Journal of Economic Psychology 100 (2024) 102681

Contents lists available at ScienceDirect

Journal of Economic Psychology

journal homepage: www.elsevier.com/locate/joep

Complexity aversion in risky choices and valuations: Moderators and possible causes

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ARTICLE INFO

Keywords:
Complexity Aversion
Risk Preferences
Valuation
Risky Choice
Cognitive Ability
Certainty Equivalent

ABSTRACT

In the age of digitalization and globalization, an abundance of information is available, and our decision environments have become increasingly complex. However, it remains unclear under what circumstances complexity affects risk taking. In two experiments with monetary lotteries (one with a stratified national sample), we investigate behavioral effects and provide a cognitive explanation for the impact of complexity on risk taking. Results show that complexity, defined as the number of possible outcomes of a risky lottery, decreased the choice probability of an option but had a smaller and less consistent effect when evaluating lotteries independently. Importantly, choices of participants who spent more time looking at the complex option were less affected by complexity. A tendency to avoid cognitive effort can explain these effects, as the effort associated with evaluating the complex option can be sidestepped in choice tasks, but less so in valuation tasks. Further, the effect of complexity on valuations was influenced by individual differences in cognitive ability, such that people with higher cognitive ability showed less complexity aversion. Together, the results show that the impact of complexity on risk taking depends on both, decision format and individual differences and we discuss cognitive processes that could give rise to these effects.

1. Introduction

In the age of globalization and digitalization, the complexity of our decision environments is ever increasing. Think—for example—of investment decisions, where a large variety of financial products is available that are highly detailed and typically come with several pages of explanations of the payoff structure. Similarly, in consumer choices such as buying a new notebook, consumers have to consider numerous technical attributes that determine the notebook's processing power, comfort of use, battery life and so on. Whereas complexity might be engaging and informative for some individuals, others might struggle to keep up with the flood of information. In any case, to help people make better decisions, it is important to understand how complexity affects their behavior. In our study, we contribute to this understanding by investigating the influence of complexity on decision making by means of risky lotteries, which allow for simple and clean manipulation of complexity based on number of attributes (outcomes).

Previous research has suggested that complexity can lead to deference or deflection of choice (Dhar, 1997a, 1997b; Tversky &

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https://doi.org/10.1016/j.joep.2023.102681

Available online 8 November 2023

Shafir, 1992), increased preference for the status quo (Boxall et al., 2009; Frank & Lamiraud, 2009), or decreasing engagement with the decision problem (Blaufus & Ortlieb, 2009). While most of these effects are widely known, the effects on choice deferral have proven difficult to replicate (Evangelidis et al., 2022). Beyond this, studies on valuations and choices under risk and uncertainty have reported that more complex risky gambles, those with higher numbers of outcomes, were chosen less often or were valued less than simple ones (Huck & Weizsäcker, 1999; Mador et al., 2000; Sonsino et al., 2002). This behavior has been explained by the notion of complexity aversion (see Mador et al., 2000; Sonsino et al., 2002). Recently, complexity aversion has also been part of an axiomatized theory of choice (Puri, 2018). Yet, in the framework of expected utility theory, such complexity aversion can lead to suboptimal decisions because people would be willing to choose options with lower expected utility to avoid complexity. Other researchers, however, found complexity neutrality in risky valuations (Bruce & Johnson, 1996). Yet other findings suggest that complexity aversion occurs only in some of the population because of individual differences (Moffatt et al., 2015).

In addition to questions regarding the existence of complexity aversion, little is known about the underlying reasons and the cognitive mechanisms that could explain when and why people avoid or undervalue complex risky options. The goal of this article is to investigate this. In the following, we review the existing literature on this question and then derive predictions from it. In particular, we focus on differences between valuation and choices and on individual differences in motivation and cognitive ability.

1.1. Differences between valuation and choice

Complexity aversion has been observed mostly in pairwise choices between simple and complex options (e.g., Huck & Weizsäcker, 1999; Moffatt et al., 2015; Sonsino et al., 2002). There is less evidence, in contrast, for a systematic negative effect of complexity in valuation tasks: Whereas individual differences in valuations of simple and complex options have been reported for intertemporal risky gambles (Mador et al., 2000), no such effect has been found for pure (not intertemporal) risky gambles (Bruce & Johnson, 1996). Qualitative differences in preferences due to presentation formats or elicitation methods in general and between valuations and choices in particular are well documented in the literature (e.g., Grether & Plott, 1979; Slovic & Lichtenstein, 1983). They have been explained through a failure of procedural invariance and a tendency to overweight attributes that match with the response scale (Tversky et al., 1990). In addition, Butler & Loomes (2007) argued that these preference reversals can be explained by some amount of preference imprecision or variability. In the following, we will outline possible reasons to expect that there could also be differences between valuation and choice with respect to the effect of complexity.

First, when choosing among options that differ in complexity, selecting the simpler alternative could be a strategy to avoid the exertion of cognitive effort needed to evaluate the more numerous outcomes of the complex option in the first place. This explanation is corroborated by previous research showing that people tend to avoid activities that demand the investment of cognitive effort (e.g., Inzlicht et al., 2018; Kool et al., 2010; Stanovich, 2018). In line with this "cognitive miser" account, participants in an experiment by Westbrook et al. (2013) willingly forwent a monetary reward if they had the option to perform a task that was less cognitively demanding than another, a behavior called cognitive effort discounting. In the context of complexity aversion, this explanation applies to choice tasks more than to valuation tasks because the evaluation of an option is much harder to avoid in a valuation task. Hence it predicts more pronounced effects of complexity aversion for choice tasks. However, complexity aversion in valuation is still plausible if people discount options because they dislike the cognitive effort associated with them.

Second, complexity aversion in choices could also be driven by preference variability (Butler & Loomes, 2007; Mador et al., 2000; Sonsino et al., 2002): If people have difficulties evaluating complex gambles, their evaluations will be noisier and more error prone. If this noise is unsystematic, it will not translate to systematically lower valuations directly, but it can trigger less consistent (i.e., less utility-maximizing) behavior. In the extreme case, excessive noise will lead to choice proportions approaching 50:50 for pairwise choices. In situations where the complex gamble is more attractive in terms of expected value or variance (as, for example, in Huck & Weizsäcker, 1999; Sonsino et al., 2002), a complexity-induced decrease in consistency could hence be interpreted as complexity aversion (see also Olschewski et al., 2018; Mechera-Ostrovsky et al., 2022). We refer to this as the noise hypothesis.

1.2. Influence of numerical cognition

Evaluating risky gambles typically requires the perception and integration of numerical information to grasp payoffs and probabilities. As mentioned above, this process will be more error prone for complex lotteries. Presumably, decision makers do not like this imprecision in the first place (Burks et al., 2009). The resulting errors also depict an additional (epistemic) risk above and beyond the (aleatory) risk due to the variance of the gamble (Fox & Ülkümen, 2011; Olschewski & Scheibehenne, 2023). Namely, the risk that the estimates of potential outcomes are imprecise and thus do not perfectly represent the true underlying reward structure. To the extent that risk-averse decision makers are aware of their increased error probability, complex gambles should receive lower valuations (see also Andersson et al., 2016).

Besides this second-order risk aversion, research on numerical cognition has further suggested that humans' number sense maps onto a compressed scale (e.g., Dehaene, 1992, 2011; Schley & Peters, 2014). This compression has been observed predominantly in non-symbolic number perception, but it has been hypothesized that compression also applies to symbolic numbers (e.g., Dehaene, 1992). In line with this, previous research found that summary statistics of number sequences (i.e., sum or mean) are systematically underestimated in decisions from experience (Olschewski et al., 2021; Scheibehenne, 2019). Presumably, these findings would generalize to decisions from description in which there is also numerical information that needs to be processed. Additionally, it has been hypothesized that there are two representations of symbolic numbers, one intuitive and compressed (logarithmic or power-function based) and the other learned and linear (e.g., Izard & Dehaene, 2008; Siegler & Opfer, 2003). To the extent that decision makers adopt the more compressed intuitive representation to mitigate complexity, complex gambles would be valued less because their expected value is underestimated.

1.3. Cognitive ability as a moderator

Irrespective of possible differences between valuation and choice, the perceived complexity of an option eventually is subjective and hence may differ between individuals. In line with this, past research found that complexity aversion is subject to individual differences (e.g., Moffatt et al., 2015; Westbrook et al., 2013; Zilker et al., 2020). One reason for these individual differences could be that people with higher cognitive abilities are less affected by complexity in the first place because they can still assess these gambles with reasonable accuracy. Likewise, if people with high cognitive ability do not need to exert as much effort to assess complex lotteries, they might discount them less than people with low cognitive ability. In support of this, past research found individual differences in the above-mentioned tendency to avoid cognitive effort (e.g., Inzlicht et al., 2018; Sandra & Otto, 2018). Furthermore, Westbrook et al. (2013) found more discounting of cognitive effort in older compared to younger adults. This age effect could be due to age-specific changes, such as recruiting of more neural resources at lower levels of cognitive load as a compensation mechanism (e.g., Grady, 2012; Schneider-Garces et al., 2010) or a decline of fluid intelligence (e.g., Bopp & Verhaeghen, 2005; Horn & Cattell, 1967). Taken together, this suggests that cognitive ability moderates complexity aversion in risky choices and possibly also in valuations.

1.4. The current study

To investigate the predictions of the different theoretical accounts and cognitive mechanisms behind complexity aversion we conducted two behavioral experiments (see Table 1 for an overview).

In the first experiment, we investigated the effect of complexity on valuations of risky lotteries, the format for which previous results were least consistent. We further employed a mean estimation task. Because preferences for complexity or risk should not affect mean estimations, this task allowed us to examine the interplay between complexity and numerical cognition. To increase generalizability, we employed a broad range of stimuli while controlling for lottery variance, skewness, and expected value. Following-up on this first experiment, we conducted a second experiment to examine whether complexity has a stronger effect on binary choices than on valuations. To examine whether a possible difference between the elicitation formats could be due to the avoidance of cognitive effort in binary choices, we further implemented two process measures of cognitive effort, looking time proportion (i.e., time spent looking at the complex option divided by time spent looking at the simple option) and decision speed. To examine cognitive ability as a potential moderator, we assessed participants' cognitive ability based on a validated matrices task and recruited a stratified national sample (age, gender, and ethnicity) of the U.S. population. As in Experiment 1, we again employed a broad range of stimuli while controlling for lottery variance, skewness, and expected value. Taken together, the two experiments explored the effect of complexity aversion in valuation and choice, investigated different underlying cognitive mechanisms, and assessed the moderating role of cognitive ability on the effect.

