.03</b>	<b>0.47</b>	<b>0.57</b>	<b>1.10</b>	<b>1.00</b>
	<i>0.089</i>	<i>0.064</i>	<i>0.031</i>	<i>0.021</i>	<i>0.089</i>	<i>0.064</i>

**Context Environment**

$\alpha, \beta$                        $\gamma$                        $\delta$

	$\alpha, \beta$		$\gamma$		$\delta$	
	Women	Men	Women	Men	Women	Men
<b>Gains</b>	<b>0.94</b>	<b>0.91</b>	<b>0.41</b>	<b>0.56</b>	<b>0.79</b>	<b>1.00</b>
	<i>0.066</i>	<i>0.065</i>	<i>0.021</i>	<i>0.025</i>	<i>0.059</i>	<i>0.075</i>
<b>Losses</b>	<b>1.20</b>	<b>0.94</b>	<b>0.47</b>	<b>0.57</b>	<b>1.06</b>	<b>1.14</b>
	<i>0.131</i>	<i>0.044</i>	<i>0.031</i>	<i>0.016</i>	<i>0.130</i>	<i>0.044</i>

All parameter estimates are significant at least at the 5%-level (t-test). The F-test for the respective vector of parameters yields significance at 1%.

**Table 5: Significant Differences in Median Probability Weights**  
*and values of t-test*

**Relative Differences by Gender**

(Female coefficient minus male coefficient)/male coefficient

		$\gamma$		$\delta$	
		Abstract	Context	Abstract	Context
<b>Gains</b>		<b>-17%</b>	<b>-27%</b>	<b>-16%</b>	<b>-21%</b>
		4.16	6.94	2.10	3.28
<b>Losses</b>		<b>-18%</b>	<b>-18%</b>	10%	-7%
		5.31	4.68	1.49	1.01

**Table 6: Significant Differences in Estimated Median Parameters**  
*and values of t-test*

**Relative Differences by Context**

(Abstract coefficient minus context coefficient)/context coefficient

		$\alpha, \beta$		$\gamma$		$\delta$	
		Gains	Losses	Gains	Losses	Gains	Losses
<b>Women</b>		<b>23%</b>	-9%	<b>14%</b>	1%	-6%	4%
		3.24	1.36	2.80	0.01	0.84	0.58
<b>Men</b>		<b>24%</b>	<b>10%</b>	0%	0%	<b>-12%</b>	<b>-12%</b>
		3.70	2.37	0.33	0.11	2.13	3.11

**Figure 1:  
Design of Computer Screen (gain domain, context treatment)**

Decision situation: 22						
	Option A	Your Choice:				Option B Guaranteed payoff amounting to:
1		A	<input type="checkbox"/>	<input type="checkbox"/>	B	20
2		A	<input type="checkbox"/>	<input type="checkbox"/>	B	19
3		A	<input type="checkbox"/>	<input type="checkbox"/>	B	18
4		A	<input type="checkbox"/>	<input type="checkbox"/>	B	17
5		A	<input type="checkbox"/>	<input type="checkbox"/>	B	16
6		A	<input type="checkbox"/>	<input type="checkbox"/>	B	15
7	Profit of CHF 20 with	A	<input type="checkbox"/>	<input type="checkbox"/>	B	14
8		A	<input checked="" type="checkbox"/>	<input type="checkbox"/>	B	13
9	probability 25%	A	<input checked="" type="checkbox"/>	<input type="checkbox"/>	B	12
10		A	<input checked="" type="checkbox"/>	<input type="checkbox"/>	B	11
11	and profit of CHF 0 with	A	<input checked="" type="checkbox"/>	<input type="checkbox"/>	B	10
12		A	<input checked="" type="checkbox"/>	<input type="checkbox"/>	B	9
13	probability 75%	A	<input checked="" type="checkbox"/>	<input type="checkbox"/>	B	8
14		A	<input checked="" type="checkbox"/>	<input type="checkbox"/>	B	7
15		A	<input checked="" type="checkbox"/>	<input type="checkbox"/>	B	6
16		A	<input checked="" type="checkbox"/>	<input type="checkbox"/>	B	5
17		A	<input checked="" type="checkbox"/>	<input type="checkbox"/>	B	4
18		A	<input checked="" type="checkbox"/>	<input type="checkbox"/>	B	3
19		A	<input checked="" type="checkbox"/>	<input type="checkbox"/>	B	2
20		A	<input checked="" type="checkbox"/>	<input type="checkbox"/>	B	1

OK

For each of the 20 lines on the screen the subject has to decide whether she prefers option A, the lottery, or option B, the guaranteed payoff in the respective line. Preference is indicated by marking the box next to A or B in each line. Suppose the subject chooses the guaranteed option for payoffs from CHF 20 to 14 and then switches to the lottery. In this case the certainty equivalent amounts to CHF 13.50. Participants are informed in the experimental instructions that option B is taken to be their choice throughout if they do not make any entries.

