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Loss Aversion under Risk: The Role of Complexity

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Abstract

In choice under risk, differences between alternative states of the world render choice environments complex. Moreover, they entail powerful experiences of loss if satisfaction falls short of prospective states that did not materialize. An increase in complexity, i.e. a larger number of differences, can have ambiguous effects on loss aversion. Complexity can direct the decision maker's attention to prospective experiences of loss but also requires a higher cognitive effort of weighting and comparing satisfaction in all states. This paper investigates empirically how loss aversion interacts with complexity. Structural estimates of preference parameters indicate an inverse-U shaped relationship between complexity and the weight of expected gain-loss utility in choice under risk.

JEL classification: C91, D01, D81, D84

Keywords: Loss Aversion, Complexity, Stochastic Reference Points

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Imagine two investment bankers' choices of effort. The first banker expects a performance based bonus and ponders her satisfaction in three prospective states of the world: no bonus, a bonus that reflects her performance, and a higher bonus. In the banker's choice of effort, complexity originates from differences between states, i.e. different levels of utility when realized and different probabilities of being realized.¹ Complexity, as a broad literature in psychology shows, attracts attention (Kahneman, 1973). If complexity in terms of different states attracts the banker's attention, she will focus on these differences and the experience of loss if her bonus falls short of a more favorable state. In a complex choice environment, choosing an effort level that avoids the powerful experience of loss when uncertainty is resolved requires careful deliberation. As an example, take the choice of little effort. With little effort, the banker's expectation of a performance based bonus is small, and so is the loss she experiences if there is no bonus. However, if she receives a bonus that reflects her low effort level, she experiences a loss in comparison to the higher bonus. In contrast, the second banker is not eligible for a bonus but expects a promotion. Because from her vantage point only two states of the world matter — she gets the promotion or not — she faces a choice under lower complexity. Lowering complexity reduces the cognitive effort of weighting and comparing all alternatives but, in the spirit of Kahneman (1973), also reduces her attention to differences between alternative states. Therefore, lowering complexity can increase or decrease the influence of expected gain-loss utility on a banker's choice of effort.²

Although complexity is a defining aspect of an uncertain world and loss aversion is central to decision-making under risk, there is no empirical evidence on the relationship of both phenomena. This paper investigates empirically how expectations affect choice under risk and pins down the interaction between loss aversion and complexity. The existing literature discusses complexity and reference-dependence separately. A large body of evidence shows that expectations over decision outcomes are important reference points in central economic decisions such as labor supply and consumption (see, e.g., Crawford and Meng, 2011; Abeler *et al.*, 2011; Wenner, 2015).³ Studying the role of complexity in choice under risk and uncertainty, Wilcox (1993), Bruce

¹While definitions of complexity vary, outcome- and probability-set size naturally correspond to complexity in choice under risk and are consistent with notions of complexity in psychology (Payne *et al.*, 1993) and the economic literature (Sonsino *et al.*, 2002; Loomes, 2005).

²Related to the idea of a trade-off between attention and cognitive effort is the finding that the influence of visual stimuli's complexity on attention follows the shape of an inverted U (Kahneman, 1973).

³For further evidence from the field on the role of expectations as reference points see Post *et al.* (2008), Card and Dahl (2011) and Pope and Schweitzer (2011). Further evidence from the laboratory is compiled by Loomes and Sugden (1987), Ericson and Fuster (2011), Baucells *et al.* (2011), Gill and Prowse (2012), Karle *et al.* (2015), and Sprenger (forthcoming).

and Johnson (1996), Huck and Weizsäcker (1999), and Sonsino *et al.* (2002) report mixed results regarding complexity's influence on deviations from expected payoff maximizing choices. In choices between lotteries with different levels of complexity, Mador *et al.* (2000) and Sonsino *et al.* (2002) find an aversion to complexity. Moffatt *et al.* (forthcoming) find that experience reduces complexity aversion.

Kőszegi and Rabin (2006, 2007), henceforth KR, capture the influence of expectations as reference points in a theoretical model.⁴ In the KR model, the decision maker experiences gains and losses if her utility exceeds or falls short of utilities in states of the world that did not materialize. To avoid losses, the decision maker compares consequences of her choice in alternative states and makes a choice that entails small differences. To provide some intuition for the mechanisms that underlie an interaction between loss aversion and complexity, we draw on evidence from psychology. On the one hand, it is well established that decision makers rather focus on differences than on absolute values (Kahneman, 2003). If differences attract attention, a large number of differences between states in complex choice environments draws the decision maker's focus to these differences, i.e. to gains and losses.⁵ On the other hand, if cognitive effort of computing expected gain-loss utility is increasing in the number of states, individuals might abstain from taking expected gain-loss utility into account if the outcome distribution is complex.⁶ This relates to evidence and models of (rational) inattention (Sims, 2003; DellaVigna, 2009) and bounded rationality (Gabaix *et al.*, 2006).

To investigate the relationship between reference-dependent preferences and complexity, we draw on data from a laboratory experiment. The experiment confronts

⁴In contrast to earlier models of disappointment aversion that use the expected consumption utility as a single reference point (Bell, 1985; Loomes and Sugden, 1986; Gul, 1991), the reference bundle in the KR model comprises the whole distribution of prospective consumption utilities. Comparing both types of models, Sprenger (forthcoming) finds an endowment effect for risk that follows from the KR model but not from the models of disappointment aversion with single reference points. Motivated by this evidence, we mainly focus on the KR model. Comparing both specifications, we provide evidence in favor of the KR model.

⁵Considering complexity in decision making is akin to taking framing effects into account. In prospect theory, framing affects preferences by increasing the salience of specific aspects of a decision problem (Kahneman and Tversky, 1979). For evidence on framing effects see, e.g., Kahneman and Tversky (1981). A related literature on focusing in economic choice discusses a tendency of decision makers to disproportionately focus on large differences (Bordalo *et al.*, 2012, 2013; Kőszegi and Szeidl, 2013).

⁶In the KR model, for a discrete probability distribution, the number of comparisons to compute expected gain-loss utility increases substantially with a rising number of alternative states. Disregarding comparisons of outcomes with themselves, in a two-outcome lottery, the decision maker in the KR model makes 2 comparisons. For a three-outcome lottery the number of comparisons rises to 6. For an m -outcome lottery the number of comparisons is $m(m - 1)$. A similar argument with respect to cognitive effort can be made for complexity in terms of heterogeneous probabilities of states. The necessity to assign different weights to comparisons if probability distributions are non-uniform renders decision making in the KR model more involved for heterogeneous probabilities than for a uniform probability distribution.

subjects with a sequence of binary choices between lotteries, varying complexity between choice sets via the number of different decision outcomes and probabilities. To reduce the experience of loss if an unfavorable outcome is drawn from the chosen lottery, subjects can forgo higher expected material payoffs and choose lotteries that expose the decision maker to smaller prospective losses. Underlying the simple binary choice between lotteries is a more involved latent structure. The experiment sets up choice sets in a way that allows us to approximate individually optimal choice of effort in working relationships, where output is a poor signal of effort and there is some probability of receiving a lower wage that is unrelated to prior effort provision. A parsimonious model predicts that in this context, loss averse decision makers exert less effort to avoid the experience of loss if the low wage is drawn.⁷ In a first step, the analogy to effort allows for an intuitive interpretation of choices, a precise quantification of deviations from expected payoff maximization and tracing out the joint influence of risk and loss aversion. In a second step, the set-up allows for the estimation of structural parameters with a binary choice model that disentangles loss aversion from risk aversion. The structural model considers the whole distribution of possible consumption utilities as a reference bundle and allows for heterogeneity in preference parameters with respect to the complexity of the lotteries.

We find that expected monetary payoff maximization or purely erratic choices cannot explain the observed choice pattern. The structural estimates of preference parameters show that a driving force behind deviations from expected payoff maximizing decisions is an aversion to losses with respect to consumption utilities in alternative states. The data indicate an inverse-U shaped relationship between complexity and the weight of expected gain-loss utility. Gain-loss utility has a large effect on choice under moderate complexity but has a small impact on decisions under low and high levels of complexity. Allowing for heterogeneity in the stochastic component of decisions, we find that results are not driven by confusion over complex lotteries but by heterogeneity in the structural parameters for risk and loss aversion. In a comparison with a model of disappointment aversion that uses the expected consumption utility as a single reference point, we provide suggestive evidence in favor of the KR model.

The remainder of the paper is organized as follows. Section 1 outlines the KR model's framework and makes predictions. Section 2 describes the experimental design and data. Section 3 discusses deviations from random and expected monetary payoff maximizing choices. Section 4 details the empirical strategy and Section 5 presents the structural estimates. Section 6 concludes.

⁷The choice of a low effort level is equivalent to choosing a lottery with smaller differences between alternative lottery outcomes.

1 Predictions

Underlying a binary choice between lotteries in the experiment is a choice between effort levels with uncertainty over future returns to effort provision. The experiment does not implement the choice of effort directly. Instead, the design allows us to approximate expected utility maximizing effort from choices between lotteries (see Section 2 for details) and to compare the empirical distributions of optimal effort levels with theoretical predictions.

The latent structure resembles a working relationship where output is a poor signal of effort, rendering wages stochastic. After the choice of effort (x), exerted effort translates into a wage consisting of a constant component plus piece rate times effort ($f_w + wx$) with probability p_w . With probability $1 - p_w$ the principal misjudges effort and the decision maker receives a fixed wage (f_l or f_h) that is unrelated to her prior effort provision.⁸ Prospective decision outcomes are

$$\begin{aligned}\pi_l(x) &= f_l - \frac{1}{2}x^2 && \text{with probability } p_l, \\ \pi_w(x) &= f_w - \frac{1}{2}x^2 + wx && \text{with probability } p_w, \\ \pi_h(x) &= f_h - \frac{1}{2}x^2 && \text{with probability } p_h,\end{aligned}\tag{1.1}$$

where $\frac{1}{2}x^2$ is a convex monetary cost of effort.⁹

We later choose piece rates and constant components such that in eq. (1.1) it holds that $f_l < f_w + wx \leq f_h$, and accordingly $\pi_l < \pi_w \leq \pi_h$. To predict the optimal choice of x , we begin by setting up a utility function. Define consumption utility from outcome k as $U_k \equiv U(\pi_k(x))$ with $k \in \{l, w, h\}$. We assume that individuals have narrow focus and that U_k takes the form

$$U_k = \frac{1 - e^{-\gamma\pi_k}}{\gamma},\tag{1.2}$$

where γ is the Arrow-Pratt measure of absolute risk aversion.¹⁰ Assuming separability, expected KR utility is

$$EU^{KR}(x) = p_l U_l + p_w U_w + p_h U_h + \eta V(x).\tag{1.3}$$

⁸Abeler *et al.* (2011) implement a real effort task with a similar structure. For simplicity, we do not address the decision problem of the principal and assume that a negative (positive) shock results in the wage f_l (f_h) without making assumptions about the mechanisms by which shocks transmit to output.

