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The relationship between ambiguity attitudes and cognitive ability

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Abstract

The present thesis investigated the relationship between cognitive ability and ambiguity attitudes. Specifically, the study focused on separating ambiguity attitudes in the gain and loss domains and used the Cognitive Reflection Test (CRT) and the Berlin Numeracy Test (BNT) to measure different components of cognitive ability. Four hypothetical situations with varying stakes and outcome domains were presented to participants to examine their attitudes toward uncertainty through binary choices between betting on a risky or an uncertain Ellsberg urn. The findings indicated a homogenous sample with only slight deviations from ambiguity neutral choices. The study found a surprising, statistically significant positive relationship between CRT scores and matching probabilities in the gain domain with low stakes, contrary to expectations based on relevant literature. The study did not find any significant relationship between other measures of cognitive ability and ambiguity attitudes.

1 Introduction

1.1 Introduction and motivation

People have to make many decisions involving uncertainty since, in most situations, the probabilities and an action's possible outcomes are unknown. Therefore, understanding the individual willingness to take risks plays an essential role in the comprehension and prediction of economic decisions, as people are facing an increasing number of decisions that involve risk (Weber, 2010).

The fundamental distinction between risk and uncertainty is whether decision makers understand the precise probabilities of possible outcomes (LeRoy & Singell Jr, 1987). Knight (1921) was one of the first authors who differentiated measurable uncertainty or risk from unmeasurable uncertainty, which exact, numerical probabilities cannot represent. Keynes (1921) came up with a similar concept in the same year. Daniel Ellsberg (1961) further explored the concept of this difference in his landmark paper. In his work, he argued that when faced with a choice between an urn with a known distribution of balls (50 red and 50 black) and another one with an unknown mix (100 balls, either red or black), people prefer to bet on a ball drawn from the former. In Ellsberg's two urn paradox, participants can bet on (1) a red ball being drawn from the urn with a known distribution of balls, (2) a black ball being drawn from the urn with a known distribution of balls, (3) a red ball being drawn from the urn with an unknown distribution of balls and (4) a black ball being drawn from the urn with an unknown distribution of balls. Typically, people choose to bet on the urn with known probability for both red and black balls, which violates the assumption of additive beliefs of the Subjective Expected Utility Theory (Savage, 1954). The preference of prospect (1) over (3) implies that people assume a higher probability of red being drawn from the urn with a 50-50 distribution while choosing prospect (2) over (4) suggests that individuals believe that the probability of a black ball being drawn from the urn with known probabilities is also higher than from the urn with unknown probabilities. This finding shows that agents have different attitudes toward risk (known probabilities) and uncertainty (unknown probabilities), most of which are ambiguity averse.

While several studies have shown that ambiguity aversion is more prevalent in the population than other ambiguity attitudes, it is often found that preference toward ambiguity depends significantly on whether outcomes are framed as gains or losses (Kocher, Lahno &

Trautmann, 2018). In contradiction with the extensive literature on ambiguity aversion in economic decision making, ambiguity-neutral or even ambiguity-seeking behavior is more recurrent in the loss domain (Kocher, Lahno & Trautmann, 2015). People use different probability weighting strategies for gains and losses: small probability events are overweighted, which means that individuals are more optimistic about gains (ambiguity-neutral or seeking behavior) and more pessimistic about losses (ambiguity-averse attitude). Conversely, people tend to underweight probabilities for events with moderate or high likelihood; hence, they are more likely to be ambiguity averse for gains and ambiguity-neutral or seeking in the loss domain.

Many empirical studies also looked at the relationship between risk and ambiguity attitudes and reported a positive correlation between ambiguity aversion and risk aversion (Trautmann & van de Kuilen, 2015). In addition, several authors found a positive relationship between attitude toward risk and ambiguity when measured for the same person with different tasks (Dimmock et al., 2016; Butler et al., 2011). There is also evidence of a high correlation between the pessimism in probability weighting for events with risk and ambiguity (for low likelihood losses and moderate probability gains) (Abdellaoui et al., 2011).

There is also growing literature on the connection between cognitive ability and attitudes toward risk and uncertainty. Previous studies mainly focus on risk attitudes, and some have shown that cognitive ability is negatively related to risk aversion (Dohmen, Falk, Huffman & Sunde, 2010). The level of numeracy seems to be an important factor in decision making and judgment, as people with a lower level of numeracy are not only more sensitive to framing effects (Reyna et al., 2009) but also estimate risk less accurately than those with higher levels of numeracy (Black, Nease & Tosteson, 1995). Prudence is pervasive among people with high cognitive ability and high education (Noussair, Trautmann & van de Kuilen, 2014). People with higher cognitive ability tend to be less risk-averse, more patient, and more likely to utilize a more complex decision making process. Despite many studies reporting a positive relationship between risk and ambiguity aversion, several authors could not report any correlation between cognitive ability and ambiguity attitudes (Sutter, Kocher, Glatzle-Rützler & Trautmann, 2013; Tymula, Rosenberg Belmaker, Roy & Levy, 2012). Many studies have investigated the relationship between cognitive ability and risk attitudes, but the correlation with ambiguity attitudes is understudied. This thesis intends to fill this gap in the literature by conducting an experiment.

Understanding the relationship between cognitive ability and ambiguity attitudes can help gain insights into how individuals respond to ambiguous situations and how this process relates to problem-solving abilities. By providing a deeper understanding of the decision making process, this research can have practical implications for various fields such as economics, finance, psychology, or marketing and contribute to developing theories of decision making under uncertainty. Additionally, understanding the factors that influence ambiguity attitudes can help policymakers by being able to predict individuals' choices regarding financial matters, insurance, investments, or medical treatments. By exploring the relationship between decision making under uncertainty and cognitive abilities, economic advisors could design better financial products and services that meet the needs of individuals with different ambiguity attitudes and cognitive abilities and could help individuals make more informed decisions. This could improve financial literacy and help to make financial education more efficient.

Moreover, with decisions involving numerical information becoming more common in society, understanding and evaluating numerical concepts bear more importance in daily life. This thesis plans to explore further insights into the decision making process under uncertainty, focusing on the relationship between cognitive abilities and ambiguity attitudes concerning prospects involving losses, with the potential to explain anomalies in economic decisions. The findings of this thesis could be essential to understand the process behind decision making in the loss domain, as many choices that people face in daily life involve potential negative outcomes.

1.2 Research questions

The research questions of this thesis are the following:

- Is there evidence that cognitive ability - measured with the Cognitive Reflection Test (CRT) - has an effect on ambiguity attitudes in the loss domain?
- To what extent is there a relationship between numeracy - measured with the Berlin Numeracy Test (BNT) - and ambiguity attitudes in the loss domain?
- Is there evidence that cognitive ability - measured with the Cognitive Reflection Test (CRT) - has an effect on ambiguity attitudes in the gain domain?
- To what extent is there a relationship between numeracy - measured with the Berlin Numeracy Test (BNT) - and ambiguity attitudes in the gain domain?

1.3 Hypotheses

Based on the relevant scientific literature, the hypotheses of this thesis are the following:

- H1. Numeracy - measured with the Berlin Numeracy Test (BNT) - is negatively correlated with ambiguity aversion in the gain domain.
- H2. Numeracy - measured with the Berlin Numeracy Test (BNT) - is negatively correlated with ambiguity aversion in the loss domain.
- H3. Cognitive ability - measured with the Cognitive Reflection Test (CRT) - is negatively correlated with ambiguity aversion in the gain domain.
- H4. Cognitive ability - measured with the Cognitive Reflection Test (CRT) - is negatively correlated with ambiguity aversion in the loss domain.