# Figures 2 – 5: Gender Specific Median Probability Weighting Functions $w(p)$

Figure 2: Abstract Gains - Women vs. Men      Figure 3: Contextual Gains - Women vs. Men

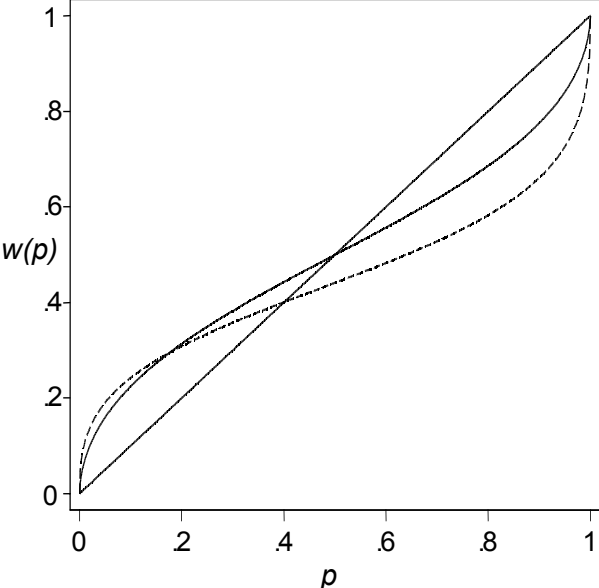
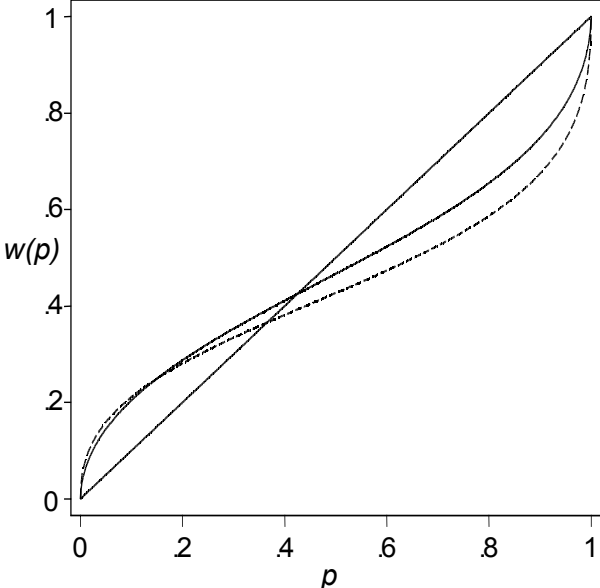
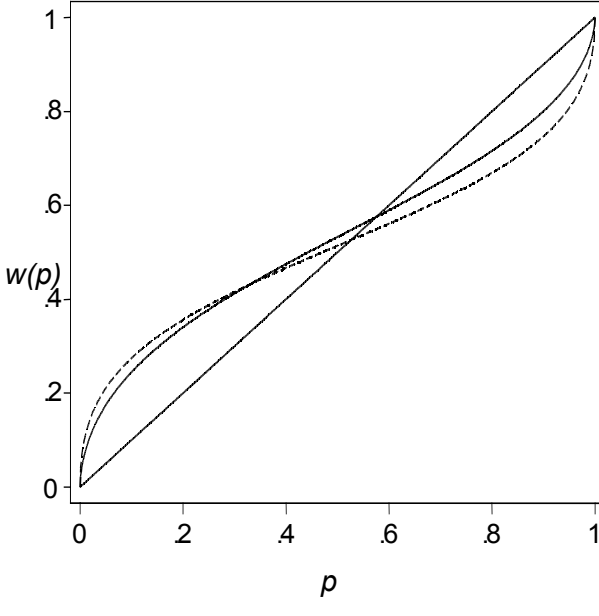
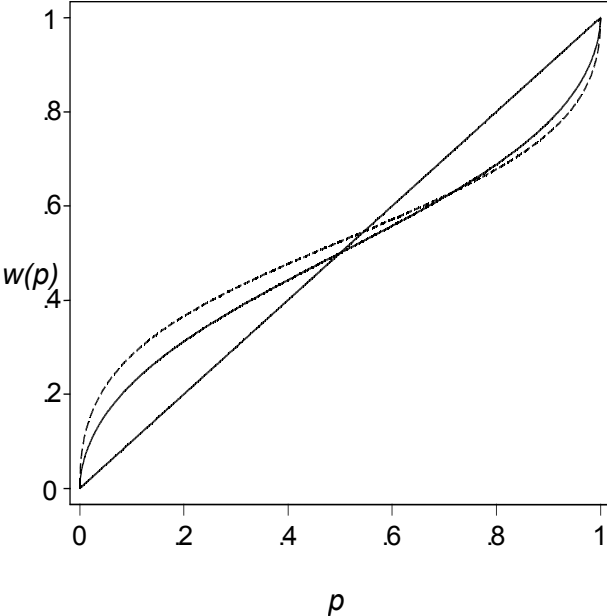