⁹Implementing a monetary cost of effort mirrors chosen effort experiments.

¹⁰Section B of the Appendix discusses estimation results for alternative specifications with constant relative risk aversion and expo-power utility.

The first three terms capture expected consumption utility. $V(x)$ captures expected gain-loss utility; η measures the weight of expected gain-loss utility. Loss averse decision makers derive expected gain-loss utility from a comparison of each outcome's consumption utility with a reference bundle. The KR model assumes that the decision maker's reference bundle comprises the entire distribution of consumption utilities. We adopt the idea of the choice-acclimating personal equilibrium in [Kőszegi and Rabin \(2007\)](#) and assume that the decision maker maximizes expected KR utility given that uncertainty is resolved after her choice of effort. With outcomes satisfying $\pi_l < \pi_w \leq \pi_h$, expected gain-loss utility in the KR model is

$$\begin{aligned} V(x) = & p_l [p_l(U_l - U_l) + p_w\lambda(U_l - U_w) + p_h\lambda(U_l - U_h)] \\ & + p_w [p_l(U_w - U_l) + p_w(U_w - U_w) + p_h\lambda(U_w - U_h)] \\ & + p_h [p_l(U_h - U_l) + p_w(U_h - U_w) + p_h(U_h - U_h)]. \end{aligned} \quad (1.4)$$

The parameter λ measures the degree of loss aversion. For a loss averse individual, the weight of expected gain-loss utility η is strictly greater than zero and λ is strictly greater than one, i.e. losses loom larger than equal-sized gains.¹¹ We will later allow η to vary with complexity. Note that because the reference bundle depends on the choice of x , reference points in the KR model are endogenous.

It is straightforward that an expected KR utility maximizing decision maker's optimal choice x^* satisfies

$$1 = \frac{p_w U'_w}{-p_l U'_l - p_h U'_h - \eta V(x)'}. \quad (1.5)$$

Intuitively, the decision maker trades off increases in U_w against reductions in U_l and U_h and losses because of deviations of outcomes from the reference bundle.

Figure 1 shows the predictions of the model for $w = 3$ and probabilities $p_l = p_w = 0.5$, i.e. $p_h = 0$.¹² Panel A illustrates a risk and loss neutral decision maker's optimal choice x_0^* .¹³ The blue solid line (red dotted line) is her utility if the higher (lower) outcome π_w (π_l) is drawn. Because an increase in x comes at a cost for both outcomes but increases only π_w , U_w increases in x whereas U_l decreases in x . To find the optimal value of x we include $-U_l$ (red solid line) and search for the value of x where marginal gains in U_w equal marginal losses in U_l . Here, $x_0^* = p_w w = 1.5$ satisfies

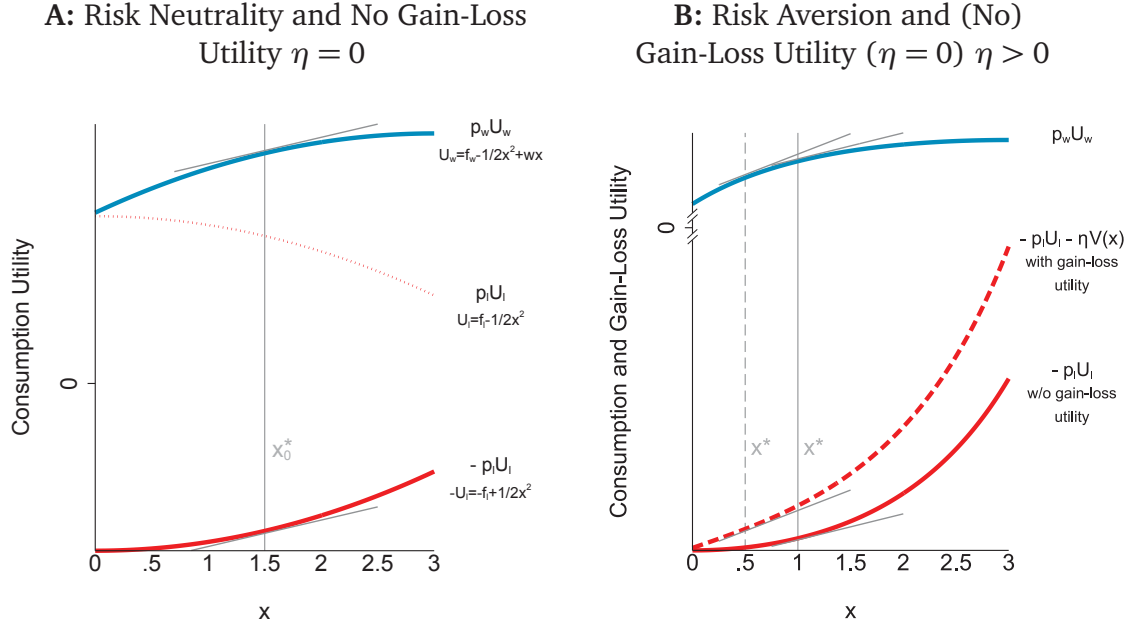
¹¹Because we only look at small stakes in the laboratory, we disregard decreasing sensitivity and assume that the value function is piece-wise linear. We do not consider probability weighting.

¹²The same parametrization was underlying one of the lottery configurations that was implemented in the experiment.

¹³Expected utility of the risk and loss neutral decision maker is $EU(x) = p_l \pi_l + p_w \pi_w + p_h \pi_h$.

the optimality condition (1.5) for a decision maker who is risk neutral and does not experience gain-loss utility.

Figure 1: Predictions for a Two-Outcome Lottery (with π_w and π_l)



Notes: The Figure shows predictions for a two-outcome lottery with $w = 3$ and probabilities $p_l = p_w = 0.5$, i.e. $p_h = 0$. For risk preferences, we set γ to 0.21. For expected gain-loss utility we set η to 1 and λ to 2.1. The blue solid lines (red dotted line) show expected consumption utilities of the higher (lower) lottery outcome. The figure includes the negation of the expected consumption utility of the lower outcome (red solid lines) and the sum over the expected consumption utility of the lower outcome and expected gain-loss utility (red dashed line). The gray vertical lines are at expected (KR) utility maximizing values of x .

Panel B shows how the decision maker's optimal choice of x changes, if she is risk averse but does not experience gain-loss utility (blue and red solid line) or if she is risk and loss averse (blue solid line and red dashed line). Because of decreasing marginal utilities and $\pi_l < \pi_w$, making the decision maker risk averse increases the slope of U_l relative to the slope of U_w . To satisfy the optimality condition (1.5), she chooses $x^* = 1$, which is lower than the risk neutral decision maker's optimal choice. If the decision maker also experiences gain-loss utility, i.e. if η in the denominator of (1.5) is strictly greater than zero, x^* drops to 0.5. This is because an increase in x increases expected losses due to a larger difference between U_l and U_w if π_l is drawn. Because losses loom larger than equal-sized gains, these losses are not offset by gains if π_w is drawn.

Setting p_l instead of p_h to zero reverses the direction of a risk and loss averse individual's predicted deviation from x_0^* . The risk and loss averse individual will optimally choose a value of x that is greater than x_0^* . For three-outcome lotteries, the

sign of predicted deviations depends on the relative strength of risk and loss aversion. For all lotteries, the size of the gap between x^* and x_0^* depends on risk preferences and the degree of loss aversion.¹⁴

2 Design & Data

Approximation of x^* with Binary Choices The design of lotteries follows the latent choice-of-effort framework but simplifies choice along two dimensions. First, individuals make discrete choices between lotteries instead of choosing x directly. Offering a binary choice set reduces the continuum of alternative lotteries to a menu with two alternatives. Second, lotteries in the choice set show prospective outcomes directly and do not detail the outcome composition from effort dependent and fixed elements.¹⁵

To approximate the value of x that maximizes expected utility for a given lottery configuration with binary choices, the experiment implements a sequence of choice sets.¹⁶ We begin an elicitation sequence with a choice set that is centered around x_0^* , the expected monetary payoff maximizing value of x (see Figure 1). Define two alternative values of x as \underline{x} and \bar{x} where $\underline{x} < \bar{x}$. Initially, the individual makes a choice between a lottery where $\underline{x} = 0$ and a lottery where $\bar{x} = 2x_0^*$. Both initial lotteries have the same expected monetary payoff. The subsequent choice set replaces the value of x of the non-chosen lottery with the mean over \bar{x} and \underline{x} . By iteratively replacing the non-chosen lottery with a lottery that implements the mean over the previous values of x , this procedure approximates the individual's expected utility maximizing value of x . The sequence stops after 4 iterations or if the follow-up lotteries' outcomes only differ in the second digit.¹⁷ Note that because outcomes of the non-chosen lottery have a zero probability of being drawn, they do not alter expected gain-loss utility of the chosen lottery in the KR model.

Figure 2 shows the implementation of a choice set for a two-outcome lottery. Each pie chart represents one lottery and includes information on possible outcomes and the probability distribution. Individuals are unaware of the payoff function underlying the outcomes and of the iterative elicitation procedure. To attenuate mistakes because of a misconception of risk, individuals can choose between two additional ways of

¹⁴For predictions with different degrees of risk and loss aversion see Figure A1 in the Appendix.