2. Experiment 1

2.1. Method

2.1.1. Material

Participants in the experiment were asked to evaluate 24 two-outcome lotteries presented on a computer screen. To each simple lottery, we matched a complex lottery with seven outcomes that had the same expected value, standard deviation, and skewness. We included two levels of expected value (low: 70–90, and high: 110–130), two levels of variance (*SD*: low: 5–20, and high: 35–50), and three levels of skewness (left: −2.25 to (−0.75), none: −0.75 to 0.75, and right: 0.75–2.25). The currency of the outcomes (e.g., £75 or

Table 1
Research Questions Addressed in the Two Experiments.

Research Question	Addressed in	Findings
Is there a behavioral effect of complexity aversion?	Exp 1 & 2	Yes, in choices. Dependent on cognitive ability in valuations.
Is it caused by a systematic bias or by unsystematic noise?	Exp 1 (& 2)	Both. Evidence for a systematic and an unsystematic effect.
Is the systematic effect a pre-ference or a perceptual bias?	Exp 1	Likely a pure preference. No evidence for perceptual bias or dislike of noisy perception.
Is the preference dependent on the dislike of cognitive effort?	Exp 2	Yes, likely. One process measure of cognitive effort (looking time pro-portion) is a credible predictor of the effect, however, another (speed) is not.
Is individual cognitive ability a moderator of the effect of complexity?	Exp 2	Yes, cognitive ability moderates complexity aversion in valuations and expected value sensitivity in choices.

Note. Exp: Experiment. Regarding the second research question, Experiment 1 was designed to test it and found evidence in support of complexity increasing unsystematic noise. While Experiment 2 was not specifically designed to test the question, it also examined the possibility of a systematic effect and found evidence in support for it.

$75) was not specified to keep the estimation and valuation task comparable. The experiment used a within-subject design with one minor adjustment: To avoid a bias due to the changing range and the maximum and minimum outcome associated therewith, we implemented two sets of complex lotteries as an additional between-subjects control factor. The range of outcomes needed to be implemented as a between-subjects variable because keeping lottery variance and skewness constant while increasing the number of outcomes inevitably increases the range. Consequently, in one set, the variance was kept constant but the range increased, and in the other set the range was kept constant, but the variance decreased. Participants were randomly assigned to one of the two control conditions.

The experiment consisted of two blocks that were presented in randomized order. In the estimation block, participants had to estimate the mean of the presented lotteries. In the valuation block, they had to indicate their minimum selling price for the lotteries presented. As an example, Fig. 1 shows a screenshot of the estimation and valuation tasks respectively. Participants indicated their answer by entering a number into an input field on the screen. To measure participants' insights into their estimation uncertainty, we asked them about their confidence after each estimation as follows: "How sure are you that your estimate is within 10 % of the actual mean?" Answers were recorded on a 7-point Likert scale ranging from *not sure at all to completely sure*.

The order of the lotteries within each block and the order of the outcomes within each lottery were randomized for each participant. To assess participants' understanding of the task, we asked them to repeat the goal of the task in their own words after reading the instructions (before the task). Additionally, we asked the participants to select which answers were considered "logically valid" in a multiple-choice question. In the instructions, we explained that answers below the lowest outcome and answers above the highest outcome of a lottery were not considered logically valid, so the question was implemented as an instruction check. Apart from participants' answers, we assessed reaction times in all elements of the experiment. At the end of the experiment, we assessed demographics (age, gender, and country of origin) and asked participants whether they had completed the experiment in good faith. Participants were encouraged to answer this question truthfully and were additionally reminded that their answer would have no consequence for them or their probability of winning the study-performance-based raffle of CHF 100.

To analyze the data, Bayesian methods were used when available. Inferences were drawn on the basis of credible intervals, Bayes factors (BFs), confidence intervals, and *p* values. Bayes factors are useful in particular in cases where frequentist *p* values indicate non-significant results because they can quantify the evidence in favor of the null hypothesis (e.g., Rouder et al., 2009). Following conventions, here we interpret Bayes factors larger than 3 as evidence for the more likely hypothesis (see also Rouder et al., 2009).

The experiment was preregistered and the preregistration, the experiment, the set of lotteries, the data, and the analysis script can be found on the Open Science Framework (OSF, https://osf.io/jpsur; https://osf.io/u5an6/). Deviations from the preregistration and their respective justifications (e.g., accounting for repeated measures in data) are reported in the text or in Supplementary Section 1.

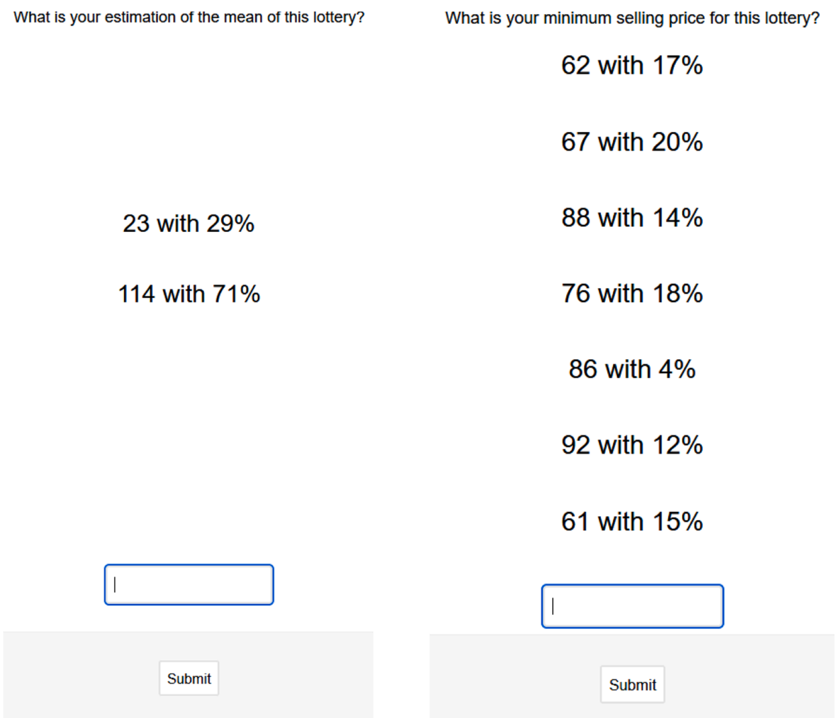

Fig. 1. *Task Examples for Estimation (Left) and Valuation (Right) in Experiment 2.* The participants could enter a number via the keyboard in both the estimation (left) and valuation (right) task. In this example, a simple lottery with two outcomes is evaluated in the estimation task and a complex lottery with seven outcomes is evaluated in the valuation task. The participants' answers were saved after clicking on the "Submit" button. There was no time limit for the task.

2.1.2. Participants and procedure

On the basis of previous research (Huck & Weizsäcker, 1999; Mador et al., 2000; Sonsino et al., 2002), we estimated the effect of complexity aversion to be small to medium. Given this, we conducted a power analysis using the pwr (Champely, 2020) package in R (R Core Team, 2020), revealing a target sample size of 147 for a power of 95 % ($\alpha = 0.05$, $d = 0.3$, two-sided) based on a paired t test intended to compare evaluations of single and complex lotteries. Informed by this, we tested a convenience sample of 131 bachelor's students in economics and management at the University of Geneva who participated in exchange for course credit and the possibility to win CHF 100 in a raffle depending on their performance. In particular, the estimation task was incentivized based on accuracy, with the students winning more points when their estimate of the mean was accurate. The valuation task was incentivized on the basis of a Becker–DeGroot–Marschak (BDM) auction (Becker et al., 1964), with the offer being drawn between the minimum and the maximum outcome of the lottery. This procedure guarantees that it is incentive compatible for participants to state the true monetary equivalent of their subjective utility for a given lottery. Both incentivization procedures were explained to the participants based on an example task in which detailed outcomes were displayed (see https://osf.io/u5an6/). At the end of the study, one lottery for each task was drawn for the points calculation. There was no deception involved in the experiment and all information provided to the participants was truthful to the authors' best knowledge. The participants were asked to make an estimate of the mean outcome and to not use a calculator or any other external aids (e.g., write anything down).

Data from 10 participants were excluded for the following (preregistered) reasons: participant requested exclusion (three), not following instructions by writing calculations down or restarting the experiment (two), completing the experiment too fast (¼ of mean time) or too slow (twice mean time; two), and not understanding the instructions in both tasks (three). Additionally, task-specific data were removed for any participant not understanding the instructions in the estimation task (seven) and for any not understanding the instructions in the valuation task (14). As the participants took a bit longer than expected to complete the experiment, the exclusion criteria for the time spent on the experiment were slightly adjusted from the preregistration, in which we specified that we would set the cut-off based on the expected time (25 min). Furthermore, the participants did poorly on the multiple-choice question designed as an instruction check, with only seven correctly selecting all three "logically valid" answers of the six alternatives presented. The vast majority of the students identified only the most probable outcome that was closest to the expected value instead of selecting all possible answers. Therefore, we concluded that the question was not asked clearly and decided not to apply this exclusion criterion as preregistered. Instead, we inverted it, excluding the answers of participants who gave an unmistakably wrong answer and chose an outcome below the minimum or above the maximum. This led to the exclusion of an additional 13 participants. While this might seem to indicate that the data quality was poor, the participants' answers in the estimation (and valuation) task were highly precise, indicating the fault lied with the instruction check and not with participants' negligence. Additionally, we did not apply the exclusion criterion intended to detect calculator use in participants (over 95 % accuracy in estimation or valuation), as we conducted the experiment in a laboratory and could therefore control for people using external aids. The remaining data set included data from 108 participants.

The experiment was built in the lab.js editor (Henninger et al., 2019) and distributed with JATOS software (Lange et al., 2015). The participants completed the experiment in a behavioral laboratory situated at the University of Geneva in April 2019. The average age of the final sample was 21.62 years ($Mdn = 21$ years, $SD = 1.79$). Fifty-five of the participants were female and 53 were male. The experiment lasted 32.1 min on average ($Mdn = 29.52$ min, $SD = 12.27$).