Figure 4: Abstract Losses - Women vs. Men

Figure 5: Contextual Losses - Women vs. Men



----- Female median      — Male median

## Figures 6 – 13: 95%-Confidence Bands of Median Probability Weighting Functions

Figure 6: Abstract Gains - Women vs. Men

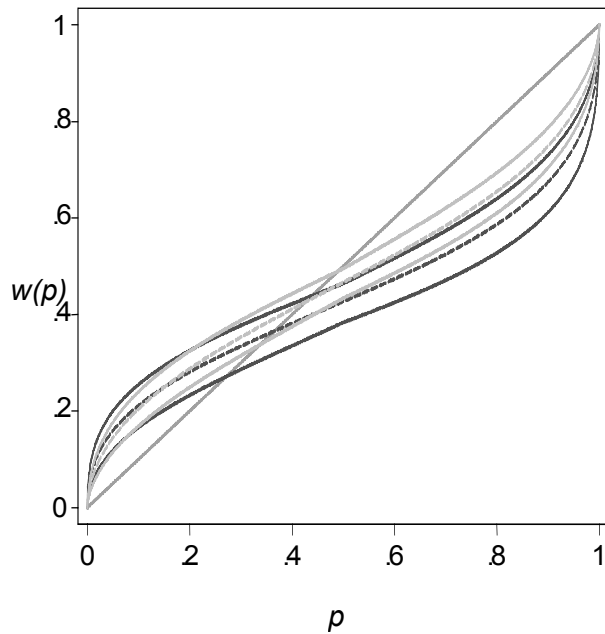


Figure 7: Contextual Gains - Women vs. Men

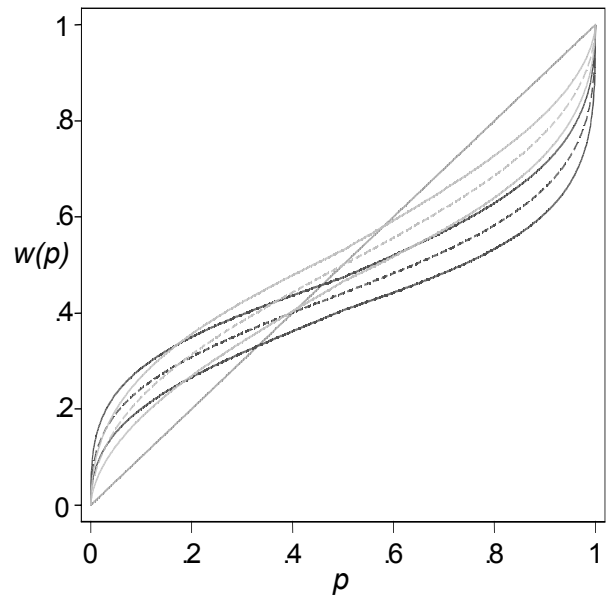


Figure 8: Abstract Losses - Women vs. Men