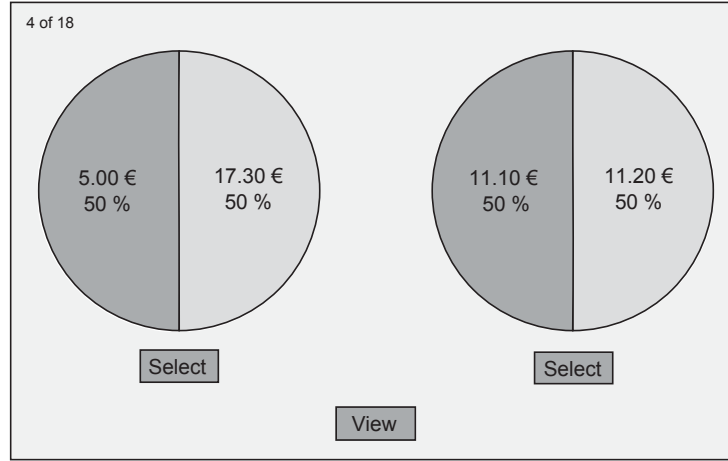
¹⁵Apart from simplifying the choices, stepping away from a design with explicit effort provision and implementing a neutral framing rules out that large fixed outcomes are perceived as efficiency wages and increase effort via sentiments of reciprocity.

¹⁶The iterative procedure is similar to the elicitation of certainty equivalents in Abdellaoui *et al.* (2008).

¹⁷Table A1 in the Appendix provides an example for the procedure.

displaying the lotteries.¹⁸

Figure 2: Implementation



Notes: The figure shows the implementation of a two-outcome lottery.

Variation of Complexity To evaluate the influence of complexity on choice, the experiment varies complexity within subjects along two dimensions: by increasing the number of different lottery outcomes and by increasing the number of different outcome probabilities. For low complexity, the experiment implements two-outcome lotteries with uniform probabilities of $\frac{1}{2}$. Moderately complex lotteries include an additional third outcome but still implement uniform probabilities of $\frac{1}{3}$. Highly complex lotteries comprise three prospective outcomes with different probabilities. Because highly complex lotteries in the experiment mirror four-outcome lotteries that include π_l or π_h twice and implement uniform probabilities of $\frac{1}{4}$, we can alternatively differentiate between two-outcome lotteries (low complexity), three-outcome lotteries (moderate complexity) and four-outcome lotteries (high complexity).

Measuring the complexity of a lottery by outcome- and probability-set size is consistent with notions of complexity in psychology (Payne *et al.*, 1993) and the economic literature (Sonsino *et al.*, 2002; Loomes, 2005; Moffatt *et al.*, forthcoming).¹⁹ Longer average decision times and a higher subjective difficulty of making a decision provide suggestive evidence for an increase in complexity in three- and four-outcome

¹⁸There was no constraint on how many times individuals could switch between display options. The probability that a participant made use of an alternative display option in a choice set was less than 1%. See Figure A2 in the Appendix for an illustration of the additional display options.

¹⁹To describe lotteries with low complexity we specify an outcome vector (π_l, π_w) or (π_w, π_h) and a one-element probability vector (p) . For moderately complex lotteries we have to specify a larger number of outcomes (π_l, π_w, π_h) . An unambiguous description of four-outcome lotteries is still more complex, requiring us to specify three outcomes (π_l, π_w, p_h) and probabilities (p_l, p_w, p_h) .

lotteries.²⁰

The experiment implements low complexity, high complexity, and moderate complexity in three blocks of choice sequences in this order. For each level of complexity an element h is randomly drawn without replacement from $\{-4.0, -3.5, -3.0, 3.0, 3.5, 4.0\}$. For each draw, the experiment implements $w = \sqrt{h^2}$ and chooses the fixed elements f_k such that the value of π_w is strictly smaller (weakly greater) than the expected material payoff $E(\pi)$ if $h < 0$ ($h > 0$). This results in a symmetric set of lotteries, where each lottery configuration $z \in \{1, 2, \dots, 18\}$ implements characteristic values of w and f_k . The experiment's 18 choice sequences leave us with a maximum of 72 choices per individual.²¹

Further Details The experiment uses a neutral terminology, referring to lotteries as alternatives. To avoid ordering effects, the ordering of lotteries in choice sets is randomized between lottery configurations. After reading the instructions, subjects answer computerized control questions, participate in the experiment and fill out a questionnaire on individual characteristics and the experiment itself.²² To incentivize decisions, one choice is randomly selected to become payoff relevant and an outcome is drawn from the chosen lottery, according to the respective probability distribution.²³ Subjects learn about the randomly selected payoff after all subjects have answered the questionnaire.

The computerized experiment took place at the Laboratory for Experimental Research Nuremberg in December 2014.²⁴ In total, 94 students participated in 3 sessions, generating 6 573 observations.²⁵ The mean payoff from the experiment was € 13.86, including the show-up fee. An average session lasted for 60 minutes.

²⁰The average decision time in two-outcome lotteries (7.15 seconds) increases by 21% in three-outcome lotteries and by 42% in four-outcome lotteries. Asked to rate the difficulty of choosing a lottery on a Likert-scale from 1 (not difficult) to 10 (very difficult), we find an average subjective difficulty of 3.11 in two-outcome lotteries. The subjective difficulty increases by 59% in three-outcome lotteries and by 112% in four-outcome lotteries. Using t-tests and individual-level cluster robust standard errors, differences between average decision times and between subjective difficulties are statistically significant at the 1% significance level. Table A9 in the Appendix shows the questions and possible answers.

²¹Table A2 in the Appendix shows the parametrization and outcomes for the first and second choice set of each lottery configuration.

²²See the Appendix for the instructions and the questionnaire.

²³Paying out one randomly selected lottery to incentivize choice can in principle cause all (chosen) lotteries to enter the reference bundle. However, based on the evidence in [Starmer and Sugden \(1991\)](#) and [Cubitt et al. \(1998\)](#) who do not find contamination effects in the random lottery incentive mechanism, we argue that subjects treat lotteries effectively in isolation.

²⁴The experiment was programmed with z-Tree ([Fischbacher, 2007](#)) and subjects were recruited with ORSEE ([Greiner, 2004](#)).

²⁵See Table A3 in the Appendix for summary statistics of the participants.

3 Deviations from Maximization of Expected Monetary Payoffs and Random Choices

Before turning to the structural analysis of risk and loss aversion, we show that maximization of expected monetary payoffs or random choices alone cannot explain the observed choice pattern. We furthermore evaluate the joint influence of risk and loss aversion on the optimal provision of effort. To test if maximization of expected monetary payoffs or random choices alone suffice to explain choice patterns, we compare empirical distributions of expected utility maximizing values of x with theoretical predictions. The experimental design allows us to approximate x_{iz}^* , individual i 's utility maximizing value of x for a given lottery configuration z . To approximate x_{iz}^* , we use choices in the last choice set of the lottery configuration's choice sequence. The approximated optimal value \hat{x}_{iz}^* is the average over the chosen lottery's latent value of $x \in \{\underline{x}_{iz}, \bar{x}_{iz}\}$ and $\frac{1}{2}(\underline{x}_{iz} + \bar{x}_{iz})$, divided by the choice sequence's upper limit of x . We end up with 1692 normalized individually optimal choices over the same domain $\hat{x}_{iz}^* \in (0, 1)$.²⁶ For all lottery configurations, the normalized expected monetary payoff maximizing value of x is $\hat{x}_0^* = 0.5$.

If decision makers randomly choose lotteries, \hat{x}^* should follow a standard uniform distribution with a density of 1 over the whole domain.²⁷ If individuals maximize expected monetary payoffs and make some random decision errors, we should see bunching around \hat{x}_0^* .

Figure 3 shows kernel density estimates (solid lines) and median values (dashed lines) of \hat{x}^* for all levels of complexity. The Figure also includes the theoretical density functions for random choices (horizontal gray lines) and \hat{x}_0^* (vertical gray lines). Because of different theoretical predictions for risk and loss aversion, we distinguish lotteries with expected monetary payoffs that are smaller (Panel A) or larger (Panel B) than π_w .

There is a substantial and significant departure from the flat density function for random choices.²⁸ Because the median of \hat{x}^* also deviates from \hat{x}_0^* , maximization of expected monetary payoffs alone cannot explain the choice pattern. The sign of

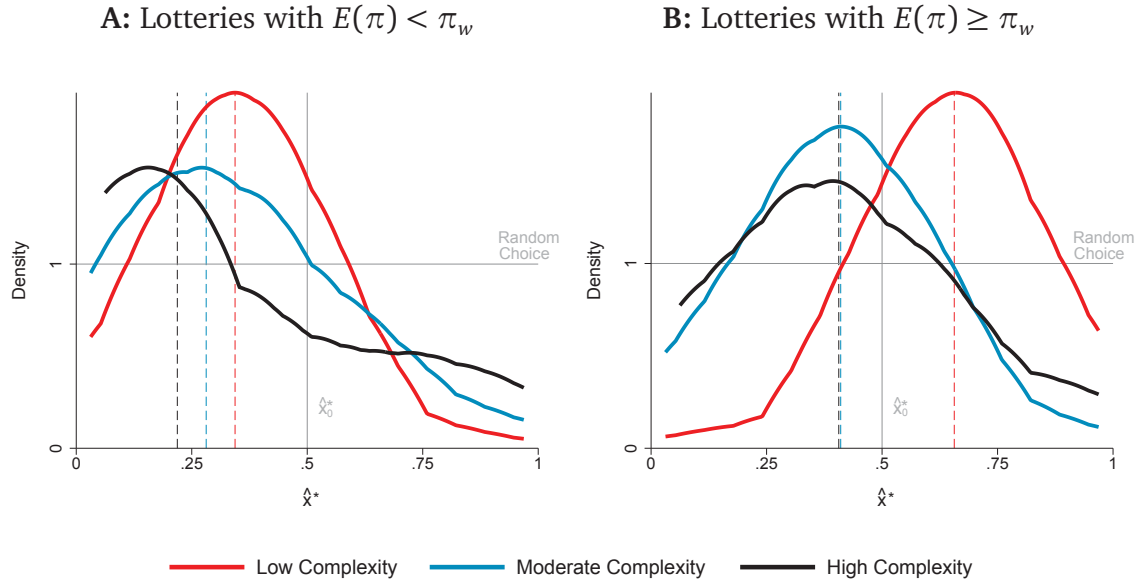
²⁶Because the experiment implements a finite number of iterations in each choice sequence, \hat{x}^* is not continuous. However, inaccuracies that stem from the approximation procedure should be negligible as the grid is fine with a constant spacing of 0.063.