2.2. Results

From the remaining data, we removed individual data points when participants' answers were out of bounds (above the maximum or below the minimum of the outcomes presented in the lottery), which led to an exclusion of 6 % of the data in the estimation task and 4 % of the data in the valuation task. Additionally, we removed data points if the participants took longer than 2 *SD*s to give an answer (4 % in the estimation task, 5 % in the valuation task), or if they took less than 2 s to give an answer (0.4 % in valuation task, no data points in estimation task) indicating insufficient attention to the task.

2.2.1. Valuation and estimation

Fig. 2 shows the individual mean valuations and estimations for simple and complex lotteries (aggregated). A two-sided paired t test on this data revealed that participants did not value complex lotteries ($M_c = 97.68$, $SD_c = 9.03$) less than simple lotteries ($M_s = 98.19$, $SD_s = 8.56$), $BF_{01} = 7.22$, $t(97) = 0.67$, $p = 0.51$, on average. The Bayes factor represents evidence against a systematic, negative influence of complexity on valuations.

Similarly, participants did not estimate complex lotteries ($M_c = 100.11$, $SD_c = 6.98$) to have a lower mean than simple lotteries ($M_s = 99.98$, $SD_s = 6.13$), $BF_{01} = 8.80$, $t(100) = -0.25$, $p = .80$, on average. The Bayes factor represents evidence against a systematic, negative influence of complexity on the perceptual level. These results for valuation and estimation were confirmed by Bayesian multilevel models with participant random intercepts and random slopes for each item-specific factor to allow for individual differences using the brms package (Bürkner, 2018) in R (R Core Team, 2020) and default priors (see Table 2 for the model summary).[1] In the first regression we used valuation as the dependent variable and the lottery complexity, expected value, variance, and skewness as

[1] We preregistered to include the factor estimation (matched) in the regression for valuation. However, as there was high collinearity between the factor estimation and expected value, $r(2{,}384) = 0.91$, $p < .001$, we dropped the factor estimation from the model and conducted a separate analysis of it instead.

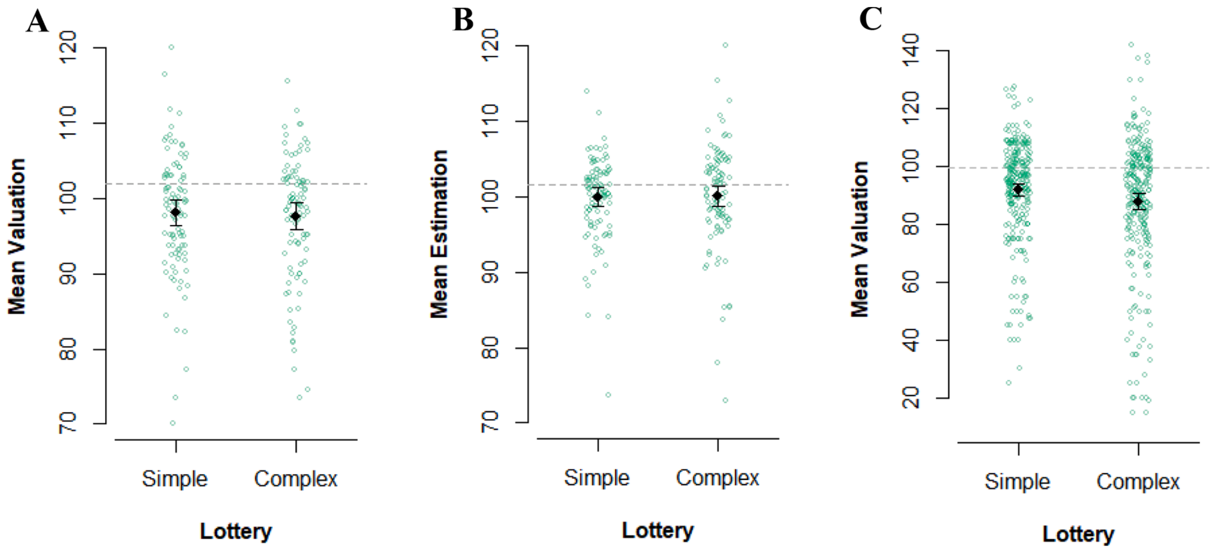

Fig. 2. *Lottery Valuations and Estimations in Experiment 1 (Panel A and B) and Valuations in Experiment 2 (Panel C) Averaged Within Participants.* The dashed lines indicate the overall mean of the experienced sequences for valuations ($M_{v1} = 101.55$) estimations ($M_{e1} = 101.53$) in Experiment 1 and Valuations in Experiment 2 ($M_{V2} = 99.62$). Error bars denote 95 % confidence intervals based on standard errors. Panel A and B show no aggregated effect of complexity in either task in Experiment 1, except slightly higher variance in the estimation of complex lotteries. Panel C shows that simple lotteries were valued slightly higher than complex lotteries on average based on the participant aggregated data in Experiment 2.

Table 2
Beta Estimates for DVs Estimation and Valuation in Experiment 1.

Factor	Estimation	Valuation
Intercept	0.37	2.05
	(1.04)	(1.28)
Complexity	0.12	−0.89
	(0.49)	(0.63)
Skewness	1.19[a]	2.62[a]
	(0.32)	(0.43)
SD	0.01	−0.14[a]
	(0.02)	(0.03)
EV	0.98[a]	0.98[a]
	(0.01)	(0.01)

Note. Standard errors are reported in parentheses. Complexity: Simple = 0 and complex = 1. SD = Standard deviation; EV = expected value.
[a] Indicates a beta estimate for which zero is not contained in the 95% credible interval.

predictors. We found that right skewness, low variance, and higher expected value led to higher valuations. Similarly, the second regression with estimation as dependent variable confirmed that complexity did not have a systematic, negative effect on estimations (see Table 2). Estimations were higher for right skewed and higher expected value lotteries. Noteworthily, a negative effect of variance (i.e., risk aversion) was only present in valuations.

2.2.2. *Influence of numerical cognition*

Addressing the correspondence between the perceptual level (estimation) and the preferential level (valuation), the multilevel model including the factor estimation only was able to predict the corresponding valuation well. However, this prediction was less precise than the prediction of the expected value of the lottery, $\beta = 0.84$, 95 % confidence interval (CI) [0.80, 0.87]. Although estimation influenced valuation, there was no evidence of a systematic bias from numerical cognition being propagated to valuations because we found evidence against a systematic influence of complexity on both the perceptual and the preferential level.

To investigate if participants perceived their estimations for complex lotteries as less precise, we aggregated confidence ratings within participants and conducted a two-sided paired Wilcoxon signed-rank test. The participants indicated higher confidence for their estimates of simple lotteries ($Mdn_s = 4.59$) compared to complex lotteries ($Mdn_c = 3.84$), $V = 4{,}307$, $p < .001$, on average. This suggests that participants were aware of the uncertainty being caused by complexity. However, as there was no systematic difference in valuations between complex and simple lotteries, this decrease in confidence apparently did not affect valuations.

While the previously assessed confidence ratings for estimations clearly differed for complex and simple lotteries, a two-sided paired t test assessing if participants gave more variable valuations to complex lotteries was non-significant, and the Bayes Factor represents evidence for the null ($M_c = 26.43$, $SD = 4.56$, $M_s = 25.76$, $SD = 3.94$), $BF_{01} = 3.91$, $t(95) = -1.30$, $p = .20$. In estimation, the test for unsystematic deviation was statistically significant according to the frequentist p value, but the Bayes Factor in favor of the alternative hypothesis remained inconclusive ($M_c = 25.40$, $SD = 4.26$, $M_s = 24.40$, $SD = 2.91$), $BF_{10} = 1.22$, $t(98) = -2.05$, $p = .04$. These analyses were additionally repeated separately for the between-subject factors of constant variance or constant range leading to similar conclusions (see Supplementary Section 2).

To shed more light on the relationship between complexity and unsystematic noise on the task level, we conducted a (pre-registered) multilevel analysis. For this, absolute deviations from the expected value of the lotteries were analyzed in a Bayesian multilevel regression model using default priors, implemented with participant random intercepts and random slopes for each factor to allow for individual differences.[2] The results, summarized in Table 3, reveal that higher complexity, deviation in estimation (matched), variance, and expected value led to higher deviation in valuations. Similarly, the model for estimations revealed that higher complexity, and variance led to higher deviations in estimation.

To illustrate, all else being equal (and not considering the deviation propagated through the log-transformed absolute estimation of the same lottery), the absolute deviation for valuations was exp(0.27) = 31 %, and the absolute deviation for estimations was exp (0.43) = 54 % higher for complex lotteries than simple lotteries.[3] Relating back to the inconclusive or non-significant findings of the t test of individual valuation and estimation variability, the multilevel model was likely more powerful to detect the effect of complexity. Additionally, the log-transformed absolute estimation was a valid predictor of the log-absolute valuation, indicating that deviations in the estimation task were partially propagated to the valuation task.

2.3. Discussion Experiment 1

We found evidence against complexity aversion in valuations according to Bayes Factors. Additionally, we could not find support for the potential perceptual mechanisms in estimation tasks through which complexity could affect valuations. While there was a slight underestimation bias, this bias was equally present in the evaluation of simple and complex lotteries. Similarly, while there was an increase of unsystematic deviation (noisy numerical cognition) in estimation due to complexity, and participants were aware of it according to their confidence ratings, this did not lower the valuations of complex lotteries compared to simple lotteries.

We found partial support for the response noise hypothesis, which assumes that complexity increases unsystematic noise in valuations. While the effect was inconclusive and non-significant on the participant level, the valuations for the complex lotteries were more variable (31 %) than the valuations for the simple lotteries on the trial level. This difference was credible and suggests that complexity increases response noise.

As mentioned in the Introduction, another potential mechanism through which complexity could affect preferences is the avoidance of cognitive effort. In this case, one would expect a difference between (binary) choices and valuations because the former allows decision makers to avoid the cognitive effort of evaluating the complex option in the first place. Additionally, one would expect a weaker effect of complexity on people with high cognitive ability (e.g., university students) because they can still assess complex lotteries with reasonable accuracy, and do not need to exert as much cognitive effort than people with lower cognitive ability. To investigate the potential mechanism of cognitive effort avoidance, we conducted a second experiment in which participants completed a valuation and a choice task along with an assessment of individual cognitive ability and two behavioral process measures of cognitive effort (looking time proportion and decision speed).