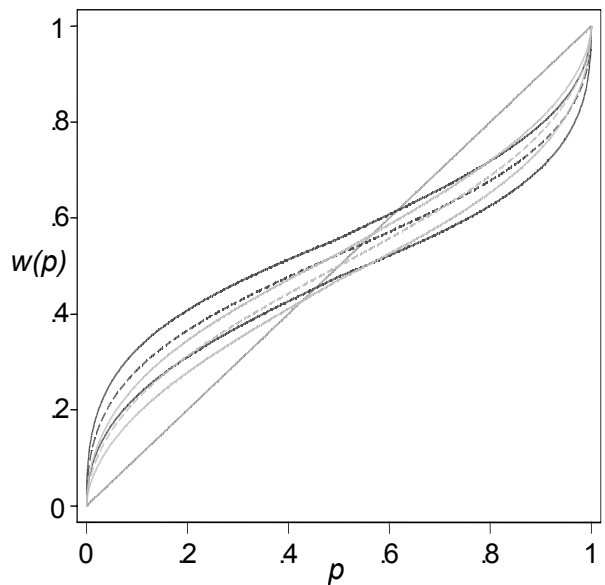
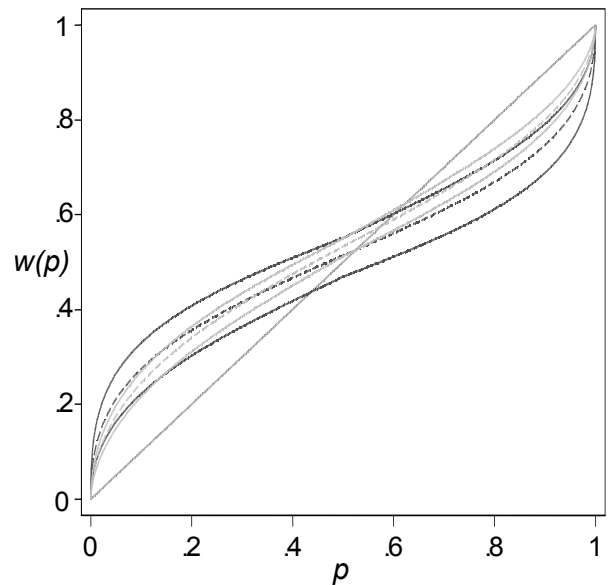
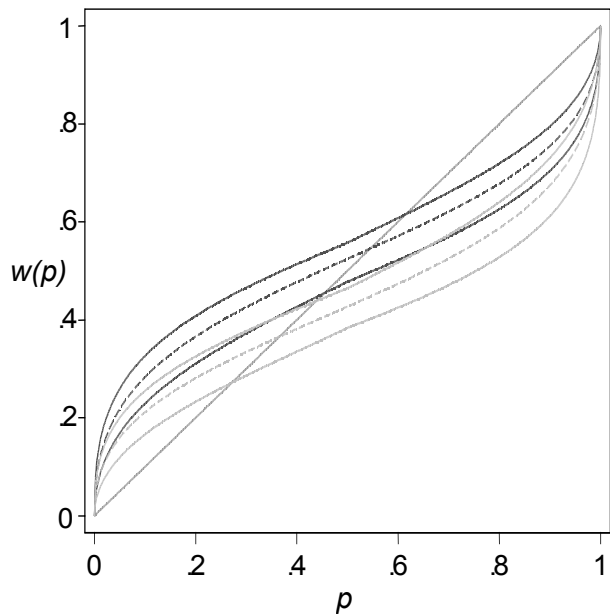


Figure 9: Contextual Losses - Women vs. Men

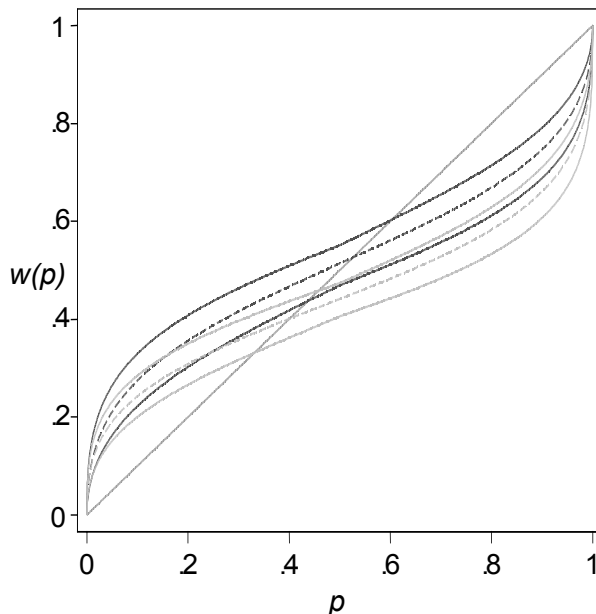


- Female median
- 95%-Confidence band, female median
- Male median
- 95%-Confidence band, male median

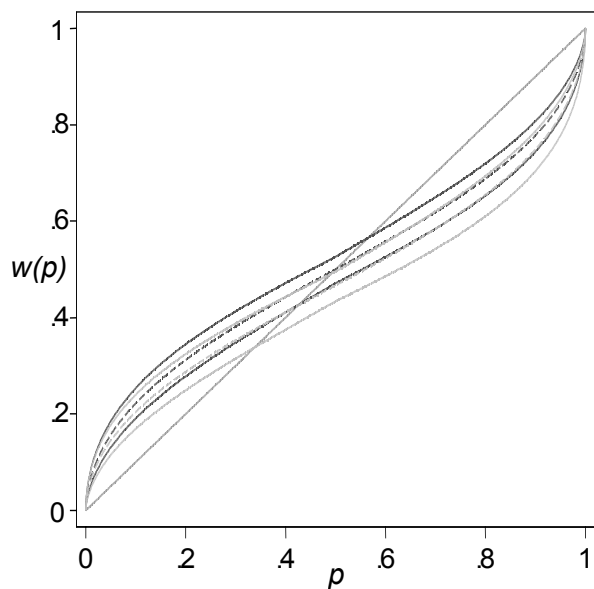
**Figure 10: Women - Abstract Losses vs. Gains**