1.4 Structure of the thesis

The remainder of this thesis is structured as follows. The second section explores the relevant literature with focus on the topics of attitudes toward uncertainty, the measures of cognitive ability and the relationship between cognitive ability and ambiguity attitudes. Section 3 details the experimental design and empirical strategy, followed by the description of the results in Section 4. Section 5 discusses the results, while Section 6 summarizes the findings and draws the conclusions and implications.

2 Literature review

2.1 Attitudes toward uncertainty

Attitude toward ambiguity reflects the differences between sources with known and unknown probabilities, and to examine it, we can compare source functions for ambiguous sources and sources with known probabilities (Abdellaoui, Baillon, Placido & Wakker, 2011). The empirical literature studying the pervasiveness and causes of ambiguity aversion has shown that ambiguity attitudes depend on several components, such as the likelihood of uncertain events, the outcome domain, and the source that creates uncertainty (Trautmann & van de Kuilen, 2015).

Ambiguity attitudes are principally explained by two components: ambiguity aversion and a-insensitivity (Dimmock, Kouwenberg & Wakker, 2016). Ambiguity aversion describes the unwillingness to bet in ambiguous situations, in which the probabilities of different outcomes are unknown (Fox, Erner & Walters, 2015), while a-insensitivity implies that individuals do not adequately differentiate between different levels of ambiguity, transforming subjective likelihoods toward 50-50 (Dimmock et al., 2016).

A key aspect of prospect theory is that risk attitudes depend on the domain of the outcome and are different for high and low-probability events (Kahneman & Tversky, 1979). The authors observe a fourfold pattern of risk attitudes. First, they detect risk aversion for moderate-to-high probability events in the gain domain and low-probability events in the loss domain. In contrast, risk-seeking is more prevalent for gains with low probability and losses with moderate-to-high probability. A similar pattern exists for ambiguity attitudes: for low-likelihood losses, people are ambiguity averse, while they are more ambiguity-seeking or neutral for moderate-to-high likelihood events in the loss domain (Baillon & Bleichrodt, 2015). The utility curvature is identified with the evaluation of outcomes relative to a reference point, which is typically assumed to be wealth zero. Cohen, Jaffray, and Said (1987) found that individual decision making under uncertainty on the gain and on the loss side is unrelated, with participants showing moderation in the domain of losses and pessimism in the domain of gains. They also reported that individuals have limited sensitivity to probabilities on the loss side. This observation was accurate for both events with risk and uncertainty, concluding that subjects sometimes equate risk with uncertainty in the loss domain.

Abdellaoui, Bleichrodt, L'Haridon, and van Dolder (2016) also showed that loss aversion is the same for risk and uncertainty; in a sense that people are more sensitive to losses than to comparable gains, when facing outcomes with unknown probabilities. Loss aversion refers to the cognitive bias that potential or experienced losses are perceived more severely than gains of the same volume. Furthermore, the authors found that utility was convex for losses and concave for gains, with a steeper utility function for losses, which indicates loss aversion. Again, these are consistent with typical findings in the literature.

Studies have shown that the size of stakes also have an effect on ambiguity attitudes. Bouchouicha et al. (2017) have found that under high stakes subjects were more ambiguity seeking for gains with small probability and for losses with large probability. Conversely, the authors reported increased ambiguity aversion for large probability gains and small probability losses.

2.2 Measuring cognitive ability

Cognitive function has two generic modes: an intuitive, responsible for quick and automatically made decisions and choices without reflection, and a slower and more deliberate controlled mode, which requires more effort (Kahneman, 2002). The cognitive reflection test, developed by Frederick (2005), consists of three problems and aims to measure cognitive reflection, which he defined as “the ability or disposition to resist reporting the response that first comes to mind” (Frederick, 2005, p.35). The author has found a correlation between the result of CRT and time preferences and risk preferences but points out that these findings require further exploration (Frederick, 2005). Other studies also indicate a relationship between CRT results and numeracy, which significantly affects economic decision making and may distort the perception of risk (Szaszi, Szollosi, Palfi & Aczel, 2017). When investigating the role of individual differences in cognitive reflection in decision making, Campitelli and Labollita (2010) found that cognitive reflection has a connection with knowledge, domain-specific heuristics, and environmental characteristics. This thinking disposition may be indispensable when decision makers adapt to different situations and environments. CRT scores show moderate or high correlation with results of other cognitive measures, such as the Scholastic Achievement Test (SAT) and the American College Test (ACT) (Frederick, 2005). A study by Toplak, West and Stanovich (2011) also found that CRT score is a unique predictor of performance on heuristics-and-biases tasks.

Individual numerical ability, also known as numeracy, plays an important role in decision making and judgment. The Berlin Numeracy Test (BNT) is specifically developed to measure statistical numeracy and risk literacy (Cokely, Galesic, Schulz, Ghazal & Garcia-Retamero, 2012). The test was validated on both Swedish student and population representative samples (Lindskog, Kerimi, Winman & Juslin, 2015).

2.3 Cognitive ability and decision making

The literature on the relationship between cognitive ability and decision making is substantial but primarily focused on risk attitudes. It has been found that the level of cognitive skills has a strong and significant relationship with economic preferences: better cognitive skills are associated with more patience and a more sizable willingness to take calculated risks (Burks, Carpenter, Goette & Rustichini, 2009). Other authors show that lower cognitive ability is related to greater risk aversion and impatience (Dohmen et al., 2010). Similarly, Benjamin, Brown, and Shapiro (2013) reported that high-school students who scored higher on standardized tests show less risk aversion for small-stakes events.

Cognitive ability also seems to be related to higher-order risk attitudes. Noussair et al. (2014) found that prudence positively correlates with education and cognitive ability, and university students make more prudent choices than the general population. Fairley and Sanfey (2020) also reported a positive correlation between IQ scores and prudence.

Borghans, Heckman, Golsteyn & Meijers (2009) and Dohmen et al. (2010) did not report any significant correlation when studying the relationship between attitudes toward ambiguity and cognitive ability. Although there is seemingly no relationship between ambiguity aversion and cognitive ability, there is some evidence that individuals with different cognitive abilities deal with choices involving probabilities differently. More intelligent individuals may opt for more complex but efficient normative decisions (Prokosheva, 2016). Chew, Ratchford and Sagi (2013) investigated the effect of attention and comprehension on ambiguity attitudes and found that high-comprehension subjects are more ambiguity averse than low-comprehension individuals, who appeared to behave randomly. Moreover, the authors showed that participants, who could attach probabilities for ambiguous events, thus, quantifying ambiguity, are more ambiguity neutral.

3 Methodology

3.1 Experimental design

This thesis aims to estimate the correlation between cognitive ability and ambiguity attitude with an online survey, which is conducted based on the relevant literature. Participants were presented with a series of questions measuring their ambiguity attitude for different sizes of gains and losses and questions measuring their cognitive ability through cognitive reflection and numeracy. Completing the survey was estimated to take 15 minutes and no compensation was offered for participants. Prior to being presented with the first question, participants were briefly informed about the purpose of the questionnaire and received instructions about the completion of the survey. After reading the introduction of the survey, participants could consent to proceed to the first question or choose the option to end the survey.

3.1.1 Ambiguity attitudes

In the first part of the survey, respondents were presented with four hypothetical situations where they had to choose between different options. In all scenarios they were presented with two urns: Urn 1 (risky urn, on the left) contained exactly X black and 10 - X red balls, Urn 2 (uncertain urn, on the right) contained 10 red and black balls, but in an unknown ratio. The experimental design is based on the matching probabilities method to measure ambiguity attitudes described in Dimmock et al., 2016.