3. Experiment 2

3.1. Method

3.1.1. Materials

We created six simple lotteries with two outcomes and matching complex lotteries with seven outcomes. The simple and complex lotteries had the same characteristics (expected value, standard deviation, and skewness) except for the number of outcomes. We included two levels of variance (*SD*: low: 5–20, and high: 35–50) and three levels of skewness (left: −2.0 to (−1.0), none: −0.5 to 0.5, and right: 1.0–2.0). As in Experiment 1, the unit of the outcomes (e.g., 110) was not specified to keep the experiments comparable. All 12 lotteries (six simple and six complex) were presented in the valuation task. For the choice task, we added five levels of expected value differences (−15 %, −7.5 %, 0 %, +7,5%, +15 %), resulting in 30 lottery pairs.

To assess cognitive ability, we used the short form of the Hagen Matrices Test (Heydasch et al., 2013), a measure previously validated against a general measure of intelligence (Intelligence Structure Test: I-S-T 2000R). The test consists of six matrices that

[2] The absolute deviations were non-normally distributed and needed to be log-transformed to reduce heteroscedasticity in the linear model. To allow for log transformation, we excluded values at exactly zero deviation (1.1% and 0.75%, negligible). We considered alternative solutions but found them to be less suitable. For example, adding a constant leads to substantial heteroscedasticity in the model and a Box–Cox transformation hinders interpretability of the results.

[3] To test the robustness of these results, we conducted the same analysis (exploratory) on the percentage absolute deviation in estimation and valuation. This analysis yielded qualitatively the same results as the original analysis, indicating the independence of the analysis on the dependent variable (absolute deviation or percentage absolute deviation).

Table 3
Beta Estimates for Log-Transformed Absolute Estimation and Valuation Deviation in Experiment 1.

Factor	Estimation noise	Valuation noise
Intercept	0.10	0.05
	(0.14)	(0.15)
Complexity	0.43[a]	0.27[a]
	(0.05)	(0.06)
LogAbsEst	–	0.14[a]
	–	(0.03)
AbsSkewness	0.07	−0.04
	(0.06)	(0.07)
SD	0.03[a]	0.03[a]
	(0.002)	(0.002)
EV	0.001	0.004[a]
	(0.001)	(0.001)

Note. Estimation errors are reported in parentheses. Complexity: Simple = 0 and complex = 1. LogAbsEst = Log-transformed absolute estimation deviation for the corresponding lottery; AbsSkewness = absolute skewness; SD = standard deviation; EV = expected value.
[a] Indicates a beta estimate for which zero is not contained in the 95% credible interval.

participants are asked to complete with the correct puzzle piece. In our data, the internal consistency of the measure was sufficiently high for a short version of the task (α = 0.65).

The experiment used a within-subject design, with all participants completing all the tasks and being presented the same lotteries and same matrices. The experiment consisted of three blocks. The order of the blocks was counterbalanced such that half of the

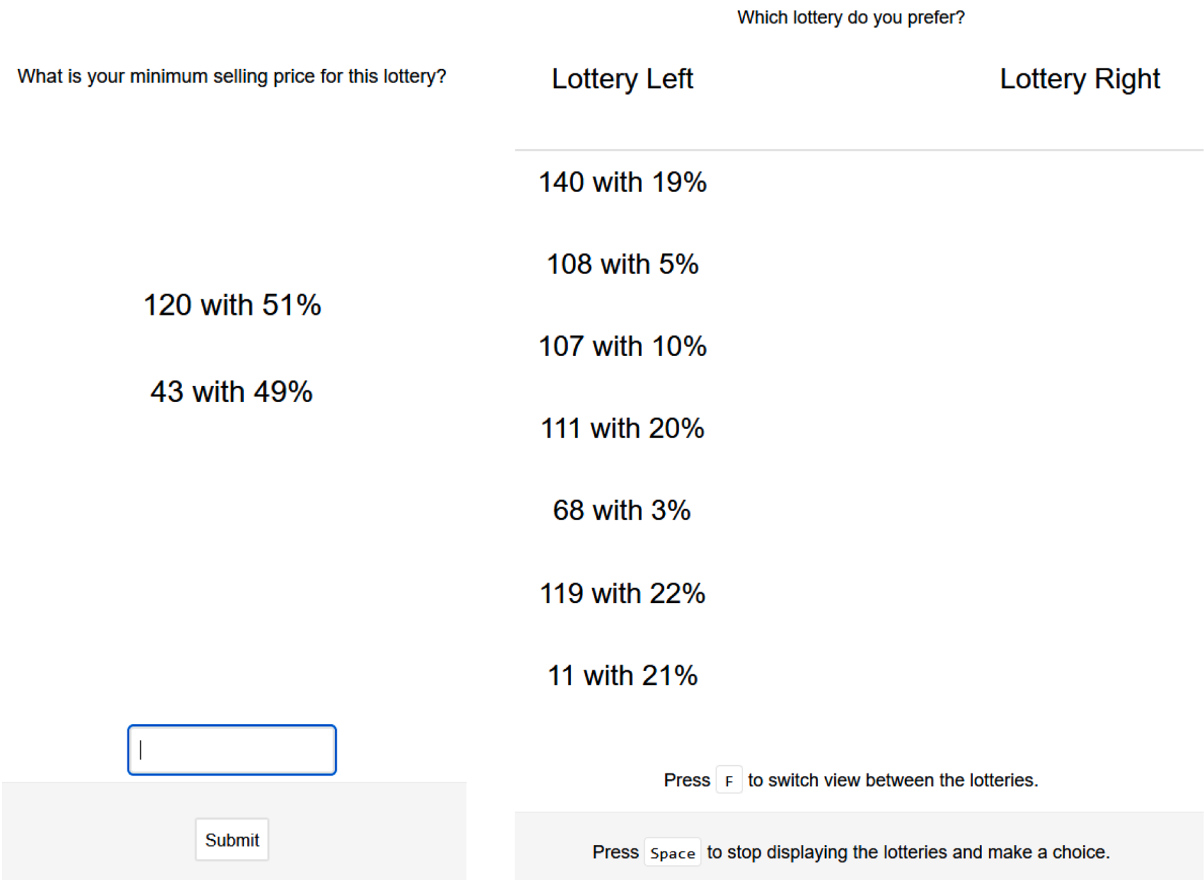

Fig. 3. *Task Examples for Valuation (Left) and Choice (Right) in Experiment 2.* Participants could enter a number via the keyboard in the valuation (left) task. In this example, a simple lottery is evaluated. In the choice task (right), participants could switch between the options by pressing the “F” key on the keyboard. In this example, the complex lottery is presented on the left and its corresponding simple lottery is presented on the right (covered). After sampling at least two times, participants could press the “Space” bar to indicate their willingness to answer. On the following page, participants were then asked to indicate their choice by pressing the left or right arrow key on the keyboard. There was no time limit for the task.

participants would start with the matrices task and the other half with the lottery tasks. The order within the lottery tasks (choice or valuation) was randomized too.

In the valuation task, participants indicated their minimum selling price by entering a number into an input field on the screen. In the choice task, participants chose the lottery they preferred out of two options displayed on the left and right side of the screen (simple and complex). To measure participants' attention, only one option was displayed at a time. Participants could press the "F" key on the keyboard to switch between the options as often as they liked. After they had accumulated enough information to make their decision, participants could press the space bar and advance to the choice screen on which they could indicate their choice by pressing the left or right arrow key. This allowed us to measure the time spent evaluating each option. The participants were familiarized to this procedure in a practice trial. Fig. 3 shows a screenshot of the valuation and choice task as an example.

The order of the lotteries within each block and the order of the outcomes within each lottery were randomized for each participant. To assess participants' understanding of the task, we employed an attention check at the beginning of each block right after the instructions, in which the participants had to indicate what they were supposed to do in the following task according to the instructions they had just read (multiple-choice question).

Besides participants' valuations and choices, we also measured response times in all elements of the experiment. At the end of the experiment, we assessed demographics (age and gender) and asked participants whether they had completed the experiment in good faith. Participants were encouraged to answer this question truthfully and were additionally reminded that their answer would have no consequence for them or their probability of winning the raffle.

To analyze the data, Bayesian methods were used when available. Inferences were drawn on the basis of credible intervals, BFs, confidence intervals, and p values as in Experiment 1. All materials can be found again on OSF (https://osf.io/p3sb7; https://osf.io/u5an6/) and deviations from the preregistration are reported in Supplementary Section 1.

3.1.2. Participants and procedure

Based on a simulation study and pilot data ($N = 60$) we determined a target sample size of $N = 330$ (details in Supplementary Section 3). To account for attrition, we tested 346 participants from a stratified national U.S. sample provided by Prolific.co. The sample was representative in terms of age, sex, and ethnicity (79 % sample accuracy). Data collection lasted several days, and participants failing attention checks were consecutively excluded from the experiment, allowing for new participants to participate. The participants received a base rate payment of £2.50 and a decision-dependent bonus ($M = £1.02$). Additionally, participants had the possibility to earn £30 in a raffle, with their chances of winning depending on the number of correctly solved matrices in the cognitive ability task. The valuation task incentivization was similar to that of the first experiment (BDM auction). Incentivization for the choice task was based on a single draw of one of the choices made by the participants and the lottery being played out. The values within the lotteries were converted such that participants received 0.5 % of the outcome in each task. Both incentivization procedures were explained to participants based on an example task in which detailed outcomes were displayed (see https://osf.io/u5an6/). There was no deception involved in the experiment and all information provided to the participants was truthful to the authors' best knowledge. The participants were asked to not use a calculator or any external aids (e.g., write anything down).

Data from 74 participants were excluded due to the following preregistered reasons: participant requested exclusion (eight), not understanding the instructions in one or more of the tasks (17), completing the experiment too fast (one quarter of mean time) or too slow (2.5 times mean time; five), selecting the option on the same side of the screen over 90 % of the time (six), and providing low quality data (more than 10 data points had to be excluded from one person, see below) (38). As participants completed the experiment faster than expected, we slightly adjusted the exclusion criteria for the time spent on the experiment from the preregistration, in which we specified that we would set the cut-off based on the expected time (30 min). The remaining data set included 272 participants.

The experiment was built and distributed in the same way as in Experiment 1. The average age of the final sample was 41.76 years ($Mdn = 40$ years, $SD = 15.12$), and 131 of the participants were female, 138 were male, and three indicated a nonbinary gender identity. The experiment lasted 24.24 min on average ($Mdn = 23.03$ min, $SD = 10.25$).