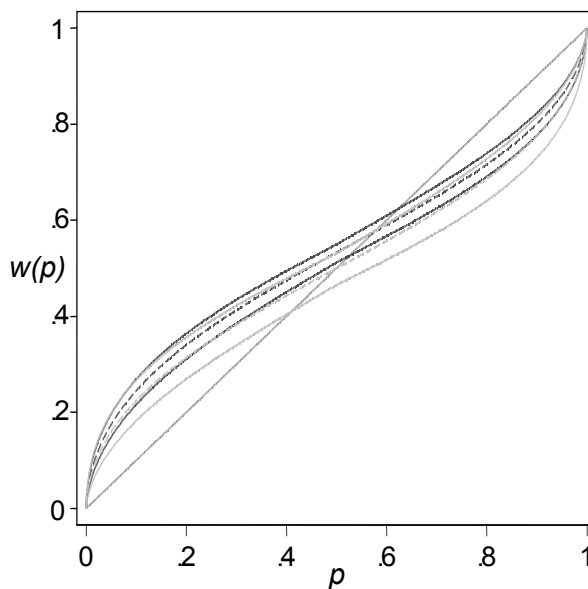
**Figure 11: Women - Contextual Losses vs. Gains**



**Figure 12: Men - Abstract Losses vs. Gains**



**Figure 13: Men - Contextual Losses vs. Gains**



- Median for loss domain
- 95%-Confidence band, median losses
- Median for gain domain
- 95%-Confidence band, median gains



## Appendix A: The Wilcoxon-Mann-Whitney Test with Bootstrap

The Wilcoxon-Mann-Whitney statistic tests the hypothesis that two independent samples  $X$ , of size  $m$ , and  $Y$ , of size  $n$ , are from populations with the same distribution. The null hypothesis, that the two samples were drawn from the same population, is tested against the alternative hypothesis, that they were not. If the distributions of the two samples do not differ in their higher moments, rejection of the null hypothesis implies that their first moments are different, i.e. that the two distributions differ in central tendency.

In the context of our paper, we are interested in whether the parameters of the value and probability weighting functions for female and male individuals are identically distributed. Let  $\theta$  represent any one of these parameters. The null hypothesis  $H_0$  asserts equality of the gender specific distributions  $G(\theta)$ :

$$H_0 : G(\theta)^{male} \stackrel{dist.}{=} G(\theta)^{female}$$

where  $\theta$  denotes the true parameter value. Since we only have estimates of  $\theta$ , denoted by  $\hat{\theta}$ , at our disposal, we cannot test  $H_0$  directly. Instead we can test the null,

$$H_0 : \tilde{G}(\hat{\theta})^{male} \stackrel{dist.}{=} \tilde{G}(\hat{\theta})^{female}$$

where  $\tilde{G}(\hat{\theta})^{male} \stackrel{dist.}{=} \hat{\theta}^{male} \equiv \{ \hat{\theta}_1^{male}, \hat{\theta}_2^{male}, \dots, \hat{\theta}_l^{male} \}$  with the subscript denoting the number of the individual concerned. The distribution of the parameter estimates for the females is defined accordingly.

For the true parameter values, the Wilcoxon-Mann-Whitney statistic is defined by

$$Z = \frac{U(\theta^{male}, \theta^{female}) - n/2}{\sqrt{n(m+n+1)/12m}}.$$

The placement of element  $\theta_i^{female}$  in sample  $\theta^{female}$  is defined as the number of lower-valued observations in  $\theta^{male}$  - the other sample - and is denoted by  $U(\theta^{male}, \theta_i^{female})$ . The mean placement  $U(\theta^{male}, \theta^{female})$  is the arithmetic mean of the  $U(\theta^{male}, \theta_i^{female})$ 's. For large sample sizes, the statistic is approximately  $N(0,1)$ <sup>1</sup>.

Since  $\theta$  is unknown, it is not obvious how good a proxy  $\tilde{G}(\hat{\theta})$  is for  $G(\theta)$  nor how safe we are in assuming that the Wilcoxon-Mann-Whitney test statistic based on  $\hat{\theta}$  is approximately normally distributed.

Instead of relying on the normal approximation, we apply a non parametric bootstrap procedure to estimate the empirical distribution of the Wilcoxon-Mann-Whitney statistic. By resampling  $\hat{\theta}$  we directly bootstrap the Wilcoxon-Mann-Whitney statistic.

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<sup>1</sup> For ties of  $\theta^{male}$  values with  $\theta^{female}$  values, a correction is employed (Siegel & Castellan 1988).

## Appendix B: Construction of the Confidence Bands of the Median Probability Weighting Functions by the Bootstrap Percentile Method

In the following we present the procedure for obtaining confidence bands for the median probability weighting functions. First, we define the median person's certainty equivalents which are used to estimate the parameters of the median functions. Then we elaborate on the bootstrap method which enables us to calculate the confidence intervals of the parameter estimates. Finally, these confidence intervals have to be combined in a specific way to render confidence bands for the probability weighting curves.

