Fighting Fire with Fire – Overcoming Ambiguity Aversion by Introducing more Ambiguity

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Abstract

Ambiguity aversion guides decision makers to choose a risky rather than an ambiguous prospect, a pattern that is not always beneficial. For example, even nowadays, private pensions often build on savings accounts, which are risky prospects with known probabilities, instead of stocks as the former ensure safe returns with fixed interest rates. In comparison, expected returns of stocks, which are ambiguous prospects with unknown probabilities, are significantly higher. This study aims at facilitating a better understanding of ambiguity aversion and suggests measures to improve decision-making. In our experiment, subjects are confronted with either decisions under risk or decisions under ambiguity. Controlling for risk attitudes, we estimate category weights in both domains and find significant differences, which indicate the present of ambiguity aversion. Contrary to our predictions on the amplifying effect of multiple sources of ambiguity, we find that category weights of ambiguity and risk converge each other when a second source of ambiguity is implemented. That is, we point out another option to deal with ambiguity when people have to choose between risky and ambiguous prospects. Instead of minimizing ambiguity, the introduction of a second source of ambiguity might help to compare alternatives with less biases through ambiguity aversion.

Key Words: Unknown source credibility, Risk, Ambiguity aversion, Uncertainty, Customer ratings

JEL Classification: C91, D01, D81

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1. Introduction

Ambiguity aversion is best desribed as the tendency to prefer risky over ambiguous prospects because of shying away from ambiguity. During this process, decisions under risk are characterized by knowledge on the outcome options and their probability of occurrence, whereas in decisions under ambiguity there is a lack of information on the output generating process (cf. Einhorn and Hogarth 1985). This preference for risky prospects is often inefficient. For instance, people often build their private pensions on private pension insurance policies with low but known returns, shying away from investments in stocks because the returns are uncertain although these promise much higher expected returns.

The effects of one source of ambiguity and the impact of ambiguity aversion on decision-making are investigated in many studies. However, little is known about the effect of different sources of ambiguity that are affective simultaneously. We address this issue by providing answers to the following research question: *What is the effect of different sources of ambiguity on decision-making in comparison with decisions under risk, when the provided information is held equal?*

Aiming at a better understanding of effects of ambiguity on individual decision-making, we conduct a laboratory experiment and compare decisions under ambiguity and risk. We control for risk preferences and hold the provided information equal, but vary the decision domain (risky lotteries or ambiguous customer rating distributions) and the accuracy (only visualization or visualization enriched with numerical information). Thereby, we can compare the effects of different as well as multiple sources of ambiguity (the domain of customer rating distributions and absence of numerical information) in a 2x2 experimental design.

Subjects behave differently between decision domains, thus indicating ambiguity aversion. Our results also suggest that these differences shrink when the fuzziness of information, i.e., exclusive visualization without numerical information, is implemented. Hence, we find evidence against an amplifying effect of multiple sources of ambiguity. Instead, subjects perceive ambiguity as binary, resulting in a more similar behavior between decision domains of customer rating distributions and lotteries. In line with literature, we find more-experienced subjects to be less effected by ambiguity when experience is domain-related.

Our results point out a different way to deal with ambiguity. As ambiguity is perceived as something binary, another source of ambiguity might be implemented in decision processes to compare ambiguous and risky prospects with fewer biases through ambiguity aversion. This might help to diminish economically unwanted behavior such as sticking to private pension insurances when planning private pensions.

The paper proceeds as follows: In Chapter 2 we survey the literature and derive research hypotheses on the similarities and dissimilarities between decisions under risk and ambiguity, the effects of multiple sources of ambiguity, and the effect of experience on decision-making under ambiguity. Chapter 3 describes the experimental design, treatment variations, and the maximum likelihood approach used for analysis as well as the operationalized hypotheses. The results are presented in Chapter 4 and the conclusion in Chapter 5.

2. Decisions Under Uncertainty

In this paper, uncertainty covers both risk and ambiguity as a collective term. Decisions under risk are defined as situations in which the future outcome is uncertain, but the possible outcomes and the statistical probabilities are known (Wakker 2010).