²⁷If individuals choose lotteries at random (e.g. by flipping a fair coin), each possible value of \hat{x}^* is chosen with the same propensity $P = \left(\frac{1}{2}\right)^4$. Because the grid on which we approximate \hat{x}^* is reasonably fine and the theoretical distribution of \hat{x}^* is bounded by values close to 0 and 1, we assume a continuous standard uniform distribution for random choices.

²⁸Figure A3 in the Appendix provides kernel densities that include individual-level cluster bootstrap confidence intervals for inference.

the median subject's deviations under low complexity follows theoretical predictions for $E(\pi) < \pi_w$ and $E(\pi) \geq \pi_w$. For inference we run quantile regressions of \hat{x}^* (centered around $\hat{x}_0^* = 0.5$) on dummies for complexity, a dummy for $E(\pi) \geq \pi_w$, and interaction terms and cluster standard errors on the individual level. We find that deviations of the median from \hat{x}_0^* are significant under all levels of complexity, irrespective of the relationship between expected material payoffs and π_w (p -values < 0.050).²⁹ Differences in the size of deviations between moderate and low complexity and between high and low complexity are significant (p -values < 0.010).³⁰

Figure 3: Deviations from Expected Payoff Maximization and Random Choices



Notes: The Figure shows kernel densities (solid lines) and the median values (dashed lines) of \hat{x}^* . Panel A (Panel B) shows choices in lotteries with an expected material payoff smaller (greater) than π_w . The Figure also includes the theoretical density functions for random choices (horizontal gray lines) and the expected monetary payoff maximizing value \hat{x}^* (vertical gray lines). Underlying the empirical distributions are 1 692 individually optimal values of \hat{x}^* . For the univariate kernel density estimations we use the Epanechnikov kernel function with a bandwidth of 0.12.

RESULT 1: *Empirical density functions deviate from theoretical predictions for random choices. Maximization of expected monetary payoffs alone cannot explain the choice pattern. Complexity affects the size of deviations.*

²⁹We center \hat{x}^* around $\hat{x}_0^* = 0.5$ and reverse the sign of \hat{x}^* for low complexity lotteries with $E(\pi) \geq \pi_w$. Reversing the sign of deviations allows us to compare the size of deviations between different levels of complexity, accounting for the fact that the direction of predicted deviations is different in lotteries with low complexity and $E(\pi) \geq \pi_w$. Table A4 in the Appendix provides estimation results.

³⁰To test whether differences in the size of deviations from \hat{x}_0^* between low and moderate (low and high) complexity are significant, we compare a model that restricts the influence of complexity to high (moderate) complexity and an unrestricted model using F-tests.

The empirical distributions of \hat{x}^* alone do not tell us what drives the deviations from expected monetary payoff maximizing choices. In particular, we cannot distinguish the effects of risk aversion from loss aversion. To find out what drives decisions, we develop an empirical model, drawing on our previous assumptions regarding the utility function, and estimate structural preference parameters with the binary choice data.

4 Binary Choice Model and Econometric Implementation

On the basis of the expected KR utility function (1.3), we set up a structural binary choice model. Individual $i \in \{1, 2, \dots, N\}$ faces $j \in \{1, 2, \dots, J_i\}$ choices between two lotteries $\underline{\Pi}_j \equiv \Pi_j(\underline{x}_j)$ and $\bar{\Pi}_j \equiv \Pi_j(\bar{x}_j)$. She chooses $\underline{\Pi}_j$, if the difference between expected utilities of the lotteries is larger than a stochastic Fechner-error $\tau_j \epsilon_{ij}$. The parameter τ_j allows for the error variance to differ from unity.³¹ We assume that ϵ_{ij} follow a standard normal distribution and later allow for arbitrary within-individual correlations by computing cluster-robust standard errors. Denote the dichotomous decision variable with Y_{ij} . If the decision maker chooses $\underline{\Pi}_j$, Y_{ij} takes the value one, and zero otherwise. We get

$$Y_{ij}(\underline{\Pi}_{ij}, \bar{\Pi}_{ij}, \theta_j, \gamma_j, \tau_j) = \mathbb{1}\{EU^{KR}(\underline{\Pi}_{ij}, \theta_j, \gamma_j) - EU^{KR}(\bar{\Pi}_{ij}, \theta_j, \gamma_j) + \tau_j \epsilon_{ij} > 0\}, \quad (4.1)$$

where $\mathbb{1}\{\cdot\}$ is the indicator function and γ_j is the Arrow-Pratt measure of absolute risk aversion. Because we cannot separately identify the gain-loss parameters λ and η (see, e.g., Crawford and Meng, 2011), we define $\theta_j \equiv \eta_j(\lambda - 1)$ as a measure of loss aversion.³² We allow for heterogeneity over the complexity of the lottery in all parameters, i.e.

$$\xi_j = g^\xi(X_{ij}\beta^\xi), \quad \xi_j \in \{\gamma_j, \theta_j, \tau_j\}. \quad (4.2)$$

The function $g^\xi(\cdot)$ allows us to put theoretical restrictions on parameters. For θ_j and τ_j we use the exponential function to rule out negative values. We do not restrict γ_j . The row vector X_{ij} has three elements: 1, an indicator variable that takes the value 1 if lotteries in i 's choice set j are moderately complex and an indicator variable for high

³¹A ceteris paribus increase in τ_j increases the propensity of choosing a lottery with lower expected KR utility. For a detailed discussion of the error specification see, e.g., Loomes (2005).

³²To estimate θ we rearrange the terms in the expected gain-loss utility, so that:

$$\eta V(x) = \theta[p_l p_h (U_l - U_h) + p_l p_w (U_l - U_w) + p_w p_h (U_w - U_h)].$$

We assume that differences in complexity influence the weight of expected gain-loss utility (η) but not the degree to which losses outweigh equal-sized gains (λ).

complexity. Because X_{ij} considers different levels of complexity with dummy variables, the model does not impose functional form restrictions on the relationship between preference parameters and complexity.

Denoting the cumulative standard normal distribution function with $\Phi(\cdot)$, the probability of observing the choice Y_{ij} is

$$\begin{aligned} \iota_{ij}(Y_{ij}, \underline{\Pi}_{ij}, \bar{\Pi}_{ij}, \theta_j, \gamma_j, \tau_j, \omega) \\ = (1 - \omega)\Phi((2Y_{ij} - 1)\frac{1}{\tau_j}\Delta EU_{ij}^{KR}(\underline{\Pi}_{ij}, \bar{\Pi}_{ij}, \gamma_j, \theta_j)) + \frac{\omega}{2}. \end{aligned} \quad (4.3)$$

To account for the possibility that subjects randomly choose a lottery because of a tremble, we follow [Harless and Camerer \(1994\)](#) and include the trembling hand parameter ω in (4.3). The parameter value of ω equals the probability of choosing a lottery at random. We follow [von Gaudecker et al. \(2011\)](#) and allow for heterogeneity in one of the parameters that govern the degree of randomness in decision making (in our case in τ).³³

The (partial) likelihood function is

$$\iota_i = \prod_{j=1}^{J_i} \iota_{ij}(Y_{ij}, \underline{\Pi}_{ij}, \bar{\Pi}_{ij}, \theta_j, \gamma_j, \tau_j, \omega). \quad (4.4)$$

The log-likelihood function is the sum of $\log(\iota_i)$ over all individuals in the sample. We employ standard techniques to maximize the log-likelihood function. For inference, we cluster standard errors on the individual level and calculate standard errors of transformed parameters using the delta method.

5 The Role of Complexity for Reference-Dependent Preferences: Structural Estimates

Turning to the structural estimates, Table 1 shows the gain-loss parameter θ under different levels of complexity. Under moderate complexity, θ is significantly larger than under low and under high complexity (p -values < 0.050). The difference between

³³We do not allow for heterogeneity in the trembling hand parameter ω . Following the argumentation in [Harless and Camerer \(1994\)](#), there is no intuitive reason for choice dependence of “errors” in terms of trembles. To capture an effect of complexity on the stochastic elements of choice, our model follows the suggestions in [Loomes \(2005\)](#) and allows for heterogeneity in τ , i.e. mistakes in the comparison of expected utilities. Instead of trembles, we could also interpret heterogeneity in ω as reflective of avoiding cognitive effort by choosing a lottery at random if the choice is difficult. However, we find that the results are robust to allowing for individual level heterogeneity in ω over the subjective difficulty of choice. Table A8 provides marginal effects on parameter estimates and cluster-robust standard errors.

$\hat{\theta}_{low}$ and $\hat{\theta}_{high}$ is not significant (p -value > 0.800). This suggests an inverse-U shaped relationship between complexity and the weight of expected gain-loss utility. Starting from a low baseline, an increase in complexity increases the weight of expected gain-loss utility. With rising complexity and cognitive effort of comparing outcomes, the weight decreases.

Table 1: Loss Aversion and Complexity – Estimates

Low Complexity	Moderate Complexity	High Complexity
0.207	1.48***	0.271
(0.430)	(0.447)	(0.260)

Notes: The number of observations is 6573. The estimation follows (4.4). Coefficients for choice under low complexity are $g^\theta(\beta_{cons}^\theta)$. Coefficients for moderate and high complexity are $g^\theta(\beta_{cons}^\theta + \beta_{moderate}^\theta)$ and $g^\theta(\beta_{cons}^\theta + \beta_{high}^\theta)$. Individual-level cluster robust standard errors are in parentheses. *** p -value < 0.01

A comparison of the preference parameters with structural estimates from previous studies on expectation-based reference-dependent preferences shows that our parameter estimates are of comparable magnitude. Crawford and Meng (2011), for example, report estimates of $\theta \equiv \eta(\lambda - 1)$ between 0.111 and 2.01, depending on the econometric specification. The results also fit the findings in Baucells *et al.* (2011), who consider a sequence of past prices as reference points in a laboratory experiment on investor selling decisions. They find evidence for loss aversion only for long prices sequences, i.e. complex choice environments in terms of our experiment.