The estimates for the (gender, environment, domain) specific median value and probability weighting functions are based on the respective median certainty equivalents  $CE_{med}$ . This vector of medians comprises  $CE_{med}^l$  for each single lottery  $l = 1, 2, \dots, 25$  in the gain and loss domains, respectively, and is calculated as follows:

$$CE_{med}^l \equiv \text{median}\{CE_1^l, CE_2^l, \dots, CE_i^l\}, \quad l \in \{1, 2, \dots, 25\} \text{ and } i \in \{1, 2, \dots\},$$

$i$  counts the number of individuals the median is calculated for (depending on gender, environment and domain).

The median person's vector of certainty equivalents  $CE_{med}$  is defined as:

$$CE_{med} \equiv \{CE_{med}^1, CE_{med}^2, \dots, CE_{med}^{25}\}.$$

Based on these  $CE_{med}$ , the domain-specific point estimator  $\hat{\xi}$  for the parameters of the value and probability weighting functions is calculated using maximum likelihood.

We estimate the distribution of the point estimator  $F_{\hat{\xi}}$  by a non parametric bootstrap (Efron 1979). The bootstrap samples  $CE_{med}^*$  are obtained by sampling  $\{CE_{med}^1, CE_{med}^2, \dots, CE_{med}^{25}\}$  with replacement. We run the bootstrap procedure with  $B = 9999$  repetitions. Analogous to  $\hat{\xi}$ ,  $\hat{\xi}^*$  is based on the bootstrap samples  $CE_{med1}^*, \dots, CE_{medB}^*$ . The estimator for  $F_{\hat{\xi}}$  is defined as:

$$\hat{F}_{\hat{\xi}}(x) \equiv P^*(\xi^* \leq x)$$

The bootstrap  $\alpha$ -percentiles define the confidence intervals for the two parameters of the Lattimore functional:

$$\left[ \hat{F}_{\hat{\delta}}^{-1}\left(\frac{\alpha}{2}\right); \hat{F}_{\hat{\delta}}^{-1}\left(1 - \frac{\alpha}{2}\right) \right], \quad \left[ \hat{F}_{\hat{\gamma}}^{-1}\left(\frac{\alpha}{2}\right); \hat{F}_{\hat{\gamma}}^{-1}\left(1 - \frac{\alpha}{2}\right) \right].$$

To construct confidence bands for the probability weighting curve, we need to examine the combined effects of both parameters. We have to minimize  $w(p)$  over  $\gamma$  and  $\delta$  for the lower confidence bound ( $\underline{w(p)}$ ) and we have to maximize  $w(p)$  over these two parameters for the upper bound ( $\overline{w(p)}$ ).

$$\underline{w(p)} \equiv \left\{ \min_{\delta, \gamma} w(p) \mid p \in [0,1], \delta \in \left[ \widehat{F}_{\delta}^{-1} \left( \frac{\alpha}{2} \right); \widehat{F}_{\delta}^{-1} \left( 1 - \frac{\alpha}{2} \right) \right], \gamma \in \left[ \widehat{F}_{\gamma}^{-1} \left( \frac{\alpha}{2} \right); \widehat{F}_{\gamma}^{-1} \left( 1 - \frac{\alpha}{2} \right) \right] \right\}$$

$$\overline{w(p)} \equiv \left\{ \max_{\delta, \gamma} w(p) \mid p \in [0,1], \delta \in \left[ \widehat{F}_{\delta}^{-1} \left( \frac{\alpha}{2} \right); \widehat{F}_{\delta}^{-1} \left( 1 - \frac{\alpha}{2} \right) \right], \gamma \in \left[ \widehat{F}_{\gamma}^{-1} \left( \frac{\alpha}{2} \right); \widehat{F}_{\gamma}^{-1} \left( 1 - \frac{\alpha}{2} \right) \right] \right\}$$

The partial derivatives of  $w(p)$  with respect to  $\gamma$  and  $\delta$  are calculated as follows:

$$\frac{\partial w(p)}{\partial \gamma} = \frac{\delta p^{\gamma} (1-p)^{\gamma} [\ln(p) - \ln(1-p)]}{[\delta p^{\gamma} (1-p)^{\gamma}]^2}$$

and

$$\frac{\partial w(p)}{\partial \delta} = \frac{p^{\gamma} (1-p)^{\gamma}}{\delta p^{\gamma} + (1-p)^{\gamma}}.$$

Examining the signs of the partial derivatives, we find that  $w(p)$  is not monotone in  $\gamma$ :

$$\frac{\partial w(p)}{\partial \delta} > 0 \text{ for } 0 < p < 1,$$

but

$$\frac{\partial w(p)}{\partial \gamma} \begin{cases} > 0 \text{ for } p > 0.5 \\ = 0 \text{ for } p = 0.5 \\ < 0 \text{ for } p < 0.5 \end{cases}$$