In comparison, ambiguity occurs in decisions when there is unknown information about the output generating process (cf. Einhorn and Hogarth 1985, p.433) and can arise due to the lack of information about source credibility and through disagreement among experts. As Camerer and Weber (1992, p.330) aptly state, "ambiguity is caused by missing information about whose belief should be believed". Einhorn and Hogarth (1985) use an experiment to show that ambiguity increases when perceived source credibility decreases. Framing information as the opinion of experts, Di Mauro and Maffioletti (2004) implement ambiguity in two different ways. They find no significant differences between best point estimates and the interval of probabilities on the perceived ambiguity of subjects. Wakker (2010) states that ambiguity also occurs in decisions with complete information about the outcomes but unknown probabilities of occurrence, so beliefs can be used to derive subjective probabilities to form expected utilities, making decisions under risk to be a special case of decisions under ambiguity. Surveying experimental studies on ambiguity, Camerer and Weber (1992, p.330) state that most empirical work in this field focuses on ambiguity that is created by uncertainty about the probabilities of occurrence.

Similarities and dissimilarities between decisions under risk and ambiguity. There are similarities as well as dissimilarities between decisions under risk and decisions under ambiguity. Pointing out *similarities*, Wu and Gonzalez (1999) propose a two-stage process in decisions under uncertainty. In the first stage, participants form subjective probabilities for events. In the second stage, these subjective probabilities are transformed to decision weights. The authors argue that decisions under risk and ambiguity may both have the underlying general principles valid under uncertainty. However, in gambles the first stage of forming subjective probabilities might be skipped. The impact of non-linear probability weighting (i.e., over-weighting small probabilities and under-weighting large probabilities) has been identified in many studies in the domain of decisions under risk (Tversky and Kahneman 1979). Tversky and Fox (1995) and Di Mauro and Maffioletti (2004) also identified this effect in the domain of ambiguity. There is much heterogeneity in ambiguity attitudes and pessimism between subjects (cf. Ahn et al. 2014). This result is similar to investigations on decisions under risk, in which heterogeneous attitudes on risk are also present (e.g., Dohmen et al. 2011). Fox and Tversky (1995) introduce the comparative ignorance hypothesis, showing in experiments that ambiguity aversion seems to disappear when participants' decisions are only in one domain (risk or ambiguity).

Ambiguity aversion is present in situations where participants face a decision between a vague prospect and a risky prospect, which is an effect that might partially explain the dissimilarities discussed next.

Dissimilarities between decisions under risk and ambiguity are highlighted by Ellsberg (1961), who shows that theories and empirical evidence on decisions under risk cannot explain decisions under ambiguity. His findings suggest that subjects prefer risky prospects above ambiguous prospects. Although Segal (1987) suggests that the Ellsberg (1961) paradox can be explained entirely by the reduction of a two-stage decision problem, Bernasconi and Loomes (1992) use an experiment to show that this reduction principle leads to other systematic violations. However, Halevy (2007) finds evidence for the proposition that attitudes to ambiguity and compound objective lotteries (i.e., decisions under risk) are closely associated. In contrast, Abdellaoui et al. (2015) show that the majority of ambiguity neutral subjects cannot reduce compound lotteries, which is evidence against the similarity of decisions under ambiguity and decisions about compound lotteries. There is inconsistent evidence on the steadiness of ambiguity attitudes in the literature. Abdellaoui et al. (2011) observe that ambiguity aversion varies widely *within subjects* across different decision categories, finding more variation for ambiguous than for risky prospects. In contrast, Attanasi et al. (2014) find that 75% of the participants act coherently with respect to their ambiguity aversion, i.e., a relatively small variation within subjects. Their results also indicate equivalence between value-ambiguity aversion and choice-ambiguity aversion. Another result is that most of the subjects who are coherently ambiguity seeking show a high risk aversion, while coherent ambiguity-averse subjects show a low level of risk aversion. Di Mauro and Maffioletti (2004) compare (within subjects) decisions under risk and ambiguity and identify the reflection effect in both domains. That is, in the gain domain, subject tend to be risk seeking for low probabilities and risk averse for high probabilities, whereas in the loss domain they are risk averse for low probabilities and risk seeking for high probabilities. Contrary to Attanasi et al. (2014), they do not find a robust correlation between risk and ambiguity attitudes on an individual level. Further insights on risk and ambiguity attitude on individual level within subject can be found in Chakravarty and Roy (2009). The results do not indicate correlation between attitudes towards risk and ambiguity. On the aggregated level, the ambiguity and risk aversion are positively correlated and they find evidence for the reflection effect under risk and ambiguity.[1] There is evidence that subjects employ different probability weighting in decisions under risk and ambiguity (Tsang 2020). Tversky and Fox (1995) explain the concept of bounded subadditivity, concluding that an event has greater impact when turning impossibility into possibility, or possibility into certainty than when it merely changes the possibility. Although this pattern is observed at decisions under risk (as shown in preceding articles) and at decisions under ambiguity, the