3.2. Results

3.2.1. Valuation

From the remaining data, we removed individual valuation trials when they were above the maximum or below the minimum of the outcomes presented in the lottery (14 % of valuation trials). To visualize the effect of complexity on valuations, we aggregated the data on the participant level and plotted the valuations (simple and complex) for every participant in Fig. 2 Panel C. The figure reveals a preference for simple lotteries: On average, participants indicated higher values for simple lotteries ($M_s = 91.92$, $SD_s = 17.29$, 95 % CI_s [89.88, 93.95]) than for complex lotteries ($M_c = 87.76$, $SD_c = 23.50$, 95 % CI_c [85.12, 90.40]).

Employing a Bayesian multilevel regression analogous to Experiment 1, with the inclusion of cognitive ability and the interaction between cognitive ability and complexity, confirmed that complexity led to lower valuations for complex compared to simple gambles (see Table 4, first column). To illustrate, all else being equal, a simple lottery evaluated by a participant with median cognitive ability ($Mdn = 4$) would be valued 2.7 % higher than a complex lottery according to the model.

Additionally, there was an interaction between complexity and cognitive ability, indicating that people with higher cognitive ability showed less undervaluation of the complex compared to the simple lottery. As can be seen in Fig. 4, the disparity between valuations of simple and complex lotteries decreased with higher cognitive ability and became undetectable at a cognitive ability level of 4 (out of 6). Note that this interaction is dependent on the scale of cognitive ability and complexity.

Finally, the multilevel model revealed that right skewness, low variance, and higher expected value led to higher valuations, replicating similar effects in Experiment 1. Since there was a systematic effect of complexity on valuation, we could not conduct an analysis of absolute deviation in valuation as in Experiment 1 (as originally planned) because such an analysis would be confounded by this systematic effect.

3.2.2. Choice

From the remaining data, we removed individual choice trials when the participants took longer than one minute or less than one second to look at a lottery in the choice task (3 % of data), indicating insufficient attention to the task. To visualize the effect of complexity on choice, we aggregated the data on the participant level and plotted the frequencies of complex choice proportions per individual in Fig. 5. As can be seen in the figure, some individuals were clearly complexity averse, as they never chose the complex option. The opposite (people always choosing the complex option) was observed in only one of 272 participants.

A multilevel Bayesian regression with choice as dependent variable (right-side option = 1, left-side option = 0; to test the influence of complexity outside the intercept), participant random intercepts and random slopes for each item-specific factor, and default priors confirmed that complex gambles were chosen less often than simple gambles (see Table 4, second column). To illustrate, all else being equal, complexity aversion in an exemplary participant with median cognitive ability ($Mdn = 4$) was offset if a complex option had a 7.4 % higher expected value than the simple lottery according to the model. Furthermore, the analysis showed that there was an interaction effect of cognitive ability and expected value difference, indicating that participants with higher cognitive ability were more sensitive to expected value differences between the options. This interaction is visualized in Fig. 6. However, there was no credible interaction effect of cognitive ability and complexity, indicating that participants with higher cognitive ability were not less complexity averse beyond being more sensitive to expected value differences. Finally, the intercept of the model was credibly positive, indicating that participants chose the right-side option more often regardless of content. Because we counterbalanced the position of the options on the screen, this preference for options on the right did not bias any of the results reported above.

3.2.3. Cognitive effort

To test the influence of cognitive effort on the dislike of complexity, we included two additional interactions in the model: looking time proportion (LTP), defined as $LTP = \frac{looking\ \ time\ \ complex}{looking\ \ time\ \ simple}$ and decision speed, defined as $\frac{60}{decision\ \ time} = choices\ \ per\ \ minute$. As decision speed (i.e., reverse of response time) is an important measure to better understand cognitive processes in preferential choice (see Clithero, 2018), we report some descriptive statistics first. On average participants made 10.11 decision per minute ($Med = 8.18$, $SD =$

Table 4
Beta Estimates of Valuation and Right-Side Option Choice in Experiment 2.

Factor	Valuation	Choice	Choice (CE)
Intercept	8.30[a]	1.23[a]	2.34[a]
	(2.75)	(0.29)	(0.31)
Complexity	−7.32[a]	−2.39[a]	−4.85[a]
	(1.53)	(0.53)	(0.55)
CogA	−0.44	−0.11	−0.07
	(0.33)	(0.08)	(0.08)
EV	0.94[a]	–	–
	(0.02)	–	–
dEV	–	1.64	1.79
	–	(1.31)	(1.38)
Skewness	1.90[a]	–	–
	(0.32)	–	–
SD	−0.22[a]	–	–
	(0.04)	–	–
Complexity × CogA	1.17[a]	0.22	0.13
	(0.40)	(0.14)	(0.14)
dEV × CogA	–	2.10[a]	2.18[a]
	–	(0.36)	(0.37)
LTP	–	–	−0.65[a]
	–	–	(0.05)
Speed	–	–	−0.01
	–	–	(0.01)
Complexity × LTP	–	–	1.47[a]
	–	–	(0.07)
Complexity × Speed	–	–	0.02
	–	–	(0.01)

Note. Estimation errors are reported in parentheses. Choice (CE) = Choice model including process measures of cognitive effort; Complexity: Simple = 0 and complex = 1 in valuations, simple option right-side = 0 and complex option right-side = 1 in choices. CogA = cognitive ability; EV = expected value; dEV = expected value difference right–left; SD = standard deviation; LTP = looking time proportion complex/simple; speed = number of decisions per minute.

[a] Indicates a beta estimate for which zero is not contained in the 95% credible interval.

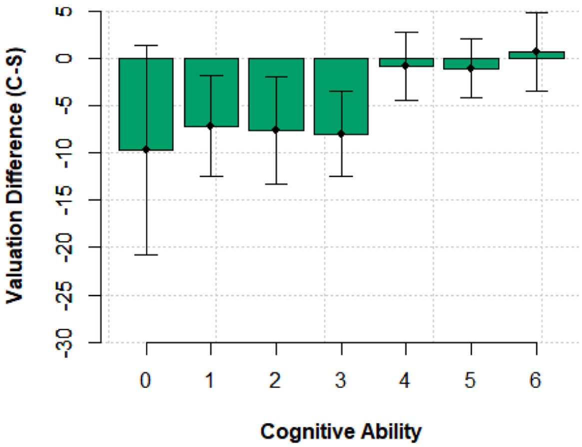

Fig. 4. *Difference in Valuation Between Simple and Complex Lotteries for Participants with Different Levels of Cognitive Ability based on Descriptives (Aggregated) in Experiment 2.* The data show that the difference decreases as cognitive ability increases. The difference disappears at a cognitive ability level of 4. Error bars denote 95 % confidence intervals based on standard errors. C = complex; S = simple.

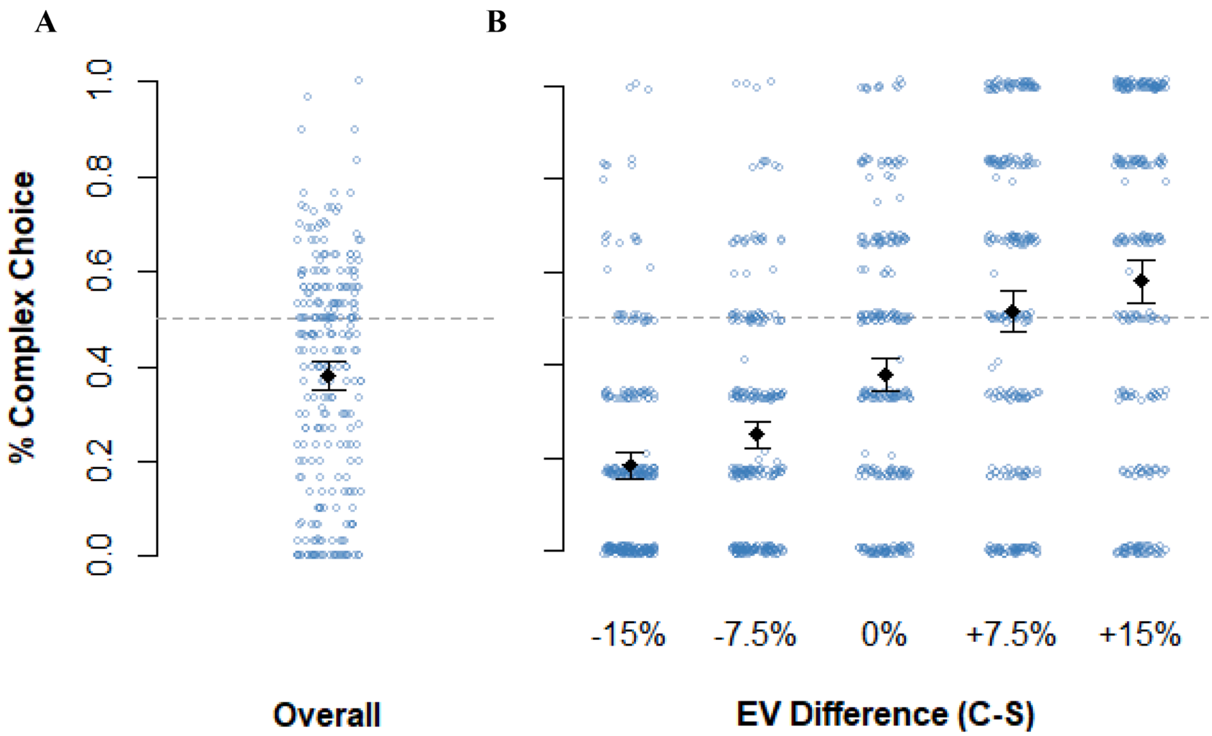

Fig. 5. *Individual Choice Proportions of the Complex Option (Panel A) and of the Complex Option Split by Expected Value (EV) Difference (Panel B) in Experiment 2.* The dashed lines indicate an unbiased choice proportion of 50 %. Dots below the dashed lines indicate complexity aversion. Error bars denote 95 % confidence intervals based on standard errors. C = Complex; S = simple. The data is aggregated within participants.

6.21). When choosing the simpler option, participants were able to make 9.35 decision per minute (*Med* = 7.81, *SD* = 5.59) and when choosing the more complex option 8.84 decision per minute (*Med* = 6.84, *SD* = 5.86) per minute.[4]

The extended regression model to predict choices revealed an interaction between LTP and complexity, indicating that the complex gamble was chosen more often when participants paid more attention to it (see Table 4, third column, and Fig. 7). Interestingly, at an LTP around 3.5, which would equal the proportion of information presented (two vs. seven outcomes), the bias disappears or even

[4] In this analysis we only used average decision speed for participants who made at least one choice for the simpler and at least one choice for the more complex option (241 participants).