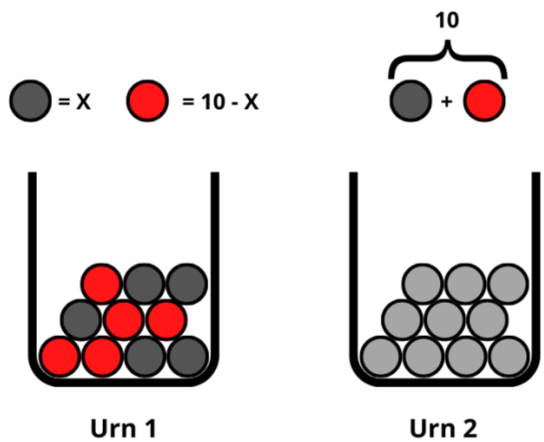


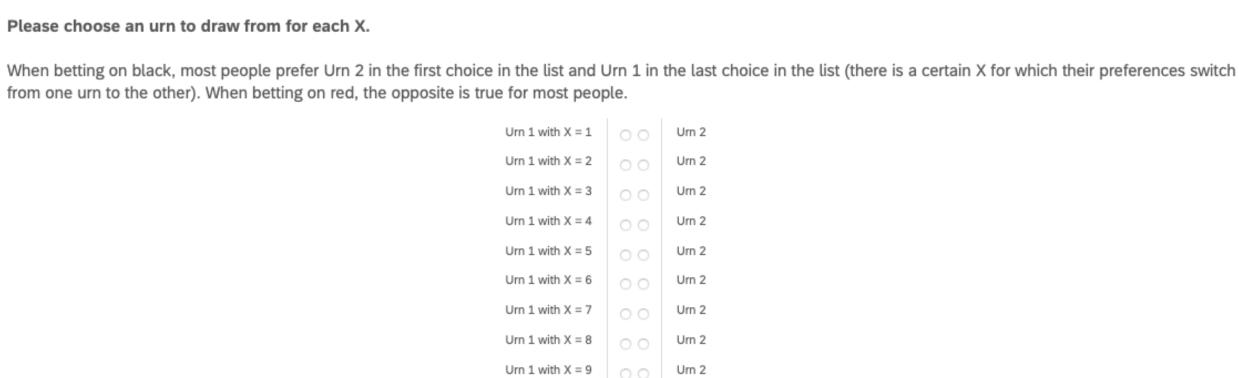
Figure 1. The risky and the uncertain urn as presented in the online survey

Respondents first had to choose a color to bet on in each scenario to control for subjective beliefs, followed by choosing an urn to draw from for each possible X (1-10), increasing X by one in each step. The risky bet involved 10%, 20%, …, 80%, 90% probability of winning or losing. R_1 denotes the event of a red ball being drawn from the risky urn (Urn 1), while B_2 denotes the event of a black ball being drawn from the uncertain urn (Urn 2), and R_2 and B_1 are defined similarly. To evaluate respondents' ambiguity attitudes to gains and losses, and to control for different stake sizes, the survey utilized the matching probabilities method with an ordered binary choice list (Holt & Laury, 2002), instead of the bisection procedure proposed by Dimmock et al. (2016). If a participant's choice from betting on the uncertain to risky urn switched between X = q and X = (q + 1), I took (q + 0.5) percent as the matching probability (Baillon & Bleichrodt, 2015), marking the probability for which the participant is indifferent between the risky and the uncertain urn. For X = 5, we can also assign a (subjective) probability of 0.5 to R_2 and B_2 for an ambiguity-neutral decision maker. Thus, ambiguity aversion can be detected by the decision maker underweighting the ambiguity neutral probabilities 0.5 of R_2 and B_2 relative to the objective probabilities 0.5 of R_1 and B_1. The choice list represented a series of situation in which the uncertain urn (Urn 2) is kept fixed, but the number of black balls in increased by one in every choice until we find the X that made the participant switch from the risky to the uncertain urn or from the uncertain to the risky urn, depending on the chosen winning color. The matching probability of the ambiguity neutral probability 0.5 of R_2, when betting on the red balls can be written as $m(0.5) = X/10$. We detected ambiguity aversion when $m(0.5) < 0.5$. The survey did not measure ambiguous Ellsberg-urn probabilities other than $p = 0.5$, thus a-insensitivity and ambiguity aversion cannot be differentiated by this method. The event specific ambiguity attitude index (AA index) was calculated based on the works of Jaffray (1989) and Kahn & Sarin (1988). AA_p shows the level of ambiguity aversion for an Ellsberg urn event with ambiguity neutral probability p, thus $AA_{0.5} = 0.5 - m(0.5)$.

The four situations had different stakes which were the following:

1. You will **receive €10 000** if a ball of your chosen color is drawn, and €0 otherwise. (High stake gain, situation 1)
2. You will **receive €100** if a ball of your chosen color is drawn, and €0 otherwise. (Low stake gain, situation 2)
3. You will lose and **have to pay €10 000** if a ball of your chosen color is drawn, and €0 otherwise. (High stake loss, situation 3)
4. You will lose and **have to pay €100** if a ball of your chosen color is drawn, and €0 otherwise. (Low stake loss, situation 4)

Participants were presented with the four scenarios in a randomized order.



Please choose an urn to draw from for each X.

When betting on black, most people prefer Urn 2 in the first choice in the list and Urn 1 in the last choice in the list (there is a certain X for which their preferences switch from one urn to the other). When betting on red, the opposite is true for most people.

Urn 1 with X = 1	Urn 2
Urn 1 with X = 2	Urn 2
Urn 1 with X = 3	Urn 2
Urn 1 with X = 4	Urn 2
Urn 1 with X = 5	Urn 2
Urn 1 with X = 6	Urn 2
Urn 1 with X = 7	Urn 2
Urn 1 with X = 8	Urn 2
Urn 1 with X = 9	Urn 2

Figure 2. The choice list presented to the participants in the online survey

3.1.2 Cognitive Reflection Test

The second section of the online survey consists of the three questions from the Cognitive Reflection Test (CRT):

1. A bat and a ball cost $1.10 in total. The bat costs $1.00 more than the ball. How much does the ball cost? _____ cents
2. If it takes 5 machines 5 minutes to make 5 widgets, how long would it take 100 machines to make 100 widgets? _____ minutes
3. In a lake, there is a patch of lily pads. Every day, the patch doubles in size. If it takes 48 days for the patch to cover the entire lake, how long would it take for the patch to cover half of the lake? _____ days (Frederick, 2005).

The correct answers to these questions are 5 cents, 5 minutes and 47 days, respectively. The CRT investigates one part of an individual's cognitive ability: the capability of overriding the intuitive mode and using the more conscious, controlled mode instead. Participants were assigned a test score between 0 and 3 based on the number of correct answers.

3.1.3 Berlin Numeracy Test

In addition to the CRT, the Berlin Numeracy Test was used to assess participants' statistical numeracy and risk literacy levels:

1. Out of 1,000 people in a small town 500 are members of a choir. Out of these 500 members in the choir 100 are men. Out of the 500 inhabitants that are not in the choir 300 are men. What is the probability that a randomly drawn man is a member of the choir? Please indicate the probability in percent.

2a. Imagine we are throwing a five-sided die 50 times. On average, out of these 50 throws how many times would this five-sided die show an odd number (1, 3 or 5)?