[1] Further dissimilarities are identified in Cooper and Rege (2011) who use an experiment to show that social interaction affects individual choices under risk and ambiguity differently. The meta analysis of Krain et al. (2006) identifies that various brain regions are active when subjects face decisions under risk or ambiguity, thereby giving evidence that decisions in both domains are processed differently.

sensitivity for probability changes s is thereby smaller for ambiguous than for risky events.

There is mixed evidence on the similarity of decisions under risk and ambiguity. Some concepts such as the reflection effect or bounded subadditivity could be identified in both domains. However, most empirical evidence speaks against similar attitudes towards (and behavior under) risk and ambiguity. Hence, we hypothesize the following:

Research Hypothesis 1. *Given the same provision of information, subjects decide differently under ambiguity in comparison to decisions under risk (**Existence of Ambiguity Aversion**).*

Multiple sources of ambiguity. Adapting the Ellsberg urn design, Eichberger et al. (2015) show that, contrary to theoretical predictions, a significant fraction of ambiguity-averse subjects does not stick to the urn with known outcomes when uncertainty about the payoff is implemented. This means that some subjects do not discriminate between the number of sources of ambiguity in decision processes, which is evidence for a binary perception of ambiguity. Moore and Eckel (2003) investigate the source of ambiguity (payoff and/or probability) and its impact on the decision between a safe or an ambiguous option. In the gain domain, ambiguity is perceived stronger when probabilities are unknown, in comparison to unknown payoffs. These effects do not add up when both sources of ambiguity are effective, but remain rather stable. Eliaz and Ortoleva (2016) use the design of Ellsberg (1961), but enhance the dimensions of ambiguity with respect to the probability of winning, the amount of the prize, and the time of payoff. Their results indicate a preference for risky choices over ambiguous choices, in other words, ambiguity aversion. In decisions without risky options, they also find that subjects choose lotteries that correspond to the strategy of reducing multiple ambiguities down to one dimension of ambiguity (due to correlations), which contrasts the binary perception of ambiguity of Eichberger et al. (2015) and Moore and Eckel (2003). Literature does not provide exhaustive evidence on the effect of multiple sources of ambiguity. However, the subjects' tendency to minimize the sources of ambiguity in Eliaz and Ortoleva (2016) corresponds to an amplifying effect of multiple sources of ambiguity. We thus hypothesize the following:

Research Hypothesis 2. *When subjects are confronted with situations under risk and ambiguity and a new source of ambiguity is introduced in both domains, this new source of ambiguity has the same impact on decision-making in both domains (**Amplifying Effect of Multiple Sources of Ambiguity**).*

Effect of experience on decision-making under ambiguity. Liu and Colman (2009) show that attitudes toward decisions under risk and ambiguity are also affected by repetition: Ambiguous options are chosen more frequently in a repeating setup. They cite Montgomery and Adelbratt (1982) who identified that subjects converge to expected value maximizers when repetitions are allowed but diverge from this strategy in one-shot settings. Conducting an experiment and creating ambiguity by letting subjects decide partially about states in the future (e.g., the temperature in Beijing on a given future day), Tversky and Fox (1995) also show support for the competence hypothesis (Heath and Tversky 1991): When subjects are familiar with a topic, they show a higher sensitivity towards probabilities, meaning that they deviate less from the expected utility theory. Furthermore, List (2004) shows that the market behavior of more-experienced participants is more in line with expected utility. In contrast, less-experienced traders show deviations that are predictable by prospect theory. Using an Ellsberg task, Güney and Newell (2015) show that ambiguity aversion can be reduced by experience in decisions under uncertainty. Hence, we hypothesize the following:

Research Hypothesis 3. *In comparison with less-experienced subjects, subjects with domain-related experience decide differently under ambiguity (**Experience and Ambiguity Aversion**).*

3. Experimental Design

3.1. Experimental structure

The design of the experiment is adapted from van Straaten et al. (2021). Originally developed to investigate aggregation heuristics in the domain of customer rating distributions, this study expands the analysis on the aggregation of lotteries and compares potential aggregation patterns in both domains. In each of the twelve periods, subjects receive a triple of lotteries and are asked to rank these lotteries in accordance with their preferences. This decision is incentivized as explained next. A period is determined by nature at the end of the experiment. Participants have a chance of 70% to play the lottery they ranked first and 30% to play the lottery they ranked second in the determined period. During payout, participants first role a ten-sided die to select the lottery relevant for the payoff.[2] Afterwards, they play this lottery to determine their payoff.

In each of the decisions a visualization of the lotteries is shown, as depicted in Figure 1.

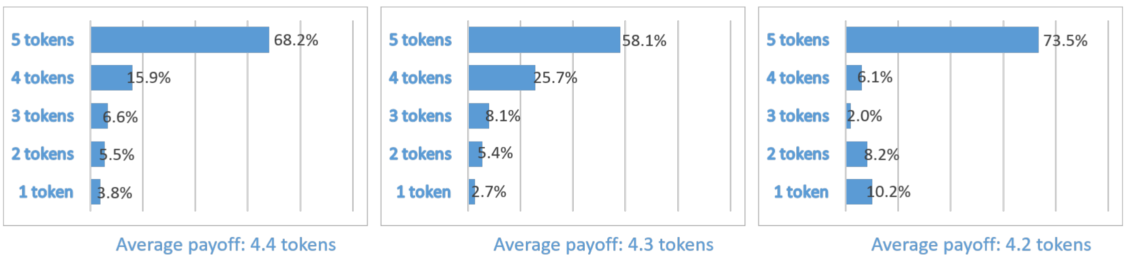

Figure 1: Illustrative triple of lotteries.

After the repeated ranking decisions, we collect data on the demographics and self-claimed risk attitudes and also ask for the employed ranking strategies.

[2] Starmer and Sugden (1991) show that using the random-lottery incentive system elicits true preferences.

Comparing the ranking decisions in the domain of risk in this experiment with the ranking decisions in the domain of ambiguity in van Straaten et al. (2021) allows us to draw an inference on the aggregation processes in different domains. We therefore briefly describe the information provided in the experiment mentioned above: First, subjects had to rank customer rating distributions (cf. Figure 2), providing the same information as in our experiment. These ranking decisions were incentivized since participants received a flash drive as payment whose customer rating distribution was ranked first with 70% or second with 30%, respectively. They also had the opportunity to win another product ranked first or second, respectively. Participants did not know which decision was linked to the flash drives or other winning categories.

We used lotteries, providing the same information as the customer rating distributions in van Straaten et al. (2021) except for the domain in which they are provided. The lotteries as depicted in Figure 1 give participants the chance of winning 1 *to* 5 experimental currency units (ECUs). The lotteries are summarized in Table B.5.

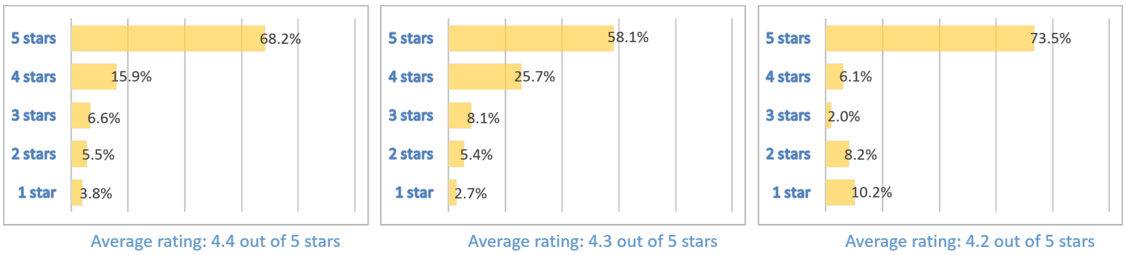

Figure 2: Illustrative triple of customer rating distributions in van Straaten et al. (2021).