Table 2: Risk Aversion and Complexity – Estimates

Low Complexity	Moderate Complexity	High Complexity
0.084	0.084**	0.278**
(0.106)	(0.028)	(0.021)

Notes: The number of observations is 6573 The estimation follows (4.4). Coefficients for choice under low complexity are $g^\gamma(\beta_{cons}^\gamma)$. Coefficients for moderate and high complexity are $g^\gamma(\beta_{cons}^\gamma + \beta_{moderate}^\gamma)$ and $g^\gamma(\beta_{cons}^\gamma + \beta_{high}^\gamma)$. Individual-level cluster robust standard errors are in parentheses. ** p -value < 0.01

Table 2 summarizes parameter estimates of the Arrow-Pratt coefficient of absolute risk aversion. We find evidence for risk aversion under all levels of complexity. Strong risk aversion in lotteries with high complexity counteracts the lower weight of expected gain-loss utility, explaining why the average individual's departure from expected

monetary payoff maximization is similar under moderate and high complexity (see Figure 3).

Estimates of the auxiliary parameters that govern the stochastic element of choice are $\hat{\omega} = 0.313$, $\hat{\tau}_{low} = 0.384$, $\hat{\tau}_{moderate} = 0.400$ and $\hat{\tau}_{high} = 0.135$.³⁴

RESULT 2: *The structural estimates of preference parameters indicate an inverse-U shaped relationship between complexity and the weight of expected gain-loss utility.*³⁵

The estimates of the loss aversion parameter suggest that loss aversion has a significant effect on choices between moderately complex lotteries. To get a better idea of the impact of expected losses on decisions, we compare predictions of \hat{x}^* with the actual mean over realizations of \hat{x}^* . First, we plug the parameter estimates of θ , γ and ω into (1.3) and use numerical optimization techniques to find the value \hat{x}^* that maximizes expected KR utility. We then make predictions without accounting for the effect of expected gain-loss utility by setting the weight of expected gain-loss utility (η) to zero.

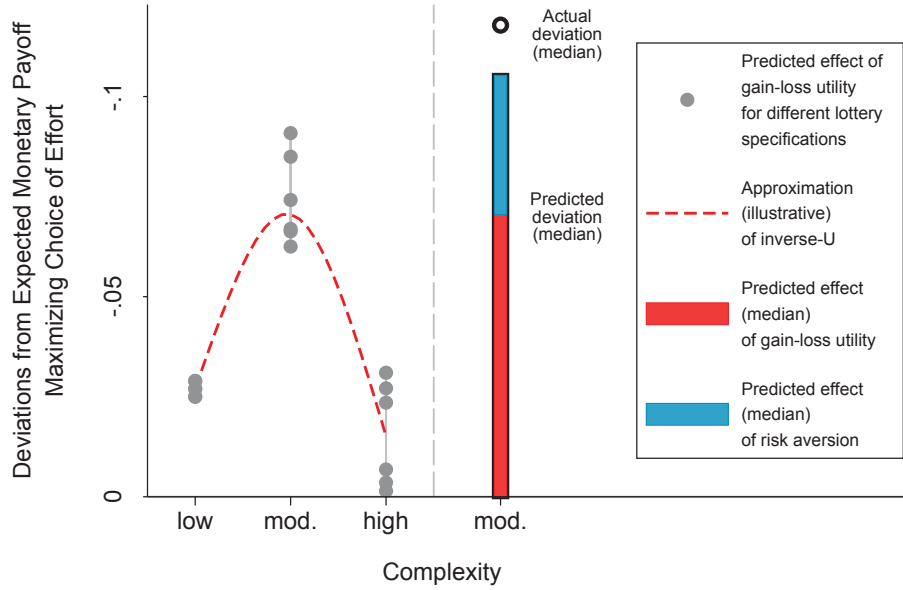
Figure 4 shows an approximation of gain-loss utility's influence on predicted deviations from expected payoff maximization under different levels of complexity (red dashed line). As before, \hat{x}^* lies in the interval $(0, 1)$, with an expected monetary payoff maximizing value of $\hat{x}_0^* = 0.5$. Consequently, the deviations from expected payoff maximization our model predicts lie in the interval $(-0.5, 0.5)$. To illustrate the magnitude of loss aversion's impact on these deviations under moderate complexity, the bar decomposes the overall deviation into its sources: Gain-loss utility (blue area) and risk aversion (red area). The decomposition shows that the influence of gain-loss utility is substantial under moderate complexity. Comparing the predicted deviation from expected payoff maximization with the median deviation in the data (black circle), we find that our prediction is fairly accurate.

RESULT 3: *Gain-loss utility has a large effect on choice under moderate complexity.*

³⁴Table A5 in the Appendix provides marginal effects on parameter estimates and cluster-robust standard errors for all model parameters.

³⁵We do not theoretically model the mechanisms underlying an interaction between complexity and loss aversion. However, the inverse-U shaped relationship is in line with a trade-off between attention and cognitive effort.

Figure 4: Influence of Gain-Loss Utility on Choice of Effort



Notes: The figure shows predictions of deviations from expected payoff maximization that we can attribute to gain-loss utility under different levels of complexity. Each gray dot represents a predictions for one of the lottery specifications. For illustrative purposes, we approximate a continuous progression of gain-loss utility's influence over different levels of complexity using a cubic spline with median values over predictions for different lottery specifications (red dashed line). To illustrate the magnitude of loss aversion's impact on these deviations under moderate complexity, the bar decomposes the overall deviation into its sources: Gain-loss utility (blue area) and risk aversion (red area). Predictions utilize the parameter estimates of θ , γ and ω . To predict choices without gain-loss utility, we use the same parameter estimates but set η , i.e. θ , to zero. We reverse the sign of \hat{x}^* for low complexity lotteries with $E(\pi) \geq \pi_w$. Reversing the sign of deviations allows us to compare the size of deviations between different levels of complexity, accounting for the fact that the direction of predicted deviations is different in lotteries with low complexity and $E(\pi) \geq \pi_w$.

A factor that is closely related to expectations and loss aversion is experience. List (2003), for example, finds no endowment effect for experienced collectors of sports memorabilia. A potential explanation for his finding is that experienced collectors expect losses of endowments in market transactions. In choice under risk, the weight of expected gain-loss utility might be affected by subjects' previous experiences with losses and disappointment in similar laboratory experiments. To test for an influence of experience, we add dummies for prior participation in laboratory experiments and a dummy for experiences with similar experiments to X_{ij} in (4.2).³⁶ We find only small and insignificant negative effects of previous participation in a large number of experiments (-0.136) and experience with similar experiments (-0.102) on the weight of expected gain-loss utility (p -values > 0.300). Experience does not attenuate

³⁶We match Individuals' answers to the questions "Have you participated in a similar experiment in the past?" and "How often (approximately) have you participated in laboratory experiments before this experiment" to the experimental data.

the influence of loss aversion on decisions in our experimental context.³⁷

RESULT 4: *Experience does not attenuate the influence of expected gain-loss utility on choices.*

The results suggest that one way in which complexity interacts with loss aversion is via cognitive effort. To lower the cognitive effort of computing prospective gains and losses, the decision maker can reduce the size of the reference bundle. We follow models of disappointment aversion (Bell, 1985; Loomes and Sugden, 1986; Gul, 1991) and consider an alternative specification with the expected consumption utility as a single reference point. We set up expected gain-loss utility in a way that covers the specification with the expected consumption utility as a single reference point and the specification with the KR model's larger reference bundle. We get

$$\begin{aligned} \eta V(x) = & \theta[p_l p_h(U_l - U_h) \\ & + \mathbb{1}\{EU \geq U_w\}(p_w p_h(U_w - U_h) + p_l p_w \kappa(U_l - U_w)) \\ & + \mathbb{1}\{EU < U_w\}(p_w p_h \kappa(U_w - U_h) + p_l p_w(U_l - U_w))], \end{aligned} \quad (5.1)$$

where κ is a weight for the additional comparisons in the KR model and EU is expected consumption utility.³⁸ If κ equals one, expected gain-loss utility is as the KR model predicts. If κ equals zero, expected gain-loss utility reduces to the specification with the expected consumption utility as a single reference point. Note that under low complexity, expected gain-loss utility is the same for both specifications. The estimate of $\hat{\kappa} = 0.921$ (p -value < 0.01) shows that the additional terms in the KR specification of expected gain-loss utility have a significant influence on choices. The evidence in favor of the KR model is in line with Sprenger (forthcoming), who finds an endowment effect for risk that follows from the KR model but not from the models of disappointment aversion with single reference points.³⁹

RESULT 5: *Reference bundles comprise the entire outcome distribution.*

³⁷Table A6 in the Appendix provides marginal effects on parameter estimates and cluster-robust standard errors for all model parameters.

³⁸See Section C of the Appendix for the derivation of eq. (5.1).

³⁹Table A7 in the Appendix provides marginal effects on parameter estimates and cluster-robust standard errors for all model parameters.

6 Conclusion

The paper investigated empirically how loss aversion interacts with complexity. The results suggest that in situations with uncertainty over prospective decision outcomes, utility is reference-dependent as the KR model predicts. However, the weight of expected gain-loss utility depends on the complexity of the choice environment. The structural estimates imply that if the choice environment is sufficiently complex, individuals deviate from rational choice to avoid losses.

The inverse-U shaped relationship between complexity and the weight of expected gain-loss utility provides a broader framework to interpret mixed previous findings on deviations from expected monetary payoff maximization in complex lotteries. Whereas [Sonsino et al. \(2002\)](#) and [Huck and Weizsäcker \(1999\)](#) found bigger deviations from payoff maximization in complex lotteries with larger outcome sets, [Bruce and Johnson \(1996\)](#) did not find an effect of the number of racers on the improvement of horse-race betters over random selection. The absence of an effect for horse-race betters is consistent with different weights of expected gain-loss utility being the driving force behind the complexity effects. All bets in the sample are on single horses and, because there are only two possible outcomes (win or loose), the complexity of the choice environment is always low. Because a larger number of racers does not affect the (low) weights of expected gain-loss utility, we do not expect an effect of the number of racers on improvements over random selection.

The larger influence of reference-dependent preferences in complex choice environments offers a novel explanation for complexity aversion ([Mador et al., 2000](#); [Sonsino et al., 2002](#)). The findings suggest that an aversion to moderately complex lotteries in choice sets that comprise an alternative with lower complexity may result from complexity, directing the loss averse decision maker's attention to prospective losses.