2b. Imagine we are throwing a loaded die (6 sides). The probability that the die shows a 6 is twice as high as the probability of each of the other numbers. On average, out of these 70 throws how many times would the die show the number 6?

3. In a forest 20% of mushrooms are red, 50% brown and 30% white. A red mushroom is poisonous with a probability of 20%. A mushroom that is not red is poisonous with a probability of 5%. What is the probability that a poisonous mushroom in the forest is red? (Cokely et al., 2012).

The correct answers are 25%, 30 out of 50 throws, 20 out of 70 throws and 50%, respectively.

The test was chosen because it can swiftly measure if an individual is low- or high-numerate. Moreover, it is the strongest predictor of comprehension of everyday risk in the general population and accounts for variance beyond other cognitive tests (Cokely et al., 2012). The survey used the adaptive, online version of the BNT which consists of four questions. From the four possible questions 2 or 3 are presented to the participants depending on their past performance in the previous questions of the test and the adaptive structure adjusts the level of difficulty of the questions presented to the respondents based on their prior success. Participants' numeracy skill-level was determined from their answers and assigned a score between 1 and 4, with 1 being the lowest and 4 being the highest.

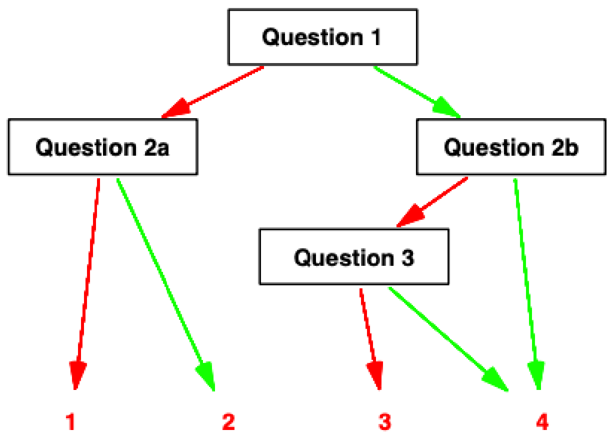


Figure 3. Adaptive structure of the Berlin Numeracy Test (Cokely et al., 2012)

3.1.4 Demographic and background variables

The last segment of the survey explores different demographic and background variables, such as gender, age and the highest level of education. These variables serve as controls in the regression analysis.

3.2 Empirical strategy

The first model estimates the effect of cognitive ability, measured by the Cognitive Reflection Test, on ambiguity attitude in the loss domain:

$$AmbAtt_i = \alpha + \beta_1 CRT_i + \beta_2 X_i + \varepsilon$$

$AmbAtt_i$= an individual's ambiguity attitude in the loss domain

CRT_i= an individual's normalized score on the Cognitive Reflection Test

X_i= the vector of control variables (age, gender and level of education)

ε= error term

The second model examines the effect of cognitive ability, measured by the Berlin Numeracy Test, on ambiguity attitude in the loss domain:

$$AmbAtt_i = \alpha + \delta_1 BNT_i + \delta_2 X_i + \varepsilon$$

$AmbAtt_i$= an individual's ambiguity attitude in the loss domain

BNT_i= an individual's normalized score on the Berlin Numeracy Test

X_i= the vector of control variables (age, gender and level of education)

ε= error term

The same models were used to estimate the effect of cognitive ability, measured by the Cognitive Reflection Test and the Berlin Numeracy Test, on ambiguity attitude in the gain domain.

4 Results

4.1 Description of the data

The data presented in this section of the thesis was collected from January 2023 to March 2023, with 188 responses received during this period. The survey was anonymously distributed through various social media platforms, and participants from different age groups, nationalities, and backgrounds were recruited through friends and family. Demographic variables are summarized in Table 1.

In terms of education level, 0.80% had completed primary school or equivalent, 5.60% had completed high school or equivalent, 40% had a Bachelor's degree or equivalent, 48.80% had a Master's degree or equivalent and 3.20% had PhD or higher. 1.60% preferred not to disclose their highest level of education.

The participants displayed an ambiguity neutral attitude towards gains and losses, as indicated by a median ambiguity attitude index of $AA_{0.5} = 0$. The sample mean for the ambiguity aversion index was -0.0032 and -0.0052 for gains and losses, respectively. Among measures of cognitive ability, the Berlin Numeracy Test showed greater variability with an average score of

2.784 and a median of 3, while the Cognitive Reflection Test had a mean score of 2.088 and a median of 3.

Table 1. Demographics

1. Age	Frequency	Percentage
Under 18	1	0,80%
18-24	32	25,60%
25-34	66	52,80%
35-44	9	7,20%
45-54	5	4,00%
55-64	4	3,20%
65 or older	7	5,60%
Prefer not to say	1	0,80%
2. Gender	**Frequency**	**Percentage**
Female	77	61,60%
Male	48	38,40%
3. Highest level of education	**Frequency**	**Percentage**
Primary School or equivalent	1	0,80%
High School or equivalent	7	5,60%
Bachelor's Degree or equivalent	50	40,00%
Master's Degree or equivalent	61	48,80%
PhD or higher	4	3,20%
Prefer not to say	2	1,60%

After removing incomplete or insufficient responses, the final sample size was 125 participants, with a gender distribution of 61.60% female and 38.40% male. The age distribution of the participants was as follows: 0.80% were under 18 years old, 25.60% were between 18-24 years old, 52.80% were between 25-34 years old, 7.20% were between 35-44 years old, 4% were between 45-54 years old, 3.20% were between 55-64 years old, 5.60% were 65 years old or older, and 0.80% preferred not to disclose their age.

Table 2. Descriptive statistics of matching probabilities

Descriptive measures	Sit 1 (High stake gain)	Sit 2 (Low stake gain)	Sit 3 (High stake loss)	Sit 4 (Low stake loss)
Mean	0,508	0,498	0,504	0,506
Median	0,550	0,550	0,550	0,550
Standard deviation	0,073	0,079	0,069	0,066
Min	0,350	0,250	0,350	0,350
Max	0,650	0,650	0,650	0,650
25th perc.	0,450	0,450	0,450	0,450
75th perc.	0,550	0,550	0,550	0,550

4.2 Ambiguity attitudes

In terms of matching probability, situation 1 (High stake gain) had the highest average matching probability of 0.508, whereas situation 2 (Low stake gain) had the lowest at 0.498. The highest number of participants displaying ambiguity aversion ($m(0.5) < 0.5$) was found in situation 2 (n = 58), while situation 1 had the lowest number of participants with ambiguity aversion (n = 50). After controlling for stake size, the average matching probability was 0.5032 for gains and 0.5052 for losses. 43 participants showed ambiguity aversion in situations involving gains, compared to 35 in situations involving losses.

Figure 4 displays the frequency distribution of the matching probabilities for the four situations, while Figure 5 compares the ambiguity aversion index distributions for gains and losses.

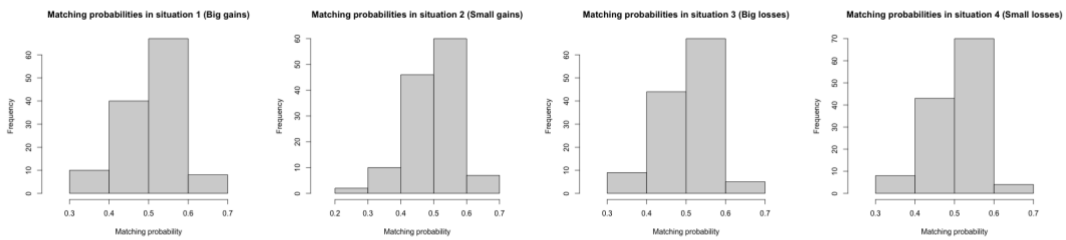


Figure 4. Frequency distribution of matching probabilities

Table 3 shows that there is a moderate positive correlation between the ambiguity aversion indexes of the four situations, with the highest correlation between gains with high and low stakes and the lowest correlation between low stakes gains and losses.