3.2. *Treatment variations*

We employ a 2x2 treatment design, varying the domain (i.e., lotteries or customer rating distributions, respectively) and the degree of the provided information (i.e., only graphical information or graphical information enriched by numerical information, respectively). Both variations correspond to changes in the degree of ambiguity.

Domain: Lotteries (Risk). In the lottery domain, subjects have to rank lotteries. All of these lotteries provide the winning probability of each outcome. The possible outcomes of the lotteries are fixed over all decisions and the range of the outcomes is cardinally scaled between 1 to 5 ECUs. The expected value of the lottery is also provided. Since all information is provided, the decisions in this treatment are solely decisions under risk.

Domain: Customer Rating Distributions (Unknown source credibility/Ambiguity). The customer rating distributions provide an aggregation of customer ratings to the linked product. The customer ratings are on the interval from 1-star (worst) to 5-star (best), which are highly subjective as they are not (necessarily) based on objective criteria. The motivation of reviewers is extremely diverse (e.g., Hennig-Thurau et al. 2004; Wu 2019). Literature shows that most customers evaluate customer reviews as an important criteria for their purchasing decisions (e.g., Cheung and Lee 2012). However, research also discovered fraudulent reviews, showing the drawbacks of customer reviews (Hu et al. 2012). Although customer reviews and ratings can provide potential customers with additional information on the quality of the products, the value of information highly depends on the source credibility. Due to source credibility, subjectivity, and an ordinal valuation scale, the information of customer rating distributions is vague. Hence, decisions in this treatment are decisions under ambiguity.

Provided Information: Clear (Graphical information enriched by numbers). We vary the information provided in the decision processes of the subjects. In this condition we show the subjects histograms of the options that have to be ranked. This information is enriched by numerical information, which means that relative frequencies and the arithmetic mean values of the options are also provided (cf. Figures 1 and 2).

Provided Information: Fuzzy (Graphical information without numbers). Under this condition the numerical information is dropped. This means that we do not display the relative frequencies or the arithmetic mean values of the options, only the histogram of the options are depicted in the decision process (cf. Figure 3). Dropping the numerical values increases ambiguity.

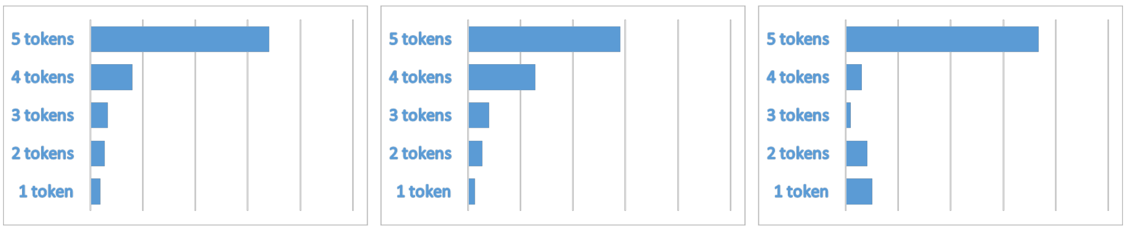

Figure 3: Illustrative triple in the lottery domain under fuzzy information.