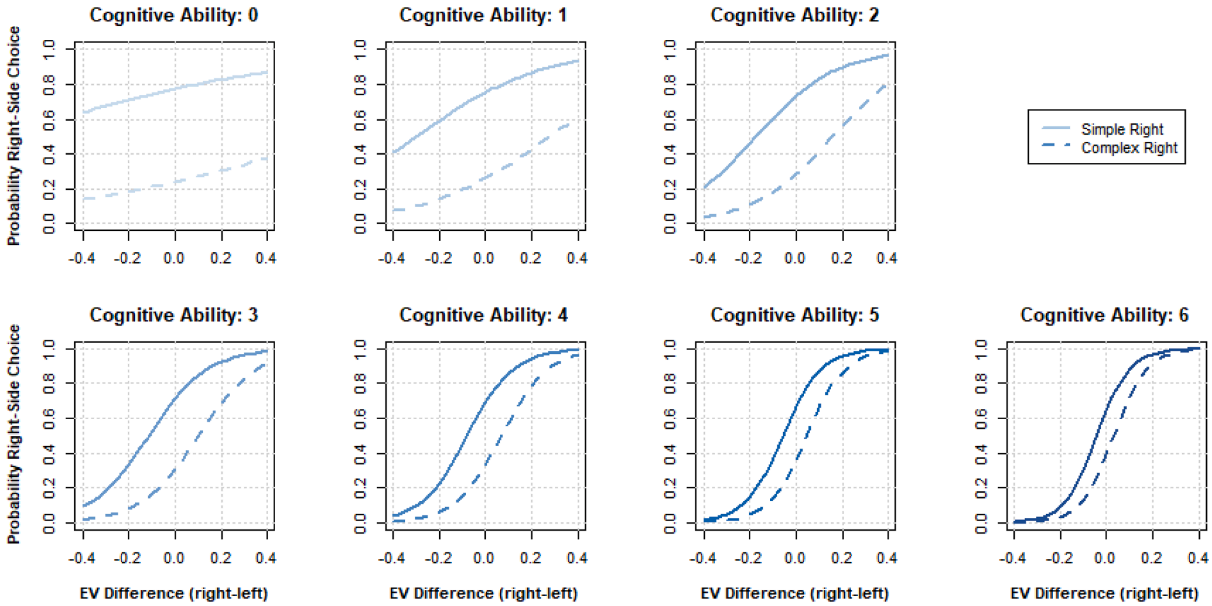

Fig. 6. *Interaction Plots for Cognitive Ability and Complexity in Choices in Experiment 2.* Higher cognitive ability leads to higher expected value (EV) sensitivity (steeper decision curve). EV differences in the experiment had a range of ±15 %. The *x* axis of the plots was extended to ±40 % to increase clarity and visibility.

inverts, as people eventually preferred the complex option. In contrast, there was no credible interaction between complexity and decision speed, indicating that complex gambles were not chosen less often during fast decisions.

3.3. Discussion Experiment 2

In a stratified national sample (79 % accuracy), we found evidence of complexity aversion in valuations and choice. In the valuation task, complex options were valued 2.7 % less than simple lotteries on average. In contrast, in the choice task, a complex option needed an expected value 7.4 % higher than the simple option to be equally attractive on average (see Fig. 6). This suggests that the effect of complexity was stronger in choices than in valuations, a valuation–choice gap. Furthermore, participants with higher cognitive ability showed less complexity aversion in valuations and more expected value sensitivity in choices. While this supports the general moderating role of individual cognitive ability, it does not support our hypothesis that cognitive ability decreases complexity aversion in choices beyond increasing expected value sensitivity. Lastly, the LTP measure of cognitive effort was a strong and credible predictor of complexity averse choice. Taken together, the observed valuation–choice gap, the partially moderating influence of cognitive ability, and the predictive quality of one of the process measures for cognitive effort are most in line with the hypothesis that complex options are chosen less often because the necessary cognitive effort to evaluate them is disliked and avoided.

4. General Discussion

Based on two experiments (one with a stratified national sample) we found that complexity affects risk taking in both, choices between two lotteries and valuations of single lotteries. Importantly, the effect of complexity was stronger in the choice than in the valuation task. In the choice task, complexity affected choice proportions only in trials where participants presumably avoided to process the complex lottery. As focusing on the easier lottery was not possible in the single valuation task, we propose the avoidance of cognitive effort as a cognitive mechanism to explain the difference between choices and valuations. Finally, to explain why the evidence for complexity aversion in valuations were ambiguous, we examined individual differences in cognitive ability. In Experiment 2, we found that only participants with lower cognitive ability discounted the complex options compared to easy ones. As Experiment 1 consisted of a student sample, we assume that cognitive ability was high in this participant pool, that way showing no effect of complexity on valuations.

4.1. The cognitive processes of complexity aversion

Furthermore, cognitive ability also affected choices. However, the moderating effect in choices was restricted to increasing expected value sensitivity. This indicates that the effect might not be as straightforward as expected. Future research could shed light on the details of this effect.

We also examined decision speed as a process measure and found that it was not a valid predictor of complexity aversion. In

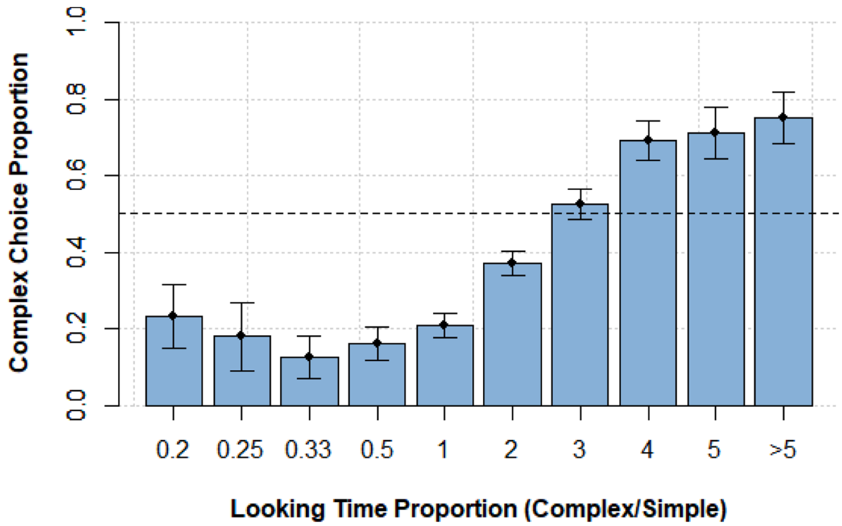

Fig. 7. *Descriptive Plot of Looking Time Proportion and the Complex Choice Proportion in Experiment 2.* Looking time proportion (LTP) was binned in nine symmetrical bins denoted by their upper limit and one summary bin (>5) and then aggregated within and eventually over all participants. Higher LTP for the complex option led to less or even an inversion of the complexity bias according to the interaction effect. Error bars denote 95 % confidence intervals based on standard errors.

general, decision speed (or response time) is an important measure of cognitive processes in economic decision making. For example, decision makers usually take longer to make decisions between options that are similar in their values compared to decisions between options with vastly different values (Clithero, 2018). Assuming that slower decision speed (or longer response time) indicates a more considerate decision process, the observed lack of a relation between decision speed and choices for complex lotteries indicates that complexity aversion should not be interpreted as general carelessness or sloppiness on the part of the study participants. This is in line with related findings showing that time pressure did not systematically affect the propensity to choose simpler options (Olschewski & Rieskamp, 2021).

We also found support for the hypothesis that complexity aversion is partly driven by response noise. More specifically, we found an increase in preference variability for complex options in the first experiment in which complexity led to substantially noisier valuations (31 %). This increase could have amplified the effect of complexity aversion reported in previous studies in which the higher expected value was predominantly assigned to the complex option and a choice of the option with lower expected value was interpreted as a potential dislike of complexity (Huck & Weizsäcker, 1999; Sonsino et al., 2002; see also Olschewski et al., 2018). Apart from that, we found no evidence in support of the hypothesis that complexity aversion results from a (perceptual) underestimation, as there was no difference in the mean estimation between complex and simple lotteries in Experiment 1.

Concerning the metacognitive awareness of noisy perception, participants indeed perceived their estimates to be less precise when evaluating complex lotteries in Experiment 1, as indicated by their confidence ratings. Hence, the complexity of lotteries can induce epistemic uncertainty about the true mean of the outcome distribution of a lottery. Epistemic uncertainty about the outcome distribution could also explain why splitting single outcomes of a lottery into two very similar outcomes can decrease its valuation compared to lotteries without split outcomes (Bernheim & Sprenger, 2020). Moreover, this uncertainty could induce a similar cognitive process as the uncertainty introduced in studies about ambiguity attitude, in which, for example, the distribution of colored balls in an urn is concealed and the participants' task is to bet on drawing a ball with a certain color (e.g., Armantier & Treich, 2016; Kovářík et al., 2016). However, in our study the participants' lower confidence in their estimates for complex lotteries did not translate to a dislike (i.e., lower valuations) for complex gambles. To the extent that decision makers are risk or ambiguity averse, this can be interpreted as maladaptive, because the confidence should reflect the degree of uncertainty about their own estimate (see also Olschewski & Scheibehenne, 2023). As a limitation, it has to be considered that the hypotheses concerning the perceptual effects could only be tested in Experiment 1, which was based on a sample of university students. It is possible that perceptual influences might be more relevant in a more heterogeneous sample.

Finally, because we controlled for skewness and variance in our lottery stimuli, we could assess the influence of these factors on valuations and estimations (see also Supplementary Section 4). Participants' risk-taking behavior was generally in line with previous findings in the literature. Participants were overall risk averse (e.g., Holt & Laury, 2002) and they preferred options with a high rare outcome (i.e., right-skewed options) over options with a low rare outcome (i.e., left-skewed options; Becker, Ert, Trautmann, & Van De Kuilen, 2021; Ebert & Wiesen, 2011; Spiliopoulos & Hertwig, 2019; Trautmann & van de Kuilen, 2018; Tversky & Kahneman, 1992). Unlike in studies in decisions from experience (Olschewski et al., 2021), the effect of variance on mean estimations was not credible. Hence, avoiding high-variance lotteries in decisions from description cannot be explained by an estimation bias. In contrast, participants estimated lotteries with high rare outcomes to have higher expected values than lotteries with low rare outcomes. Thus, part of the supposed preference for right-skewed lotteries could be explained by perceiving right-skewed lotteries to have the higher expected value.