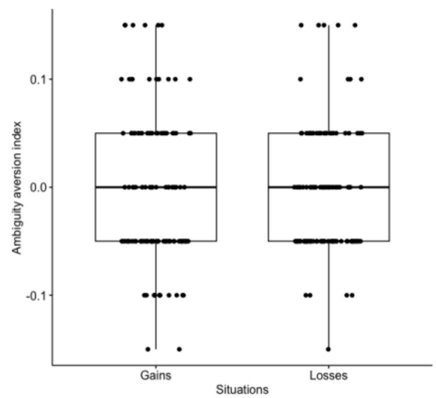


Figure 5. Distribution of the ambiguity aversion index

4.3 Cognitive ability

Table 4 shows the descriptive statistics of the scores obtained from the Cognitive Reflection Test and the Berlin Numeracy Test. The level of correlation between the CRT and BNT score is 0.425 (p-value = 0.000), which indicates that there is a moderate level correlation between the cognitive reflection and numeracy skills of the participants.

Table 3. Pairwise correlations of ambiguity aversion indexes

	(1)	(2)	(3)	(4)
(1) Gains - high stakes	1,000			
(2) Gains - low stakes	0,586	1,000		
	(0,000)			
(3) Losses - high stakes	0,388	0,376	1,000	
	(0,000)	(0,000)		
(4) Losses - low stakes	0,483	0,298	0,421	
	(0,000)	(0,001)	(0,000)	1,000

Table 4. Descriptive statistics of cognitive ability tests

Cognitive ability test	Mean	Median	SD	Min	Max	25th perc.	75th perc.
CRT	2,088	3,000	1,122	0,000	3,000	1,000	3,000
BNT	2,784	3,000	1,175	1,000	4,000	2,000	4,000

Table 5 depicts that most of the subjects managed to answer all 3 questions correctly in the Cognitive Reflection Test, which signals a high level of cognitive reflection. Based on this finding, we can state that the majority of the participants have the ability to override the response that first comes to their mind intuitively and answer rationally. The average score obtained in the CRT was 2.088. Out of the 125 subjects, 54 (43.20%) managed to obtain the maximum score of 4 in the Berlin Numeracy Test, indicating a high level of numeracy, which plays an important role in judgment and decision making.

Table 5. Frequency distribution of cognitive ability scores

CRT scores	Frequency	Percentage
0	19	15,20%
1	16	12,80%
2	25	20,00%
3	65	52,00%
BNT scores	Frequency	Percentage
1	21	16,80%
2	39	31,20%
3	11	8,80%
4	54	43,20%

4.4 Cognitive ability and ambiguity attitudes

Table 6-9 displays the results of the OLS regressions of participants' measures of cognitive ability and indicators of ambiguity attitude. Table 6-7 presents the results of regression analysis where the dependent variables are the matching probabilities of the four different situations: gains with high stakes, gains with low stakes, losses with high stakes and losses with low stakes, while the independent variable is the normalized score obtained in the BNT and CRT, respectively. Age, gender and highest level of education were included in the models as controls. Table 8-9 shows the outputs of OLS regressions with the ambiguity aversion index (AA) obtained in the situations with gains and losses as dependent variables, while the independent variable is the normalized BNT and CRT score.

It is important to note that the R-squared values can be considered low in every case displayed in Table 6-9, which indicates that the variance in the dependent variable is not well explained by the independent variables in the regression models.

Table 6. Matching probabilities and numeracy measured by the BNT

	Dependent variable			
	MP Gains - high stakes	MP Gains - low stakes	MP Losses - High stakes	MP Losses - low stakes
BNT	-0,008	0,025	-0,001	-0,014
	(0,017)	(0,019)	(0,016)	(0,016)
Age	-0,0004	0,004	0,004	-0,0003
	(0,005)	(0,005)	(0,004)	(0,004)
Gender	0,016	0,006	-0,023*	-0,001
	(0,014)	(0,015)	(0,012)	(0,012)
Education	0,007	-0,003	-0,0003	0,010
	(0,008)	(0,009)	(0,008)	(0,007)
Constant	0,481***	0,480***	0,512***	0,482***
	(0,034)	(0,037)	(0,032)	(0,031)
Observations	125	125	125	125
R-squared	0,019	0,021	0,033	0,020
Adjusted R2	-0,014	-0,012	0,0004	-0,013
Residual Std. Error (df = 120)	0,074	0,079	0,069	0,067
F Statistic (df = 4; 120)	0,567	0,628	1,012	0,615

Note: * p<0,1; ** p<0,05; *** p<0,01

4.4.1 Cognitive ability and ambiguity attitudes in the gain domain

H1. Numeracy - measured with the Berlin Numeracy Test (BNT) - is negatively correlated with ambiguity aversion in the gain domain.

Table 6 displays negative coefficients indicating a weak negative relationship between numeracy, as measured by the Berlin Numeracy Test, and matching probabilities in situation 1 (gains with high stakes), and a weak positive relationship in situation 2 (gains with low stakes). It is important to note that these coefficients are small, indicating a lack of strong relationship between the variables, and the results are not statistically significant at any level. Consequently, the null hypothesis of no relationship between the measure of numeracy and the indicator of ambiguity attitude cannot be rejected, and H1 cannot be confirmed.

Turning to Table 8, we observe a negative coefficient of -0.008 for the BNT score, indicating a weak negative relationship with the ambiguity aversion index for gains. However, once again, the results lack statistical significance at any level of significance.

H3. Cognitive ability - measured with the Cognitive Reflection Test (CRT) - is negatively correlated with ambiguity aversion in the gain domain.

Table 7 displays coefficients indicating a weak negative correlation between the normalized Cognitive Reflection Test score and the matching probabilities in situation 1, and a positive relationship in situation 2. While the results for situation 1 lack statistical significance at any level of significance, the results for situation 2 are significant at the $p < 0.1$ level.

In Table 9, we examine the relationship between the ambiguity aversion index for gains and cognitive ability measured by the CRT. The coefficient of -0.015 suggests a weak negative relationship, but the result is not statistically significant. Therefore, we cannot reject the null hypothesis, and H3 cannot be confirmed based on the study's findings.

4.4.2 Cognitive ability and ambiguity attitudes in the loss domain

H2. Numeracy - measured with the Berlin Numeracy Test (BNT) - is negatively correlated with ambiguity aversion in the loss domain.

The results displayed in Table 6 suggest that there is a weak negative correlation between matching probabilities in the situations involving losses (situation 3 and 4) and numeracy measured by the Berlin Numeracy Test. The results are not statistically significant at any level.