Therefore, the confidence bands have to be constructed in the following way:

For  $p < 0.5$  follows:

$$\underline{w(p)} \equiv \left\{ w(p) \mid p \in [0, 0.5[, \delta = \widehat{F}_{\delta}^{-1} \left( \frac{\alpha}{2} \right), \gamma = \widehat{F}_{\gamma}^{-1} \left( 1 - \frac{\alpha}{2} \right) \right\}$$

$$\overline{w(p)} \equiv \left\{ w(p) \mid p \in [0, 0.5[, \delta = \widehat{F}_{\delta}^{-1} \left( 1 - \frac{\alpha}{2} \right), \gamma = \widehat{F}_{\gamma}^{-1} \left( \frac{\alpha}{2} \right) \right\}$$

and for  $p \geq 0.5$ :

$$\underline{w(p)} \equiv \left\{ w(p) \mid p \in [0.5, 1], \delta = \widehat{F}_{\delta}^{-1} \left( \frac{\alpha}{2} \right), \gamma = \widehat{F}_{\gamma}^{-1} \left( \frac{\alpha}{2} \right) \right\}$$

$$\overline{w(p)} \equiv \left\{ w(p) \mid p \in [0.5, 1], \delta = \widehat{F}_{\delta}^{-1} \left( 1 - \frac{\alpha}{2} \right), \gamma = \widehat{F}_{\gamma}^{-1} \left( 1 - \frac{\alpha}{2} \right) \right\}$$

## **Appendix C**



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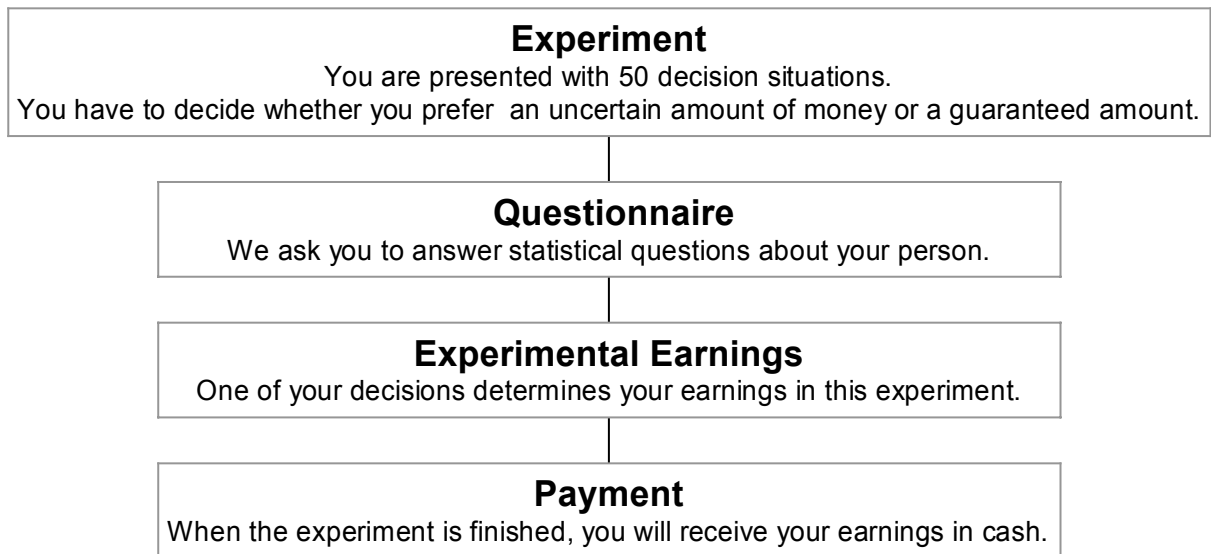
## Experimental Instructions

You are about to participate in an economic experiment. This experiment is part of a research project conducted by the Institute of Economic Research and sponsored by the Swiss Federal Institute of Technology Zurich (ETHZ). The objective of this experiment is to analyze financial decision making.

You will receive a lump sum payment of CHF 10 for participating in the experiment. In the course of the experiment, you will have the chance of earning an additional income. The amount of this additional payment depends on the decisions you will make during the experiment and on chance. **Therefore it is in your interest to read the following instructions carefully.** Your earnings will be paid out to you in cash immediately after the completion of the experiment.

**During the whole course of the experiment communication between participants is not allowed. Participants who do not abide by this rule will be excluded from the experiment and all payments. If you have questions please ask the experimenters.**

The following table gives an overview of the experiment. All steps are explained in detail below.



**If you have any questions during the course of the experiment, please ask the experimenters.** There will be a test run in order to familiarize you with the procedure.