4.2. Implications

Response noise in valuations and estimations was substantially higher for complex lotteries compared to their simpler counterparts. As this noise effect was already present on the estimation level, this implies that it was most likely caused by errors during information integration because more information has to be integrated for complex lotteries. An increase of unsystematic noise is something that future experiment designs should account for. To avoid inferring bias when there is only noise, experimental designs with symmetrical stimuli variation should be employed. Likewise, deviations from a decision proportion of 100 % should be interpreted cautiously because a decision process with maximum noise will lead to a choice proportion of 50:50.

Biased preferences for complex lotteries were especially prevalent in choices, but less robust in valuations. We explained the difference between the elicitation formats with a dislike of cognitive effort. This implies that future experimental designs should take complexity into account because eliciting risk preferences from stimuli that differ in complexity can lead to unintentionally biased data. Moreover, the moderating influence of cognitive ability suggests that individual differences play an important role in how people cope with complexity. This is in line with previous research on individual differences (Moffatt et al., 2015) and age effects (Zilker et al., 2020) in complexity aversion. Hence, complexity aversion is not universally observed for all participants in all situations. Also in our study some participants expressed robust preferences for complex lotteries both in valuation and choice (see Supplementary Section 3), and complexity aversion in choice was influenced by participants' age (see Supplementary Section 5). Individual heterogeneity also relates to research examining how higher levels of education or quantitative sophistication affect attitudes towards ambiguity and compound risk (Abdellaoui et al., 2015; Aydogan et al., 2023; Chew et al., 2018).

Finally, the observed quantitative valuation–choice gap in the dislike of complexity suggests that the bias can be reduced by presenting alternatives one at a time (valuation). Presumably, this is because this format requires participants to engage with every option and makes the differences in complexity less salient (for similar observations for ambiguity attitudes see Du & Budescu, 2005; Fox & Tversky, 1995). In other words, valuations were less biased by complexity than choices and might be the preferable paradigm to measure risk preferences if differing complexity between target options cannot be avoided.

4.3. Limitations and future research

One could have expected an effect of cognitive ability on complexity aversion also in choice, assuming that cognitive ability reduces cognitive effort in choices the same way as in valuations. While we did not find a direct significant interaction, we found a moderating influence of cognitive ability on expected value sensitivity. In our experimental design, a decision maker who is more sensitive to expected value will be less affected by complexity. This interaction provides indirect evidence for reduced complexity aversion (stemming from an unsystematic effect in asymmetrical experimental designs) in choices for people with high cognitive abilities. Moreover, it is possible that there is an interaction between cognitive ability and cognitive effort, meaning that cognitive ability might have lost its predictive validity because cognitive effort was the stronger predictor in the model. However, more research is necessary to confirm these relations.

Further, we interpreted the time spent evaluating each option (LTP) as a measure of attention and reported a disappearance or inversion of the bias at sufficient attention in the choice task. However, the causal direction could also be reversed. Assuming the bias is a plain preference (not dependent on the avoidance of cognitive effort), the LTP could be an expression of preference, as it has been shown that people look longer at options they prefer (e.g., Shimojo et al., 2003). We find both directions plausible; the effect is likely bidirectional (Krajbich et al., 2010; Smith & Krajbich, 2019). Interestingly, Zilker and Pachur (2020) did not find that option complexity contributes to age effects in framing, loss aversion, or delay discounting. These findings conflict with our assumption of a relatively general mechanism (avoidance of cognitive effort) as the most probable explanation of complexity aversion.

Our results are subject to our implementation of the two experiments and the chosen analyses. First, we used the number of outcomes as a manipulation of complexity, but there are many different ways in which complexity can be introduced in decisions under risk (e.g., Armantier & Treich, 2016). Future research can reveal whether different (e.g., text-based complexity) or more extreme (e.g., more than seven outcomes in a lottery) manipulations of complexity lead to the same pattern of results. Second, the participants' incentives differed between Experiment 1 and 2. Whereas the outcomes in Experiment 1 were translated into tombola tickets for an additional lottery, in Experiment 2 they were directly transferred to a monetary bonus. This difference should be taken into account in particular when comparing valuations of complex lotteries between the two experiments. In general, the monetary incentives in our experiments were relatively small and complexity aversion might reduce if incentives increase (but see, Armantier & Treich, 2016). Third, as we excluded participants that took much longer (or shorter) to complete the experiment as the average participant in our samples, this could potentially lead to a biased sample excluding participants, who thoroughly try to process information for complex lotteries. However, as the number of participants excluded according to their time spent on the experiment was small (two in Experiment 1 and five in Experiment 2), this was not a practical concern, and the conclusions we drew from the main analyses all remained unchanged when we included these participants.

Finally, future research should investigate how dislike of cognitive effort shapes behavior beyond controlled lab experiments, for example, in investment decisions, consumer choice, and potentially also more general learning contexts in which cognitive effort plays a central role. To the degree that individual differences in dislike of cognitive effort are partially learned through the association of invested effort and received reward (e.g., Inzlicht et al., 2018), complexity preferences might be malleable. Moreover, this would suggest that complexity aversion can be unlearned. Future experiments could explore this possibility, as it could inform intervention designs intended to reduce complexity aversion.

4.4. Conclusion

In daily life, people face ever-increasing complexity in many domains such as financial and consumer decisions. We showed that differences in complexity systematically impact risk taking and that individuals with low cognitive abilities dislike complex options in particular. On a societal level, this mechanism has the potential to increase income and wealth inequality, as people with low cognitive abilities might shy away from complex, but highly rewarding options such as investing in stocks. We also showed that the impact of complexity on risk taking can be mitigated when presenting options sequentially, rather than simultaneously. Thus, it is important for researchers to understand and model the effect of complexity on preferential decisions and for choice architects to take option complexity into account when designing choice environments to guarantee a level playing field for all individuals.

5. Authors' note

All data, materials and preregistration are available on OSF: https://osf.io/u5an6/. This research has been funded by the Swiss National Science Foundation (SNSF) Grant Nr. 100014_175849. We thank Anita Todd for editing the manuscript. Due to unforeseen circumstances, Yvonne Oberholzer was not able to fully read and edit the final version of the manuscript after the revisions that we made in response to the reviewers' comments.

CRediT authorship contribution statement

Yvonne Oberholzer: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **Sebastian Olschewski:** Conceptualization, Funding acquisition, Methodology, Supervision, Writing – review & editing. **Benjamin Scheibehenne:** Conceptualization, Funding acquisition, Methodology, Supervision, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary material

Supplementary material to this article can be found online at https://doi.org/10.1016/j.joep.2023.102681.

References

Abdellaoui, M., Klibanoff, P., & Placido, L. (2015). Experiments on compound risk in relation to simple risk and to ambiguity. *Management Science, 61*(6), 1306–1322.

Andersson, O., Holm, H. J., Tyran, J.-R., & Wengström, E. (2016). Risk aversion relates to cognitive ability: Preferences or noise? *Journal of the European Economic Association, 14*(5), 1129–1154. https://doi.org/10.1111/jeea.12179

Armantier, O., & Treich, N. (2016). The rich domain of risk. *Management Science, 62*(7), 1954–1969.

Aydogan, I., Berger, L., & Bosetti, V. (2023). *Unraveling Ambiguity Aversion* (No. 2023-iRisk-01).

Becker, C. K., Ert, E., Trautmann, S. T., & Van De Kuilen, G. (2021). Experiencing risk: Higher-order risk attitudes in description-and experience-based decisions. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 47*(5), 727.

Becker, G. M., Degroot, M. H., & Marschak, J. (1964). Measuring utility by a single-response sequential method. *Behavioral Science, 9*(3), 226–232. https://doi.org/10.1002/bs.3830090304

Bernheim, B. D., & Sprenger, C. (2020). On the empirical validity of cumulative prospect theory: Experimental evidence of rank-independent probability weighting. *Econometrica, 88*(4), 1363–1409.

Blaufus, K., & Ortlieb, R. (2009). Is simple better? A conjoint analysis of the effects of tax complexity on employee preferences concerning company pension plans. *Schmalenbach Business Review, 61*(1), 60–83. https://doi.org/10.1007/BF03396780

Bopp, K. L., & Verhaeghen, P. (2005). Aging and verbal memory span: A meta-analysis. *The Journals of Gerontology: Series B, 60*(5), P223–P233. https://doi.org/10.1093/geronb/60.5.P223

Boxall, P., (Vic) Adamowicz, W. L., & Moon, A. (2009). Complexity in choice experiments: Choice of the status quo alternative and implications for welfare measurement. *Australian Journal of Agricultural and Resource Economics, 53*(4), 503–519. https://doi.org/10.1111/j.1467-8489.2009.00469.x

Bruce, A. C., & Johnson, J. E. V. (1996). Decision-making under risk: Effect of complexity on performance. *Psychological Reports, 79*(1), 67–76. https://doi.org/10.2466/pr0.1996.79.1.67

Bürkner, P.-C. (2018). Advanced Bayesian multilevel modeling with the R package brms. *The R Journal, 10*(1), 395–411.

Burks, S. V., Carpenter, J. P., Goette, L., & Rustichini, A. (2009). Cognitive skills affect economic preferences, strategic behavior, and job attachment. *Proceedings of the National Academy of Sciences, 106*(19), 7745–7750. https://doi.org/10.1073/pnas.0812360106

Champely, S. (2020). *pwr: Basic functions for power analysis. R package version 1.3-0* [Computer software manual]. https://CRAN.R-project.org/package=pwr.

Chew, S. H., Miao, B., & Zhong, S. (2018). *Ellsberg meets Keynes at an urn.* Working paper.

Butler, D. J., & Loomes, G. C. (2007). Imprecision as an account of the preference reversal phenomenon. *American Economic Review, 97*(1), 277–297.

Clithero, J. A. (2018). Response times in economics: Looking through the lens of sequential sampling models. *Journal of Economic Psychology, 69*, 61–86.

Dehaene, S. (1992). Varieties of numerical abilities. *Cognition, 44*(1), 1–42. https://doi.org/10.1016/0010-0277(92)90049-N

Dehaene, S. (2011). *The number sense: How the mind creates mathematics* (Revised and Updated Edition). USA: Oxford University Press.