Table 7. Matching probabilities and cognitive ability measured by the CRT

	Dependent variable			
	MP Gains - high stakes	MP Gains - low stakes	MP Losses - High stakes	MP Losses - low stakes
CRT	-0,004	0,034*	0,021	0,009
	(0,018)	(0,019)	(0,017)	(0,017)
Age	-0,0004	0,004	0,004	-0,0004
	(0,005)	(0,005)	(0,004)	(0,004)
Gender	0,016	0,006	-0,021*	0,002
	(0,013)	(0,014)	(0,013)	(0,012)
Education	0,006	-0,002	-0,001	0,009
	(0,008)	(0,009)	(0,008)	(0,007)
Constant	0,479***	0,469***	0,496***	0,468***
	(0,035)	(0,038)	(0,033)	(0,032)
Observations	125	125	125	125
R-squared	0,017	0,032	0,045	0,016
Adjusted R2	-0,016	-0,001	0,013	-0,017
Residual Std. Error (df = 120)	0,074	0,079	0,069	0,067
F Statistic (df = 4; 120)	0,519	0,977	1,421	0,480

Note: * p<0,1; ** p<0,05; *** p<0,01

Table 8. Ambiguity aversion index and numeracy measured by the BNT

	Dependent variable	
	AA Gains	AA Losses
BNT	-0,008 (0,016)	0,008 (0,013)
Age	-0,002 (0,004)	-0,002 (0,004)
Gender	-0,011 (0,013)	0,012 (0,011)
Education	-0,002 (0,008)	-0,005 (0,006)
Constant	0,019 (0,034)	0,003 (0,037)
Observations	125	125
R-squared	0,009	0,019
Adjusted R2	-0,024	-0,014
Residual Std. Error (df = 120)	0,069	0,057
F Statistic (df = 4; 120)	0,279	0,569

Note: * p<0,1; ** p<0,05; *** p<0,01

In Table 8, the coefficient of BNT indicates a weak positive relationship between numeracy and the ambiguity aversion index for losses, but it is important to note that the results, again, are not statistically significant. Therefore, the null hypothesis cannot be rejected and H2 cannot be confirmed based on these findings.

H4. Cognitive ability - measured with the Cognitive Reflection Test (CRT) - is negatively correlated with ambiguity aversion in the loss domain.

The coefficients presented in Table 7 indicate that there is a slightly positive relationship between cognitive ability measured by the Cognitive Reflection Test and matching probabilities measured in situations with both high and low stake losses, however the results are not statistically significant.

The relationship between ambiguity aversion index for losses and cognitive reflection indicated by the normalized CRT score is weakly negative based on the findings displayed in Table 9. The results lack statistical significance at any level, thus the null hypothesis cannot be rejected and H4 cannot be confirmed.

Table 9. Ambiguity aversion index and cognitive ability measured by CRT

	Dependent variable	
	AA Gains	AA Losses
CRT	-0,015 (0,017)	-0,015 (0,014)
Age	-0,002 (0,004)	-0,002 (0,004)
Gender	-0,011 (0,012)	0,009 (0,010)
Education	-0,002 (0,008)	-0,004 (0,006)
Constant	0,026 (0,033)	0,018 (0,027)
Observations	125	125
R-squared	0,014	0,025
Adjusted R2	-0,019	-0,007
Residual Std. Error (df = 120)	0,068	0,057
F Statistic (df = 4; 120)	0,422	0,778

Note: * p<0,1; ** p<0,05; *** p<0,01

4.5 Robustness check

In the following section, I present the series of robustness checks conducted to check the validity and reliability of the results reported in the previous section of the thesis. The results of the alternative models are presented in Table 10-12 (Appendix B).

Instead of the BNT and CRT scores normalized to be between 0 and 1, the actual test scores were used in the regressions estimating the effect of cognitive ability measures on the ambiguity aversion index and matching probabilities obtained in situations with different outcome domains and varying stake sizes. The raw test scores varied between 1 and 4, with 4 being the highest, in case of the Berlin Numeracy Test and between 0 and 3, with 3 being the maximum, in case of the Cognitive Reflection Test.

The results obtained from these OLS regression do not significantly differ from the results reported in Table 6-9 in terms of the size or the of the effect, the direction of the relationship between the dependent and independent variables, or the statistical significance of the findings.

5 Discussion

5.1 Conclusion

A nuanced understanding of the relationship between different components of cognitive ability and ambiguity attitudes can aid researchers in identifying distinct decision making techniques, with practical implications for policy makers. The increased knowledge about the decision making process under uncertainty and the factors that influence it extends beyond theoretical considerations, as most real-life decisions involve prospects with imprecise probabilities.

This thesis aimed to investigate the relationship between cognitive reflection and numeracy components of cognitive ability and ambiguity aversion in the gain and loss domains. The Cognitive Reflection Test (Frederick, 2005) and the Berlin Numeracy Test (Cokely et al., 2012) were used to measure cognitive reflection skills and numerical ability, respectively. Four hypothetical situations with varying stakes and outcome domains were presented to participants, and their attitudes toward uncertainty were examined through binary choices between betting on a risky or an uncertain Ellsberg urn. The experimental design was based on Dimmock et al. (2016).

The sample's homogenous findings on ambiguity aversion indicated only slight deviations from ambiguity neutral choices, making comparisons to relevant literature challenging. However, the results on ambiguity neutral attitudes are consistent with Baillon and Bleichrodt (2015), which found that people tend to underweight moderate and high probability events and overweight low probability events, leading to ambiguity aversion for low-likelihood losses and ambiguity seeking or neutrality for moderate-to-high likelihood losses. The prospect theory (Kahneman & Tversky, 1979) suggests a more diverse pattern of ambiguity attitudes depending on the outcome domain. While the study did not find such a pattern, it expected ambiguity seeking or neutral behavior for low probability gains and moderate-to-high probability losses and pronounced ambiguity aversion for moderate-to-high likelihood gains and low probability losses.

Surprisingly, the study found a statistically significant, positive relationship between normalized CRT scores and the matching probabilities obtained in the situation with low stakes in the gain domain, contrary to relevant literature's expectations of a likely negative relationship between cognitive ability and ambiguity attitudes. The study did not find any statistically significant relationship between other measures of cognitive ability and ambiguity attitudes measured by the binary choice list in the four different situations.

5.2 Limitations

It is important to acknowledge the limitations that may affect the scope and generalizability of the findings of the thesis. This following section highlights some of the key limitations of the study and discusses how they may have influenced the results and conclusions.

Firstly, one of the main limitations of the thesis is the sample size. Despite the effort made to recruit a diverse set of subjects, the participants are not representative of the population, which limits the generalizability of the findings. Additionally, the feedback from subjects indicated that the design of the survey was too complex, which led to some participants not finishing the survey or giving insufficient answers to the questions. These factors resulted in having to remove some subjects from the already limited sample.

Another potential limitation is the lack of monetary incentives. Given the survey was not part of a well-funded project, I was not able to provide real incentives to the participants, thus they only faced hypothetical situations with higher and lower stakes to measure their ambiguity attitude. This could lead to their choices being different from those in real-life situations.

Moreover, it should be noted that the survey instrument used in this study employed a binary choice list method to measure ambiguity. While this approach has been used in previous research, it does not provide the most precise measure of ambiguity attitudes and the implemented version only accounts for the ambiguity aversion part of the ambiguity attitude, it says nothing about the a-sensitivity level of the subjects. Other methods can offer more nuanced and accurate measures and future research could consider using more refined methods.

An additional limitation of this study is that some of the questions used to measure cognitive ability may be familiar to participants, which could impact the validity of the results. Familiarity with the questions could lead participants to recall their previous responses or to guess the correct answer, rather than engaging with the question. As a result, the accuracy of the cognitive ability measurements may be compromised, which again, could limit the generalizability of the findings.

In addition to these limitations, the statistical techniques used to analyze the data may have had their own limitations, such as assumptions about normality or homogeneity of variance. It is important to keep these limitations in mind when interpreting the results and drawing conclusions. The low R-squared values displayed in the regression output tables (Table 6-9) indicate that the model used in the thesis is not a good fit for the data and cannot explain the variance in the dependent variable by the independent variables well.