## The Experiment

This experiment consists of 50 decision situations. There are two different types of decisions: investment and insurance decisions. In an investment decision, you will have the possibility of either making an investment that yields, with a given probability, a profit (option A), or of placing your money with a bank which will pay you a fixed interest on your investment (option B). In insurance decisions, you will be endowed with a certain amount of money (endowment). You will have to decide whether you will cover the cost of a potential repair of your portable computer on your own (option A) or whether you will take out insurance against the cost of repair at a fixed insurance premium (option B). You will be given all the relevant information in each decision situation: the possible profit or the cost of the incidental repair with the respective probabilities, interest for sure or the insurance premium for sure and the endowment where applicable.

You take your decisions independently of all other participants in this experiment. So you may work at your own pace.

All the decision situations are completely independent of each other. A choice you made in one decision situation does not affect any of the other decision situations. Gains and losses from different decision situations are not offset, either.

The following examples show what these two types of decision situations look like (see screenshots 1 and 2 in the appendix)<sup>2</sup>. Each decision situation is displayed on a screen. The screen consists of 20 lines. You have to decide for **every** line whether you prefer option A or option B. Option A is the uncertain alternative and is the same for every line while the guaranteed option B takes 20 different values. For investment decisions the guaranteed

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<sup>2</sup> These screenshots were included in the original German version of the instructions. For a sample see Figure 1.

options are ordered in descending sequence. For insurance decisions the guaranteed options are ordered in ascending sequence.

- **Investment Decisions**

Look at the decision situation on screenshot 1. Option A is specified as follows: You have the opportunity of investing in a company. When you choose this option you can earn a profit of CHF 40 with a probability of 50%. On the other hand you have a 50% probability of making no profit. But you also have the opportunity of placing your money with a bank. For this option B, the interest payment varies from CHF 40 to CHF 2. For each of these guaranteed interest payments you have to decide whether you prefer to invest in the company or whether you prefer to place your money with the bank. Let's assume that from CHF 40 to CHF 18 you prefer to receive the interest payment and from CHF 16 to CHF 2 you prefer to invest. On your screen, this decision is entered as follows: you have to click on option A from line 13 (where option B gives you CHF 16) downwards. If you don't change anything, the computer assumes you always prefer option B. Once you have finished filling in your decisions, click OK. The next decision situation will appear on your screen.

- **Insurance Decisions**

For the insurance decisions, imagine that you have just bought a portable computer and you have still CHF 80 left (your endowment). You know that with a certain probability a repair of your portable computer will be necessary in the near future. This repair would cost you CHF 80. You can take the risk of paying for the repair yourself. Or you can take out insurance that covers the cost of repair. For this insurance you have to pay a fixed premium.

Look at the decision situation on screenshot 2. The cost of repair (option A) is shown as CHF 80. While the cost of repair occurs with a probability of 20%, with a probability of 80% there will be no repair needed. The insurance premium (option B) takes values from CHF 4 to CHF 80. In this example the endowment is CHF 80. Let's assume that you prefer the insurance premium up to the amount of CHF 20 to the probability of 20% of paying the cost of repair of CHF 80. In this case, you tick option A from line 7 (where option B equals CHF 24) downwards. After pressing the OK button, the next decision situation appears on your screen.

After 50 decision situations you are asked to complete a questionnaire.

## **Filling in the Questionnaire**

With the questionnaire we want to gather data about your person. We need the data to interpret the results of the experiment. We kindly ask you to complete **the whole** questionnaire. The data will be processed anonymously.

**All data is used exclusively for scientific purposes.**

## Calculation of your Payment

By the end of the experiment, you have processed 50 decision situations. One of these will determine the amount of money you will be paid. A decision situation is drawn for payment as follows: By rolling dice, one decision situation and a specific line of this decision situation are randomly chosen. Every decision situation is drawn with the same probability. If you have chosen the guaranteed option, you will receive the corresponding amount of money. If you have chosen the uncertain option it will be determined by rolling dice which outcome you will receive. You will personally roll the dice in different colors under our observation.

**Example of an investment decision:** Let's assume that by rolling dice you have identified line 7 in our example on screenshot 1. In line 7 you have preferred option B = CHF 28. You will receive CHF 28 plus the lump sum payment of CHF 10, i.e. a total payment of CHF 38.

**Example of an insurance decision:** Let's assume that by rolling dice you have identified line 6 in our example on screenshot 2. In line 6 you have preferred option A. Let's assume that rolling dice determines that no repair is needed. In this case, you will receive the endowment of CHF 80 plus the lump sum payment of CHF 10. This makes a total of CHF 90. Now let's assume that by rolling dice you determine that a repair is needed. Your payment will comprise the endowment of CHF 80 minus the cost of repair of CHF 80 plus the lump sum payment of CHF 10 which sums up to a total payment of CHF 10.

## Payment

Once the experiment is finished, you will receive the lump sum payment of CHF 10 plus the payment from the experiment.

After all participants have read and understood these instructions, we will start a test run.

***Do you have any questions?***