The non-trivial interaction between complexity and loss aversion suggests that the design of optimal incentives depends on task heterogeneity, in the same spirit in which optimal incentives depend on individual level heterogeneity in risk aversion ([Bellemare and Shearer, 2013](#)). [Kőszegi \(2014\)](#) discuss optimal contracts in a principal agent model with expectation based reference dependence. Coming back to the analogy of x to effort, monetary incentives are less effective if output is a poor signal of effort and the outcome distribution of the task is complex. The structural estimates indicate that lower effort levels under moderate complexity do not reflect a higher propensity of decision errors in the spirit of [Sonsino et al. \(2002\)](#) but are driven by expected gain-loss utility. Considering differences in the weight of expected gain-loss utility

as a determinant of the effectiveness of incentives complements [Abeler and Jäger \(forthcoming\)](#), who attribute a lack of reactions to changes in taxation to a limit in the taxpayer's capacity to process information in highly complex tax schemes.

On a more general note, the results are in line with a central premise of psychology—context matters—and suggest that conclusions about preferences should be drawn against the backdrop of the choice environment. Naturally, in the context of a controlled laboratory experiment, we condense choice environments by restricting the number of available candidates for reference points. It is up to future research to extend the design to include alternative reference points such as peers' payoffs and to look at alternative ways to vary complexity.

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Appendix

A Tables and Figures

Table A1: Example of a Choice Sequence

	Alternative 1			Alternative 2			Choice
	π_l	π_w	latent \underline{x}	π_l	π_w	latent \bar{x}	
1	9.50	9.70	0	5.00	14.20	3.00	Alternative 1
2	9.50	9.70	0	8.40	13.10	1.50	Alternative 1
3	9.50	9.70	0	9.20	11.70	0.75	Alternative 2
4	9.40	10.80	0.375	9.20	11.70	0.75	Alternative 1

Notes: The table shows a choice sequence for an exemplary two-outcome lottery configuration with $w = 3$ and probabilities $p_l = p_w = 0.5$, i.e. $p_h = 0$. We denote lottery outcomes with π_l and π_w . The lower (higher) latent value of x in the choice set is \underline{x} (\bar{x}).

Table A2: Parametrization

	x = 0										x = x ₀ [*]						x = 2x ₀ [*]								
	w	p _l	p _w	p _h	x ₀ [*]	π _l	π _w	π _h	E(π)		π _l	π _w	π _h	E(π)		π _l	π _w	π _h	E(π)		π _l	π _w	π _h	E(π)	
E(π) < π _w	3.0				1.5	9.5	9.7		9.6		8.4	13.1		10.8		5.0	14.2		9.6						
	3.5	50%	50%	-	1.8	11.1	11.3	-	11.2		9.6	15.9	-	12.8		5.0	17.4	-	11.2						
	4.0				2.0	13.0	13.2		13.1		11.0	19.2		15.1		5.0	21.2		13.1						
E(π) ≥ π _w	3.0				1.5		5.0	14.0	9.5			8.4	12.9	10.7			9.5	9.5		9.5					
	3.5	-	50%	50%	1.8	-	5.0	17.3	11.2		-	9.6	15.8	12.7	-		11.1	11.2	11.2						
	4.0				2.0		5.0	21.0	13.0			11.0	19.0	15.0			13.0	13.0	13.0						
E(π) < π _w	3.0				1.0	7.0	13.3	19.4	13.2		6.5	15.8	18.9	13.7		5.0	17.3	17.4	13.2						
	3.5	33%	33%	33%	1.2	7.7	16.1	24.4	16.1		7.0	19.5	23.7	16.7		5.0	21.5	21.7	16.1						
	4.0				1.3	8.6	19.5	30.2	19.4		7.7	23.9	29.3	20.3		5.0	26.6	26.6	19.4						
E(π) ≥ π _w	3.0				1.0	7.0	7.1	19.3	11.1		6.5	9.6	18.8	11.6		5.0	11.1	17.3	11.1						
	3.5	33%	33%	33%	1.2	7.7	7.8	24.4	13.3		7.0	11.2	23.7	14.0		5.0	13.2	21.7	13.3						
	4.0				1.3	8.6	8.7	30.2	15.8		7.7	13.1	29.3	16.7		5.0	15.8	26.6	15.8						
E(π) < π _w	3.0				0.8	6.1	15.5	20.0	15.4		5.8	17.5	19.7	15.7		5.0	18.9	18.9	15.4						
	3.5	25%	25%	50%	0.9	6.5	19.2	25.3	19.1		6.1	21.9	24.9	19.5		5.0	23.8	23.8	19.1						
	4.0				1.0	7.0	23.4	31.4	23.3		6.5	26.9	30.9	23.8		5.0	29.4	29.4	23.3						
E(π) ≥ π _w	3.0				0.8	6.1	6.2	19.9	9.6		5.8	8.2	19.6	9.9		5.0	9.6	18.8	9.6						
	3.5	50%	25%	25%	0.9	6.5	6.6	25.2	11.2		6.1	9.3	24.8	11.6		5.0	11.2	23.7	11.2						
	4.0				1.0	7.0	7.1	31.3	13.1		6.5	10.6	30.8	13.6		5.0	13.1	29.3	13.1						

Notes : The table shows the parametrization of the experiment for all lottery configurations (rows) and different latent values of x (columns). We denote lottery outcomes with π_k and probabilities with p_k , where $k \in \{l, w, h\}$. $E(\pi)$ is the expected monetary payoff of the lottery. The expected monetary payoff maximizing value of x is x_0^* .

Table A3: Summary Statistics

	Mean	SD	Min	Max
Age	22.5	2.91	18	33
Length of University Studies in Years	2.09	1.93	0	11
1 = Female	0.76	0.43		
Experience (Laboratory):				
Number of Prior Participations	6.91	4.06	0	20
1 = Experience in Similar Experiments	0.52	0.50		
Payoff in Euro	13.86	7.60	5	31.4

Notes: The table shows summary statistics for the 94 participants.

Table A4: Deviations of Median Choice of Effort from the Expected Monetary Payoff Maximizing Choice

Constant	-0.156** (0.018)
1 = $E(\pi) \geq \pi_w$	0.000 (0.021)
1 = Moderate Complexity	-0.063** (0.031)
1 = Moderate Complexity & $E(\pi) \geq \pi_w$	0.125** (0.036)
1 = High Complexity	-0.125** (0.037)
1 = High Complexity & $E(\pi) \geq \pi_w$	0.188** (0.047)

Notes: The number of observations is 1 692. The quantile regression evaluates deviations of the median values of \hat{x}^* from $\hat{x}_0^* = 0.5$. Explanatory variables are dummies for different levels of complexity, a dummy for $E(\pi) \geq \pi_w$, and interaction terms. The constants represents the deviation of the median value of \hat{x}^* from \hat{x}_0^* under low complexity. Individual-level cluster robust standard errors are in parentheses. *** p -value < 0.01, ** p -value < 0.05

Table A5: Marginal Effects on Parameter Estimates

	θ	γ	τ	ω
Constant	0.207 (0.430)	0.084 (0.106)	0.384* (0.340)	0.313** (0.097)
1 = Moderate Complexity	1.28** (0.631)	-0.001 (0.114)	0.017 (0.467)	
1 = High Complexity	0.064 (0.505)	0.193* (0.110)	-0.248 (0.352)	

Notes: The number of observations is 6573. Estimation follows (4.4). The constants represent parameter values for choice under low complexity. We calculate marginal effects of increasing complexity as $g^\xi(\beta_{cons}^\xi + \beta_{moderate}^\xi) - g^\xi(\beta_{cons}^\xi)$, i.e. $g^\xi(\beta_{cons}^\xi + \beta_{high}^\xi) - g^\xi(\beta_{cons}^\xi)$. Individual-level cluster robust standard errors are in parentheses. The p -value of τ_{cons} is for a two-sided Wald test against 1. All other p -values are for two-sided Wald tests against 0. *** p -value < 0.01, ** p -value < 0.05, * p -value < 0.1

Table A6: Marginal Effects on Parameter Estimates with Heterogeneity over Experience

	θ	γ	τ	ω
Constant	0.300 (0.245)	0.055 (0.071)	0.355* (0.201)	0.301** (0.068)
1 = Moderate Complexity	1.27** (0.641)	0.035 (0.066)	-0.090 (0.221)	
1 = High Complexity	-0.240 (0.221)	0.289** (0.076)	-0.297 (0.188)	
1 = Prior Participation in ...				
... 5 < n < 15 Experiments	0.498** (0.249)	-0.079* (0.039)	0.847* (0.500)	
... $n \geq 15$ Experiments	-0.136 (0.222)	0.074 (0.064)	-0.061 (0.206)	
... Similar Experiments	-0.102 (0.107)	0.032 (0.036)	-0.060 (0.128)	

Notes: The number of observations is 6573. Estimation follows (4.4) but additionally allows for heterogeneity over experience. The constants represent parameter values of individuals who participated in 5 or less experiments and have no experience with similar experiments for choice under low complexity. We calculate marginal effects of increasing complexity as $g^\xi(\beta_{cons}^\xi + \beta_{moderate}^\xi) - g^\xi(\beta_{cons}^\xi)$, i.e. $g^\xi(\beta_{cons}^\xi + \beta_{high}^\xi) - g^\xi(\beta_{cons}^\xi)$. The calculation of marginal effects of experience follows the same logic. Individual-level cluster robust standard errors are in parentheses. The p -value of τ_{cons} is for a two-sided Wald test against 1. All other p -values are for two-sided Wald tests against 0. *** p -value < 0.01, ** p -value < 0.05, * p -value < 0.1

Table A7: Comparison of the KR Model's Specification of the Reference Bundle to a Specification with the Expected Consumption Utility as a Single Reference Point

	κ	θ	γ	τ	ω
Constant	0.921*** (0.250)	0.206 (0.436)	0.084 (0.108)	0.380* (0.340)	0.321*** (0.121)
1 = Moderate Complexity		1.42** (0.567)	-0.000 (0.116)	0.028 (0.464)	
1 = High Complexity		0.076 (0.516)	0.192* (0.111)	-0.244 (0.352)	