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Appendix

Appendix A. Design of the survey

Section 1. Introduction and consent

Dear respondent,

My name is Violetta Szalóki, I am an MSc Economics student at Tilburg University. I am conducting a study for my master's thesis about the relationship of cognitive ability and decision making. I would like to invite you to take part in my survey, which takes about 15 minutes.

The data of this survey will be kept private and your answers will be anonymous. Your identity can not be linked to the research data, and no identifiers that link you to this study will be included in any sort of report that might be published.

Participation in the study is completely voluntary. You may withdraw your consent at any time. If you choose to not be in this study or stop in the middle, all data regarding your choices and information will be discarded.

In case you have any questions about the survey, please email me: a.v.szaloki@tilburguniversity.edu.

Thank you for your participation!

Would you like to participate in the survey?

- I have read the above description of the study and I voluntarily agree to participate in the survey
- I do not wish to participate in the survey

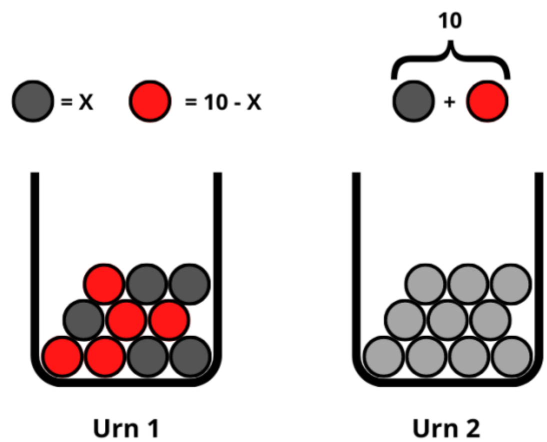
Section 2a. Ellsberg urns - Introduction

You will be presented with four hypothetical situations where you have to choose between different options. Please try to imagine yourself in these situations and make your decisions according to your preferences.

Section 2b. Ellsberg urns - High stake gains

You are presented with two urns. Urn 1 (on the left) contains exactly X black and 10 - X red balls, Urn 2 (on the right) contains 10 red and black balls, but in an unknown ratio. You have to choose an urn to draw from.

You will **receive €10 000** if a ball of your chosen color is drawn, and €0 otherwise.



First, please choose which color you want to bet on.

If you choose red and a red ball is drawn, you receive €10 000, and €0 otherwise. Similarly, if you choose black and a black ball is drawn, you receive €10 000, and €0 otherwise.

- Red
- Black

Please choose an urn to draw from for each X.

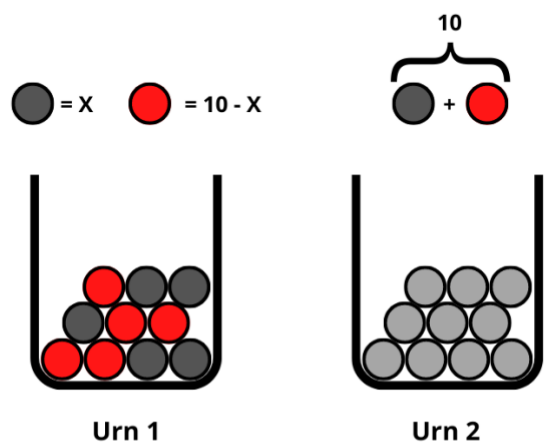
When betting on black, most people prefer Urn 2 in the first choice in the list and Urn 1 in the last choice in the list (there is a certain X for which their preferences switch from one urn to the other). When betting on red, the opposite is true for most people.

Urn 1 with X = 1	○ ○	Urn 2
Urn 1 with X = 2	○ ○	Urn 2
Urn 1 with X = 3	○ ○	Urn 2
Urn 1 with X = 4	○ ○	Urn 2
Urn 1 with X = 5	○ ○	Urn 2
Urn 1 with X = 6	○ ○	Urn 2
Urn 1 with X = 7	○ ○	Urn 2
Urn 1 with X = 8	○ ○	Urn 2
Urn 1 with X = 9	○ ○	Urn 2

Section 2c. Ellsberg urns - Low stake gains

You are presented with two urns. Urn 1 (on the left) contains exactly X black and 10 - X red balls, Urn 2 (on the right) contains 10 red and black balls, but in an unknown ratio. You have to choose an urn to draw from.

You will **receive €100** if a ball of your chosen color is drawn, and €0 otherwise.



First, please choose which color you want to bet on.

If you choose red and a red ball is drawn, you receive €100, and €0 otherwise. Similarly, if you choose black and a black ball is drawn, you receive €100, and €0 otherwise.

- Red
- Black

Please choose an urn to draw from for each X.

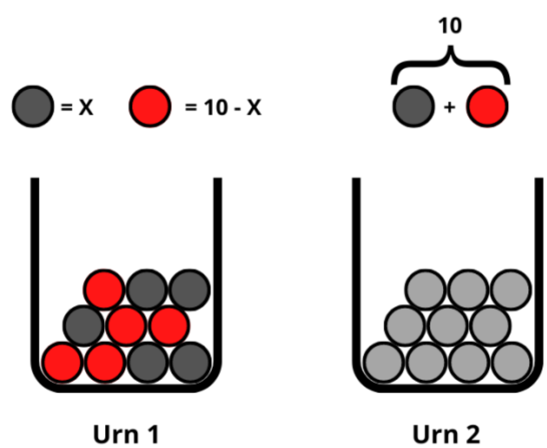
When betting on black, most people prefer Urn 2 in the first choice in the list and Urn 1 in the last choice in the list (there is a certain X for which their preferences switch from one urn to the other). When betting on red, the opposite is true for most people.

Urn 1 with X = 1	○	○	Urn 2
Urn 1 with X = 2	○	○	Urn 2
Urn 1 with X = 3	○	○	Urn 2
Urn 1 with X = 4	○	○	Urn 2
Urn 1 with X = 5	○	○	Urn 2
Urn 1 with X = 6	○	○	Urn 2
Urn 1 with X = 7	○	○	Urn 2
Urn 1 with X = 8	○	○	Urn 2
Urn 1 with X = 9	○	○	Urn 2

Section 2d. Ellsberg urns - High stake losses

You are presented with two urns. Urn 1 (on the left) contains exactly X black and 10 - X red balls, Urn 2 (on the right) contains 10 red and black balls, but in an unknown ratio. You have to choose an urn to draw from.

You will **lose and have to pay €10 000** if a ball of your chosen color is drawn, and €0 otherwise.



First, please choose which color you want to bet on.

If you choose red and a red ball is drawn, you have to pay €10 000, and €0 otherwise. Similarly, if you choose black and a black ball is drawn, you have to pay €10 000, and €0 otherwise.

- Red
- Black

Please choose an urn to draw from for each X.

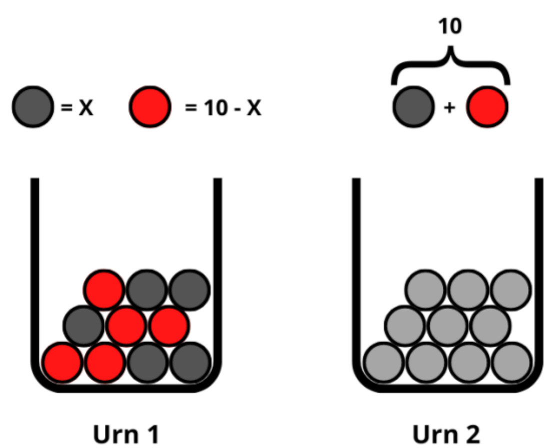
When betting on black, most people prefer Urn 1 in the first choice in the list and Urn 2 in the last choice in the list (there is a certain X for which their preferences switch from one urn to the other). When betting on red, the opposite is true for most people.