The treatment variations are depicted in Figure 4. **Clear Lotteries (CL)** represents the treatment without any ambiguity as lotteries are the decision domain and both graphical and numerical information is provided. **Clear Ratings (CR)** and **Fuzzy Lotteries (FL)** are the treatments with medium levels of ambiguity. In CR, source of ambiguity is the unknown source credibility of the customer rating distributions. In FL, the ambiguity arises by the exclusive graphical illustrations of the options without numerical information. In **Fuzzy Ratings (FR)** there are two sources of ambiguity affective due to the lack of quantitative information

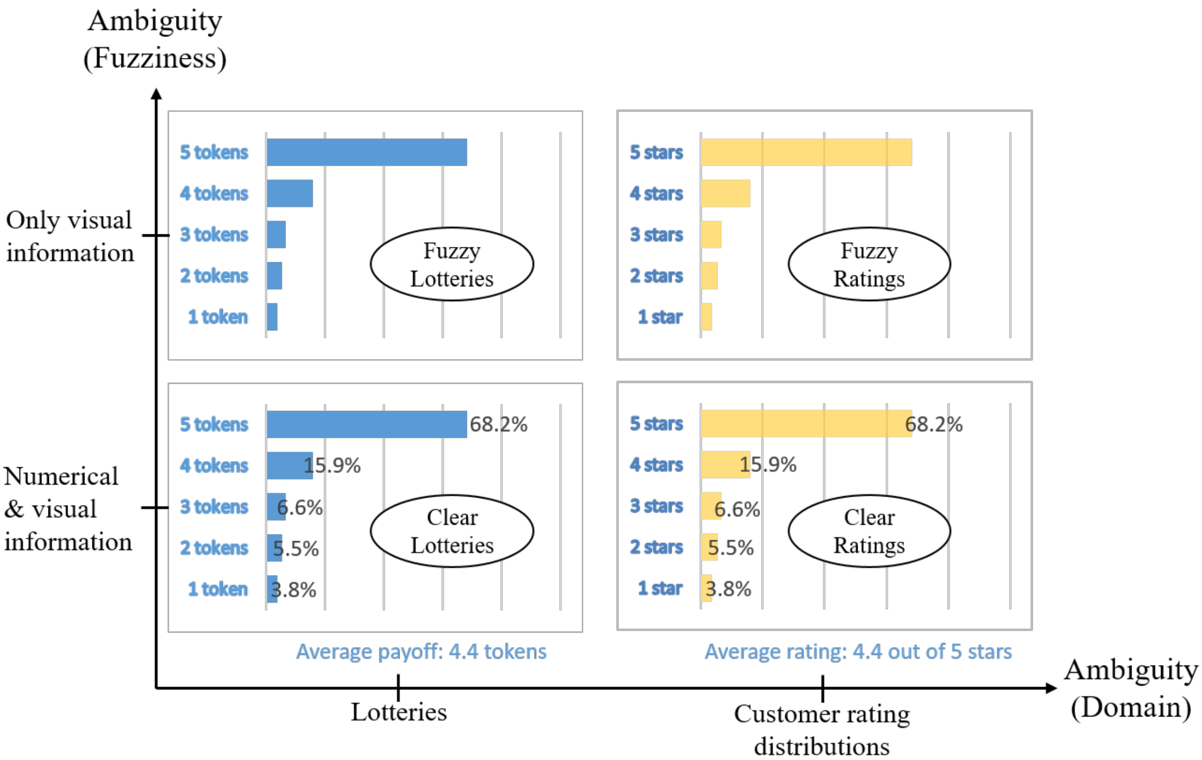

Figure 4: Treatment variations in 2x2 experimental design

and the unknown source credibility of the underlying customer ratings.

3.3. *Experimental Procedure*

We used data of van Straaten et al. (2021) collected in four sessions (2 CR, 2 FR) in December 2018. In addition, we conducted four sessions (2 CL, 2 FL) in December 2018 with the lottery treatments. Each subject participated only in one session. Overall, 218 subjects participated in this experiment.

We recruited the subjects from our pool of approximately 2,700 subjects using ORSEE (Greiner 2015). The procedure was the same in every session. The subjects were randomly allocated to cubicles separated by screening walls and received printed instructions. Participants had the possibility to ask questions in private to the experimenter for clarification. Afterwards, the experiment was started on the computers using the software z-tree (Fischbacher 2007). We gathered additional information using a questionnaire after the experiment. Finally, participants were called separately by their cubicle ID, the lottery was played and paid out, and the subjects were dismissed.