Notes: The number of observations is 6573. Estimation follows (4.4) with expected gain-loss utility as in (5.1). In addition to restricting θ and τ as outlined in Section 4, the estimation restricts ω to its theoretical domain $[0, 1]$ by estimating $\omega = \frac{1}{1+e^{\beta\omega}}$. The constants represent parameter values for choice under low complexity. We calculate marginal effects of increasing complexity as $g^{\xi}(\beta_{cons}^{\xi} + \beta_{moderate}^{\xi}) - g^{\xi}(\beta_{cons}^{\xi})$, i.e. $g^{\xi}(\beta_{cons}^{\xi} + \beta_{high}^{\xi}) - g^{\xi}(\beta_{cons}^{\xi})$. Individual-level cluster robust standard errors are in parentheses. The p -value of τ_{cons} is for a two-sided Wald test against 1. All other p -values are for two-sided Wald tests against 0. *** p -value < 0.01, ** p -value < 0.05, * p -value < 0.1

Table A8: Marginal Effects on Parameter Estimates with Heterogeneity in Trembles

	θ	γ	τ	ω
Constant	0.206 (0.432)	0.084 (0.107)	0.381* (0.338)	0.317** (0.114)
1 = Moderate Complexity	1.34** (0.677)	-0.003 (0.121)	0.039 (0.563)	
1 = High Complexity	0.076 (0.508)	0.194* (0.113)	-0.238 (0.359)	
1 = Moderate Difficulty of Choice				0.010 (0.190)
1 = High Difficulty of Choice				-0.084 (0.129)

Notes: The number of observations is 6573. Estimation follows (4.4) but also allows for some heterogeneity in ω over the subjective difficulty of choice. To measure the subjective increase in difficulty under moderate and high complexity, we use questionnaire responses to the question "How difficult was making a choice [under low, moderate and high complexity] for you?". We define a dummy for moderate (high) difficulty that takes the value 1 in moderately and highly complex lottery choices if the individual's subjective assessment of difficulty more than 50% but not more than 150% (150% or more) above the individual's assessment for lottery choice under low complexity. The constants represent parameter values for choice under low complexity. We calculate marginal effects of increasing complexity as $g^{\xi}(\beta_{cons}^{\xi} + \beta_{moderate}^{\xi}) - g^{\xi}(\beta_{cons}^{\xi})$, i.e. $g^{\xi}(\beta_{cons}^{\xi} + \beta_{high}^{\xi}) - g^{\xi}(\beta_{cons}^{\xi})$. Individual-level cluster robust standard errors are in parentheses. The p -value of τ_{cons} is for a two-sided Wald test against 1. All other p -values are for two-sided Wald tests against 0. *** p -value < 0.01, ** p -value < 0.05, * p -value < 0.1

Table A9: Questionnaire

1	Gender: {male, female}
2	Year of birth: {1960, 1961, ..., 2000}
3	Start of studies (at a German university): {2000, 2001, ..., 2014}
4	Field of study: {Economic Sciences, Economics, Business Administration, Social Sciences, Economic Education, Other}
5	Have you participated in a similar experiment in the past: {Yes, No}
6	How often (approximately) have you participated in laboratory experiments before this experiment: {0, 1, ..., 30}
	How difficult was making a choice for you? State if choosing an alternative was easy (1) or hard (10). You can also choose an answer in between.
7.1	The choice between alternatives with two possible payoffs was: {1, 2, ..., 10}
7.2	The choice between alternatives with three possible payoffs and equal probabilities was: {1, 2, ..., 10}
7.3	The choice between alternatives with three possible payoffs and different probabilities was: {1, 2, ..., 10}
8	How much effort did you put into making your choices in the same way, you would make your choices outside of the laboratory? State if you put little effort (1) or a lot of effort (10) into it. You can also choose an answer in between: {1, 2, ..., 10}

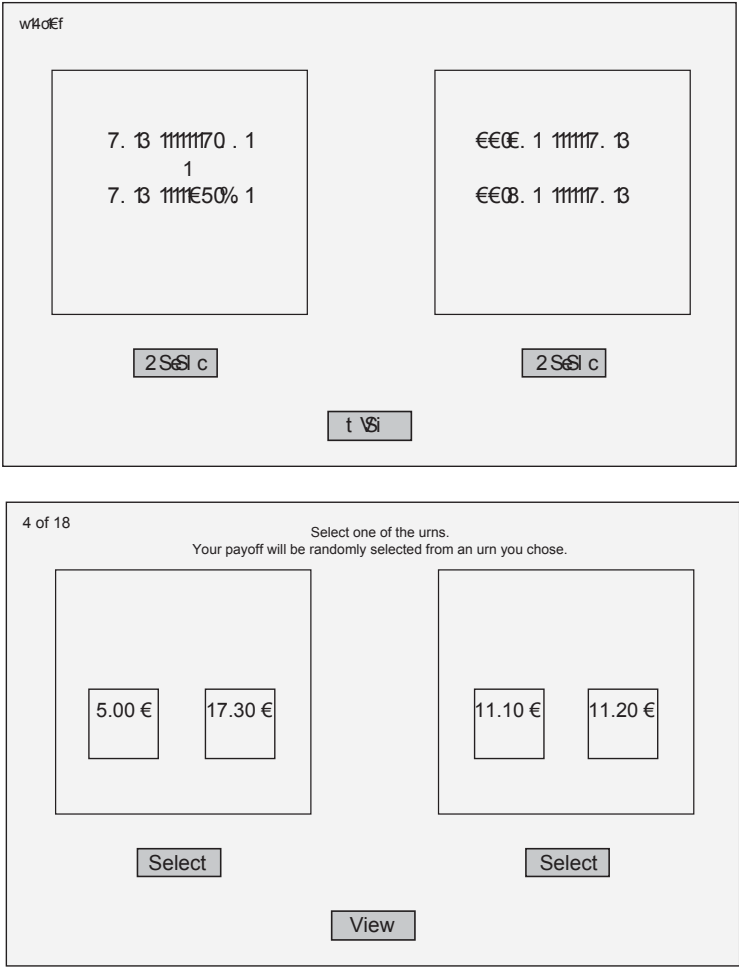
Notes: The table shows questions and possible answers {in curly brackets}. The questionnaire was implemented in z-Tree.

Figure A1: Predictions



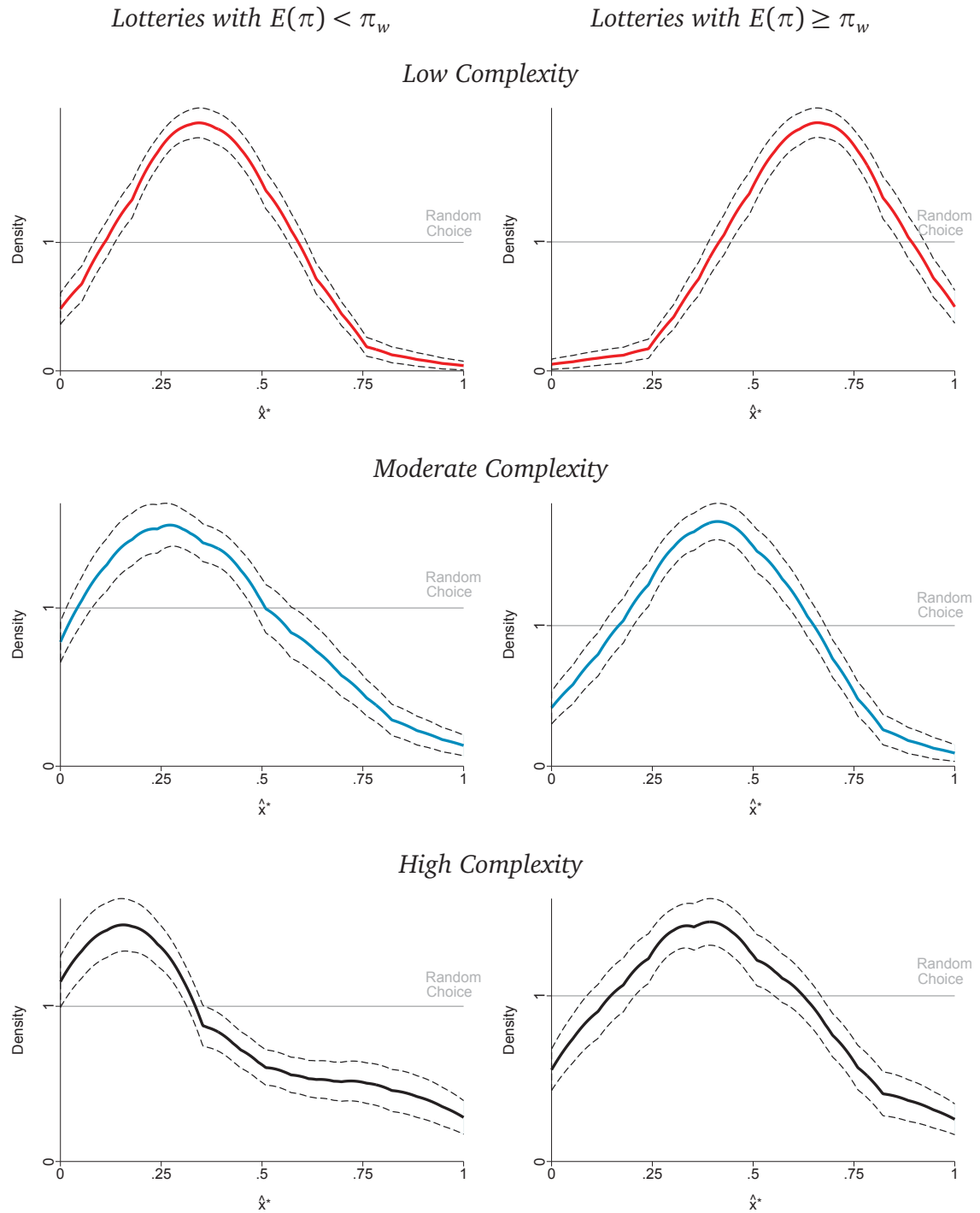
Notes: The Figure shows Predictions of \hat{x}^* with (1.3) for different degrees of risk and loss aversion in lotteries that implement $w = 3$. For the exact parametrization of the lotteries see Table A2. To make predictions we plug parameter values of γ and θ into (1.3) and use numerical optimization techniques to find the optimal value of x .

Figure A2: Implementation



Notes: The figure shows the implementation of the additional display options for a two-outcome lottery.