Urn 1 with X = 1	○ ○	Urn 2
Urn 1 with X = 2	○ ○	Urn 2
Urn 1 with X = 3	○ ○	Urn 2
Urn 1 with X = 4	○ ○	Urn 2
Urn 1 with X = 5	○ ○	Urn 2
Urn 1 with X = 6	○ ○	Urn 2
Urn 1 with X = 7	○ ○	Urn 2
Urn 1 with X = 8	○ ○	Urn 2
Urn 1 with X = 9	○ ○	Urn 2

Section 2e. Ellsberg urns - Low stake losses

You are presented with two urns. Urn 1 (on the left) contains exactly X black and 10 - X red balls, Urn 2 (on the right) contains 10 red and black balls, but in an unknown ratio. You have to choose an urn to draw from.

You will **lose and have to pay €100** if a ball of your chosen color is drawn, and €0 otherwise.



First, please choose which color you want to bet on.

If you choose red and a red ball is drawn, you have to pay €100, and €0 otherwise. Similarly, if you choose black and a black ball is drawn, you have to pay €100, and €0 otherwise.

- Red
- Black

Please choose an urn to draw from for each X.

When betting on black, most people prefer Urn 1 in the first choice in the list and Urn 2 in the last choice in the list (there is a certain X for which their preferences switch from one urn to the other). When betting on red, the opposite is true for most people.

Urn 1 with X = 1	○	○	Urn 2
Urn 1 with X = 2	○	○	Urn 2
Urn 1 with X = 3	○	○	Urn 2
Urn 1 with X = 4	○	○	Urn 2
Urn 1 with X = 5	○	○	Urn 2
Urn 1 with X = 6	○	○	Urn 2
Urn 1 with X = 7	○	○	Urn 2
Urn 1 with X = 8	○	○	Urn 2
Urn 1 with X = 9	○	○	Urn 2

Section 3. Cognitive Reflection Test

Please answer the following questions. The answers will consist of numbers.

A bat and a ball cost $1.10 in total. The bat costs $1.00 more than the ball. How much does the ball cost?

If it takes 5 machines 5 minutes to make 5 widgets, how long would it take 100 machines to make 100 widgets?

In a lake, there is a patch of lily pads. Every day, the patch doubles in size. If it takes 48 days for the patch to cover the entire lake, how long would it take for the patch to cover half of the lake?

Were you familiar with any of the previous 3 questions?

- No
- Yes, with one of them

- Yes, with two of them
- Yes, with all of them

Section 4. Berlin Numeracy Test

Please answer the questions that follow. Do not use a calculator but feel free to use a scratch paper for notes.

Out of 1,000 people in a small town 500 are members of a choir. Out of these 500 members in the choir 100 are men. Out of the 500 inhabitants that are not in the choir 300 are men. What is the probability that a randomly drawn man is a member of the choir? Please indicate the probability in percent.

Imagine we are throwing a five-sided die 50 times. On average, out of these 50 throws how many times would this five-sided die show an odd number (1, 3 or 5)?

Imagine we are throwing a loaded die (6 sides). The probability that the die shows a 6 is twice as high as the probability of each of the other numbers. On average, out of these 70 throws how many times would the die show the number 6?

In a forest 20% of mushrooms are red, 50% brown and 30% white. A red mushroom is poisonous with a probability of 20%. A mushroom that is not red is poisonous with a probability of 5%. What is the probability that a poisonous mushroom in the forest is red?

Section 5. Demographics

How old are you?

- Under 18
- 18-24
- 25-34
- 35-44
- 45-54
- 55-64

- 65 or older
- Prefer not to say

What is your gender?

- Male
- Female
- Non-binary / third gender
- Prefer not to say

What is the highest level of education you have completed?

- Primary School or equivalent
- High School or equivalent
- Bachelor’s Degree or equivalent
- Master’s Degree or equivalent
- PhD or higher
- Prefer not to say

Section 6. End of survey

We thank you for your time spent taking this survey.

Your response has been recorded.

Appendix B. Robustness checks

Table 10. Matching probabilities and BNT

	Dependent variable			
	MP Gains - high stakes	MP Gains - low stakes	MP Losses - high stakes	MP Losses - low stakes
BNT (raw)	-0.003	0.008	-0.0003	-0.005
	(0.006)	(0.006)	(0.005)	(0.005)
Age	-0.0004	0.004	0.004	-0.0003
	(0.005)	(0.005)	(0.004)	(0.004)
Gender	0.016	0.006	-0.023*	-0.001
	(0.014)	(0.015)	(0.013)	(0.012)
Education	0.007	-0.003	-0.0003	0.010
	(0.008)	(0.009)	(0.008)	(0.007)
Constant	0.484***	0.472***	0.512***	0.487***
	(0.036)	(0.039)	(0.034)	(0.033)
Observations	125	125	125	125
R-squared	0.019	0.021	0.033	0.020
Adjusted R2	-0.014	-0.012	0.0004	-0.013
Residual Std. Error (df = 120)	0.074	0.079	0.069	0.067
F Statistic (df = 4; 120)	0.567	0.628	1.012	0.615

Note: * p<0,1; ** p<0,05; *** p<0,01

Table 11. Matching probabilities and CRT

	Dependent variable			
	MP Gains - high stakes	MP Gains - low stakes	MP Losses - high stakes	MP Losses - low stakes
CRT (raw)	-0.001	0.011*	0.007	0.003
	(0.006)	(0.006)	(0.006)	(0.005)
Age	-0.0004	0.004	0.004	-0.0004
	(0.005)	(0.005)	(0.004)	(0.004)
Gender	0.016	0.006	-0.021*	0.002
	(0.013)	(0.014)	(0.013)	(0.012)
Education	0.006	-0.002	-0.001	0.009
	(0.008)	(0.009)	(0.008)	(0.007)
Constant	0.479***	0.469***	0.496***	0.468***
	(0.035)	(0.038)	(0.033)	(0.032)
Observations	125	125	125	125
R-squared	0.017	0.032	0.045	0.016
Adjusted R2	-0.016	-0.001	0.013	-0.017
Residual Std. Error (df = 120)	0.074	0.079	0.069	0.067
F Statistic (df = 4; 120)	0.519	0.977	1.421	0.480

Note: * p<0,1; ** p<0,05; *** p<0,01

Table 12. Ambiguity aversion index and cognitive abilities

	Dependent variable			
	AA Gains	AA Losses	AA Gains	AA Losses
BNT (raw)	-0.003	0.003		
	(0.005)	(0.004)		
CRT (raw)			-0.005	-0.005
			(0.006)	(0.005)
Age	-0.002	-0.002	-0.002	-0.002
	(0.004)	(0.004)	(0.004)	(0.004)
Gender	-0.011	0.012	-0.011	0.009
	(0.013)	(0.011)	(0.012)	(0.010)
Education	-0.002	-0.005	-0.002	-0.004
	(0.008)	(0.006)	(0.008)	(0.006)
Constant	0.022	0.0004	0.026	0.018
	(0.034)	(0.028)	(0.033)	(0.027)
Observations	125	125	125	125
R-squared	0.009	0.019	0.014	0.025
Adjusted R2	-0.024	-0.014	-0.019	-0.007
Residual Std. Error (df = 120)	0.069	0.057	0.068	0.057
F Statistic (df = 4; 120)	0.279	0.569	0.422	0.778

Note: * p<0,1; ** p<0,05; *** p<0,01