Dhar, R. (1997a). Consumer preference for a no-choice option. *Journal of Consumer Research, 24*(2), 215–231. https://doi.org/10.1086/209506

Dhar, R. (1997b). Context and task effects on choice deferral. *Marketing Letters, 8*(1), 119–130. https://doi.org/10.1023/A:1007997613607

Du, N., & Budescu, D. V. (2005). The effects of imprecise probabilities and outcomes in evaluating investment options. *Management Science, 51*(12), 1791–1803.

Ebert, S., & Wiesen, D. (2011). Testing for prudence and skewness seeking. *Management Science, 57*(7), 1334–1349.
Evangelidis, I., Lev, J., & Simonson, I. (2022). A reexamination of the impact of decision conflict on choice deferral. *Management Science, Forthcoming.*
Fox, C. R., & Tversky, A. (1995). Ambiguity aversion and comparative ignorance. *The Quarterly Journal of Economics, 110*(3), 585–603.
Fox, C. R., & Ülkümen, G. (2011). Distinguishing two dimensions of uncertainty. In W. Brun, G. Keren, G. Kirkeboen, & H. Montgomery (Eds.), *Perspectives on thinking, judging, and decision making* (pp. 21–35). Oslo, Norway: Universitetsforlaget.
Frank, R. G., & Lamiraud, K. (2009). Choice, price competition and complexity in markets for health insurance. *Journal of Economic Behavior & Organization, 71*(2), 550–562. https://doi.org/10.1016/j.jebo.2009.04.005
Grady, C. (2012). The cognitive neuroscience of ageing. *Nature Reviews Neuroscience, 13*(7), 491–505. https://doi.org/10.1038/nrn3256
Grether, D. M., & Plott, C. R. (1979). Economic theory of choice and the preference reversal phenomenon. *American Economic Review, 69*(4), 623–638.
Henninger, F., Shevchenko, Y., Mertens, U. K., Kieslich, P. J., & Hilbig, B. E. (2019). lab.js: A free, open, online study builder. *PsyArXiv*. https://doi.org/10.31234/osf.io/fqr49
Heydasch, T., Haubrich, J., & Renner, K.-H. (2013). The short version of the Hagen Matrices Test (HMT-S): A 6-item induction intelligence test. *Methods, Data, Analyses, 7*(2). https://doi.org/10.12758/MDA.2013.011
Holt, C. A., & Laury, S. K. (2002). Risk aversion and incentive effects. *American Economic Review, 92*(5), 1644–1655. https://doi.org/10.1257/000282802762024700
Horn, J. L., & Cattell, R. B. (1967). Age differences in fluid and crystallized intelligence. *Acta Psychologica, 26*, 107–129. https://doi.org/10.1016/0001-6918(67)90011-X
Huck, S., & Weizsäcker, G. (1999). Risk, complexity, and deviations from expected-value maximization: Results of a lottery choice experiment. *Journal of Economic Psychology, 20*(6), 699–715. https://doi.org/10.1016/S0167-4870(99)00031-8
Inzlicht, M., Shenhav, A., & Olivola, C. Y. (2018). The effort paradox: Effort is both costly and valued. *Trends in Cognitive Sciences, 22*(4), 337–349. https://doi.org/10.1016/j.tics.2018.01.007
Izard, V., & Dehaene, S. (2008). Calibrating the mental number line. *Cognition, 106*(3), 1221–1247. https://doi.org/10.1016/j.cognition.2007.06.004
Kovářík, J., Levin, D., & Wang, T. (2016). Ellsberg paradox: Ambiguity and complexity aversions compared. *Journal of Risk and Uncertainty, 52*, 47–64.
Krajbich, I., Armel, C., & Rangel, A. (2010). Visual fixations and the computation and comparison of value in simple choice. *Nature Neuroscience, 13*(10), 1292–1298. https://doi.org/10.1038/nn.2635
Kool, W., McGuire, J. T., Rosen, Z. B., & Botvinick, M. M. (2010). Decision making and the avoidance of cognitive demand. *Journal of Experimental Psychology. General, 139*(4), 665–682. https://doi.org/10.1037/a0020198
Lange, K., Kühn, S., & Filevich, E. (2015). "Just Another Tool for Online Studies" (JATOS): An easy solution for setup and management of web servers supporting online studies. *PLoS ONE, 10*(6), Article e0130834. https://doi.org/10.1371/journal.pone.0130834
Mador, G., Sonsino, D., & Benzion, U. (2000). On complexity and lotteries' evaluation—Three experimental observations. *Journal of Economic Psychology, 21*(6), 625–637. https://doi.org/10.1016/S0167-4870(00)00023-4
Mechera-Ostrovsky, T., Heinke, S., Andraszewicz, S., & Rieskamp, J. (2022). Cognitive abilities affect decision errors but not risk preferences: A meta-analysis. *Psychonomic Bulletin & Review*. https://doi.org/10.3758/s13423-021-02053-1
Moffatt, P. G., Sitzia, S., & Zizzo, D. J. (2015). Heterogeneity in preferences towards complexity. *Journal of Risk and Uncertainty, 51*(2), 147–170. https://doi.org/10.1007/s11166-015-9226-3
Olschewski, S., Newell, B. R., Oberholzer, Y., & Scheibehenne, B. (2021). Valuation and estimation from experience. *Journal of Behavioral Decision Making, 34*(5), 729–741. https://doi.org/10.1002/bdm.2241
Olschewski, S., & Rieskamp, J. (2021). Distinguishing three effects of time pressure on risk taking: Choice consistency, risk preference, and strategy selection. *Journal of Behavioral Decision Making, 34*(4), 541–554. https://doi.org/10.1002/bdm.2228
Olschewski, S., Rieskamp, J., & Scheibehenne, B. (2018). Taxing cognitive capacities reduces choice consistency rather than preference: A model-based test. *Journal of Experimental Psychology: General, 147*(4), 462–484. https://doi.org/10.1037/xge0000403
Olschewski, S., & Scheibehenne, B. (2023). What's in a sample? How sampling information affects epistemic uncertainty and risk-taking. *PsyArXiv*. https://doi.org/10.31234/osf.io/hf8dm
Puri, I. (2018). *Preference for simplicity*. Available at SSRN 3253494.
R Core Team. (2020). R: A language and environment for statistical computing. [Computer software manual]. R Foundation for Statistical Computing. https://www.R-project.org/.
Rouder, J. N., Speckman, P. L., Sun, D., Morey, R. D., & Iverson, G. (2009). Bayesian t tests for accepting and rejecting the null hypothesis. *Psychonomic Bulletin & Review, 16*, 225–237.
Sandra, D. A., & Otto, A. R. (2018). Cognitive capacity limitations and need for cognition differentially predict reward-induced cognitive effort expenditure. *Cognition, 172*, 101–106. https://doi.org/10.1016/j.cognition.2017.12.004
Scheibehenne, B. (2019). The psychophysics of number integration: Evidence from the lab and from the field. *Decision, 6*(1), 61–76. https://doi.org/10.1037/dec0000089
Schley, D. R., & Peters, E. (2014). Assessing "economic value": Symbolic-number mappings predict risky and riskless valuations. *Psychological Science, 25*(3), 753–761. https://doi.org/10.1177/0956797613515485
Schneider-Garces, N. J., Gordon, B. A., Brumback-Peltz, C. R., Shin, E., Lee, Y., Sutton, B. P., Maclin, E. L., Gratton, G., & Fabiani, M. (2010). Span, CRUNCH, and beyond: Working memory capacity and the aging brain. *Journal of Cognitive Neuroscience, 22*(4), 655–669. https://doi.org/10.1162/jocn.2009.21230
Shimojo, S., Simion, C., Shimojo, E., & Scheier, C. (2003). Gaze bias both reflects and influences preference. *Nature Neuroscience, 6*(12), 1317–1322. https://doi.org/10.1038/nn1150
Siegler, R. S., & Opfer, J. E. (2003). The development of numerical estimation: Evidence for multiple representations of numerical quantity. *Psychological Science, 14*(3), 237–243. https://doi.org/10.1111/1467-9280.02438
Slovic, P., & Lichtenstein, S. (1983). Preference reversals: A broader perspective. *The American Economic Review, 73*(4), 596–605.
Smith, S. M., & Krajbich, I. (2019). Gaze amplifies value in decision making. *Psychological Science, 30*(1), 116–128.
Sonsino, D., Benzion, U., & Mador, G. (2002). The complexity effects on choice with uncertainty—Experimental evidence. *The Economic Journal, 112*(482), 936–965. https://doi.org/10.1111/1468-0297.00073
Spiliopoulos, L., & Hertwig, R. (2019). Nonlinear decision weights or moment-based preferences? A model competition involving described and experienced skewness. *Cognition, 183*, 99–123. https://doi.org/10.1016/j.cognition.2018.10.023
Stanovich, K. E. (2018). Miserliness in human cognition: The interaction of detection, override and mindware. *Thinking & Reasoning, 24*(4), 423–444. https://doi.org/10.1080/13546783.2018.1459314
Trautmann, S. T., & van de Kuilen, G. (2018). Higher order risk attitudes: A review of experimental evidence. *European Economic Review, 103*, 108–124.
Tversky, A., & Kahneman, D. (1992). Advances in prospect theory: Cumulative representation of uncertainty. *Journal of Risk and Uncertainty, 5*(4), 297–323. https://doi.org/10.1007/BF00122574
Tversky, A., & Shafir, E. (1992). Choice under conflict: The dynamics of deferred decision. *Psychological Science, 3*(6), 358–361. https://doi.org/10.1111/j.1467-9280.1992.tb00047.x
Tversky, A., Slovic, P., & Kahneman, D. (1990). The causes of preference reversal. *The American Economic Review, 80*(1), 204–217.
Westbrook, A., Kester, D., & Braver, T. S. (2013). What is the subjective cost of cognitive effort? Load, trait, and aging effects revealed by economic preference. *PLoS ONE, 8*(7), Article e68210. https://doi.org/10.1371/journal.pone.0068210
Zilker, V., Hertwig, R., & Pachur, T. (2020). Age differences in risk attitude are shaped by option complexity. *Journal of Experimental Psychology: General, 149*(9), 1644–1683. https://doi.org/10.1037/xge0000741
Zilker, V., & Pachur, T. (2020). Does option complexity contribute to the framing effect, loss aversion, and delay discounting in younger and older adults? *Journal of Behavioral Decision Making*. https://doi.org/10.1002/bdm.2224 [Advance online publication].