Figure A3: Deviations from Random Choices with 95% Confidence Intervals



Notes: The Figure shows kernel densities (solid lines) with 95% confidence intervals (dashed lines). The Figure also includes the theoretical density functions for random choices (horizontal gray lines). Underlying the empirical distributions are 1 692 individually optimal values of \hat{x}^* . For the univariate kernel density estimations we use the Epanechnikov kernel function with a bandwidth of 0.12. To construct confidence intervals we use an individual-level cluster bootstrap with 1000 repetitions.

B Alternative Specifications of the Utility Function

In the following, we consider a utility function with constant relative risk aversion and expo-power utility as alternatives to the specification in (1.2).

Constant Relative Risk Aversion

The estimation follows (4.4) but uses

$$U_k = \begin{cases} \frac{\pi_k^{1-\rho}-1}{1-\rho} & \text{for } \rho > 0, \rho \neq 1 \\ \ln(\pi_k) & \text{for } \rho = 1, \end{cases}$$

instead of (1.2). Here, ρ is the Arrow-Pratt measure of constant relative risk aversion. In a first step we allow for heterogeneity in ρ over all levels of complexity. Because the parameter estimates of ρ under low (0.999) and moderate complexity (0.971) are only marginally different from 1, we implement $U_k = \ln(\pi_k)$ for low and moderate complexity and estimate a single parameter ρ for high complexity.

Table B1: Parameter Estimates (Utility Function with Constant Relative Risk Aversion)

	Low Complexity	Moderate Complexity	High Complexity
θ	0.166* (0.085)	1.03** (0.352)	0.050 (0.295)
ρ	—	—	2.65** (0.170)

Notes: The number of observations is 6573. The estimates of parameters under low complexity are $g^\xi(\beta_{cons}^\xi)$. The estimates of parameters under moderate high complexity are $g^\theta(\beta_{cons}^\xi + \beta_{moderate}^\xi)$ and $g^\theta(\beta_{cons}^\xi + \beta_{high}^\xi)$. Estimates for the auxiliary parameters that govern the stochastic element of choice are $\hat{\omega} = 0.282$, $\hat{\tau}_{low} = 0.101$, $\hat{\tau}_{moderate} = 0.116$ and $\hat{\tau}_{high} = 0.007$. The estimates of ω (τ) are statistically different from zero (one) under all levels of complexity (p -values < 0.050). Individual-level cluster robust standard errors are in parentheses. ** p -value < 0.01 , * p -value < 0.05 .

Table B1 reports the estimates. The results are similar to the specification with constant absolute risk aversion. Again, there is evidence for an inverse-U shaped relationship between complexity and the weight of expected gain-loss utility. The estimate of ρ suggests stronger risk aversion in choice under high complexity. This finding is in line with the significantly larger Arrow-Pratt coefficient of constant absolute risk aversion under high complexity.

Expo-Power Utility

The estimation follows (4.4) but uses Holt and Laury's (2002) specification of the flexible expo-power utility function (Saha, 1993)

$$U_k = \frac{1 - e^{-\alpha \pi_k^{1-\sigma}}}{\alpha},$$

instead of (1.2). With expo-power utility, decision makers exhibit constant absolute risk aversion of α if $\sigma = 0$ and constant relative risk aversion of σ if α goes to 0.

Table B2: Parameter Estimates (Expo-Power Utility)

	Low Complexity	Moderate Complexity	High Complexity
θ	0.155* (0.094)	2.15** (0.586)	0.631* (0.260)
σ	0.999** (0.000)	-0.463* (0.278)	-0.913** (0.245)
α	0.024 (0.015)	0.024 (0.015)	0.024 (0.015)

Notes: The number of observations is 6573. The estimates of parameters under low complexity are $g^\xi(\beta_{cons}^\xi)$. The estimates of parameters under moderate high complexity are $g^\theta(\beta_{cons}^\xi + \beta_{moderate}^\xi)$ and $g^\theta(\beta_{cons}^\xi + \beta_{high}^\xi)$. We estimate the auxiliary parameters at $\hat{\omega} = 0.327$, $\hat{\tau}_{low} = 0.000$, $\hat{\tau}_{moderate} = 1.68$ and $\hat{\tau}_{high} = 3.44$. The trembling hand parameter ω is significantly different from zero (p -value < 0.010) and $\hat{\tau}_{low}$ is significantly different from one (p -value < 0.010). $\hat{\tau}_{moderate}$ and $\hat{\tau}_{high}$ are not significantly different from one (p -values > 0.300). Individual-level cluster robust standard errors are in parentheses. *** p -value < 0.01 , ** p -value < 0.05 , * p -value < 0.1 .

Table B2 reports the parameter estimates with expo-power utility, allowing for heterogeneity over complexity in θ , σ , and τ .⁴⁰ Again, we find evidence for an inverse-U shaped relationship between complexity and the weight of gain-loss utility. For low complexity the estimated risk preferences suggest an aversion to risk over the whole domain of lottery outcomes. For moderately and highly complex lotteries, the estimates suggest an S-shaped utility function that results in risk seeking for lotteries with low outcomes and risk aversion for high-outcome lotteries.

⁴⁰The algorithm did not reach convergence for a specification that allows for heterogeneity in α , or heterogeneity in σ and α .

C Gain-Loss Utility with Flexible Reference Bundle

To investigate the composition of the reference bundle, we combine a specification with the KR model's reference bundle and a specification with the expected consumption utility as a single reference point.

KR – Consumption Utilities as Reference Bundle

With $\theta \equiv \eta(\lambda - 1)$, we get

$$\eta V(x) = \theta[p_l p_h(U_l - U_h) + p_l p_w(U_l - U_w) + p_w p_h(U_w - U_h)].$$

Disappointment Aversion – Expected Consumption Utility as Reference Point

If expected consumption utility is strictly smaller than the consumption utility of π_w , i.e. $EU < U_w$, expected gain-loss utility is

$$\begin{aligned} V(x) &= p_l \lambda [U_l - (p_l U_l + p_w U_w + p_h U_h)] \\ &\quad + p_w [U_w - (p_l U_l + p_w U_w + p_h U_h)] \\ &\quad + p_h [U_h - (p_l U_l + p_w U_w + p_h U_h)], \\ &= p_l \lambda [(p_w + p_h)U_l - p_w U_w - p_h U_h] \\ &\quad + p_w [-p_l U_l + (p_l + p_h)U_w - p_h U_h] \\ &\quad + p_h [-p_l U_l - p_w U_w + (p_l + p_w)U_h], \\ &= \lambda [p_l p_w (U_l - U_w) + p_l p_h (U_l - U_h)] \\ &\quad - p_l p_w (U_l - U_w) \\ &\quad - p_l p_h (U_l - U_h). \end{aligned}$$

After equivalently deriving expected gain-loss utility for $EU \geq U_w$, we can rearrange the terms to get

$$\eta V(x) = \begin{cases} \theta [p_l p_w (U_l - U_w) + p_l p_h (U_l - U_h)] & \text{for } EU < U_w, \\ \theta [p_w p_h (U_w - U_h) + p_l p_h (U_l - U_h)] & \text{for } EU \geq U_w. \end{cases}$$

Combining Both Specifications

We end up with

$$\begin{aligned}\eta V(x) = & \theta [p_l p_h (U_l - U_h) \\ & + \mathbb{1}\{EU \geq U_w\} (p_w p_h (U_w - U_h) + p_l p_w \kappa (U_l - U_w)) \\ & + \mathbb{1}\{EU < U_w\} (p_w p_h \kappa (U_w - U_h) + p_l p_w (U_l - U_w))],\end{aligned}$$

where κ is a weight for the additional comparisons in the KR model. If κ equals one, expected gain-loss utility is as the KR model predicts. If κ equals zero, expected gain-loss utility reduces to the specification with the expected consumption utility as a single reference point.

D Instructions

Instructions

Welcome to the experiment.

Please turn off your mobile phone. If you have any questions, please raise your hand. Somebody will come to you and answer your question. From now on, communication with other participants is forbidden.

The Experiment

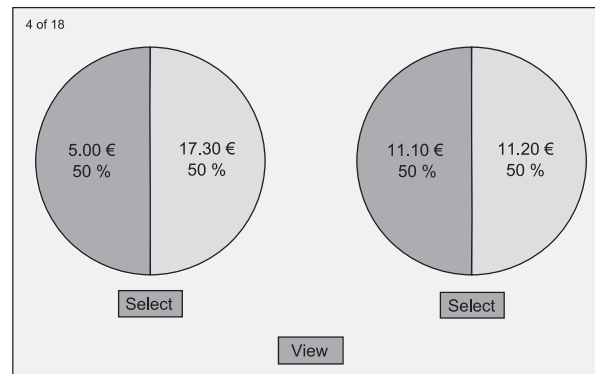
The purpose of the experiment is the analysis of economic choice behavior. The experiment consists of 18 sections. In each section you make choices between Alternative A and Alternative B.

At the end of the experiment one of your choices is randomly selected. The probability of being selected is the same for all of your choices. Out of the alternative, which you have chosen, one of the payoffs is then randomly selected. You will receive the payoff in cash after the experiment. Your payoff will at least amount to 5.00 €.

The data is anonymized for evaluation.

To begin a section, click **Start**. It follows a diagram of the two alternatives.

Example:



If you choose Alternative A (left), and this choice is randomly selected, you receive 5.00 € with a probability of 50% and 17.30 € with a probability of 50%. If you choose Alternative B (right), and this choice is randomly selected, you receive 11.10 € with a probability of 50% and 11.20 € with a probability of 50%.

The size of the slices is proportional to the probability, of the corresponding payoff being selected.

By clicking on **View** you can display the alternatives as tables or urns. You can switch between the views as often as you want. By clicking on the symbol in the upper left corner of the screen, you can open a calculator.

Your Choice

You choose one of the two alternatives.

Attention: There are no „right“ or „wrong“ choices. Make the choice that corresponds to your preferences.

To choose an alternative, click on below the respective alternative. You cannot change previous choices.

After you have decided, again two alternatives will be displayed. One of the alternatives is identical to the alternative which you have chosen before. Now you decide again for one of the alternatives.

Think about which one of the displayed alternatives you prefer. Make your choice independent of your previous choices.

Attention: Each of your choices can be randomly selected for payoff. Therefore you should make each choice as if it determined your payoff.

Next section

After a certain number of choices, a new section commences.

End of the experiment

After you have made all of your choices, we ask you to complete a short questionnaire. Please behave quietly after answering the questionnaire, so you do not distract the other participants.