3.4. *Identification of treatment effects*

For each subject we estimate the weight (i.e., the subjective importance) of each category. For instance, some subjects might only focus on the best category (the 5 ECU or the 5-star ratings) when ranking the triple of alternatives and others on the worst outcomes (the 1 ECU or 1-star ratings). There might also be subjects who inherently employ the arithmetic mean, weighting each category according to its scale value. The estimated category weights correspond to the preferences of the subjects. Hence, we can compare these category weights between subgroups to test our hypotheses.

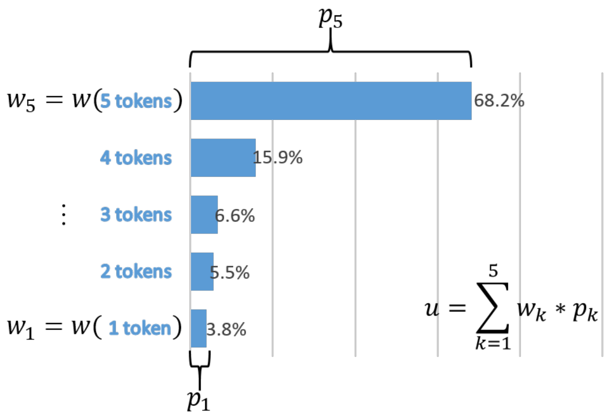

Figure 5: Calculation of latent utility by considering category weights $w_1, ..., w_5$ and probabilities $p_1, ..., p_5$.

In particular, we assume the latent utility u_i of a lottery or a product with the shown customer rating distributions of subject i to be given by the weighted average mean with given category probabilities $p_1, ..., p_5$ and unknown category weights $w_1, ..., w_5$ (cf. Figure 5):

$$u^i = \sum_{k=1}^{5} w_k^i p_k \tag{1}$$

We assume that subjects derive their latent utilities and rank the chosen product in accordance with their latent utilities, hence using the Plackett-Luce model for rank data (Plackett 1975; Luce 1959). The probability π_{klj} of observing a ranking with options j, k, l with highest latent utility of k, followed by l, and j is then:

$$\pi_{klj} = \frac{u_k}{u_j + u_k + u_l} * \frac{u_l}{u_j + u_l} * \frac{u_j}{u_j} \tag{2}$$

For the purpose of easier interpretation we implement following constraints:

$$\sum_{k=1}^{5} w_k = 0 \tag{3}$$

$$\sum_{k=1}^{5} |w_k| = 1 \tag{4}$$

With a maximum likelihood analysis we estimate the category weights $w_1^i, ..., w_5^i$ for each subject i. These category weights are then compared between the four treatments. Since the provided information is held equal between treatments, differences must be due to treatment variation.

For reference we use the expected utility weights, namely the weights that correspond to the employment of the arithmetic mean:

$$w_k \stackrel{!}{=} k \Rightarrow u_{AM} = \sum_{k=1}^{5} k * p_k \ .$$

Under consideration of constraints 3 and 4, the reference weights are:

$$(w_1^{AM}, w_2^{AM}, w_3^{AM}, w_4^{AM}, w_5^{AM}) = (-\frac{1}{3}\,,\ -\frac{1}{6}\,,\ 0\,,\ +\frac{1}{6}\,,\ +\frac{1}{3})$$

3.5. Operationalization of hypotheses

Research hypothesis 1 states that subjects make different decisions under ambiguity in comparison to decisions under risk. With regard to the experimental design and its specified treatments we divide it into the two following hypotheses:

Hypothesis 1. *(a) Subjects weight categories under unknown source credibility, i.e., ambiguity, differently in comparison to risk. (b) Subjects weight categories under fuzzy probabilities, i.e., ambiguity, differently in comparison to decisions under risk.*

$$weights^{CR} \neq weights^{CL}$$
$$weights^{CL} \neq weights^{FL}$$

Research hypothesis 2 states that multiple sources of ambiguity have an amplifying effect. Hence, we expect that the effect of a new source of ambiguity on decisions under risk and decisions under (another source of) ambiguity is the same. We hypothesize the following:

Hypothesis 2. *Differences in category weights between decisions under risk and ambiguity remain constant when a fuzziness of information is introduced into both domains as a new source of ambiguity.*

$$\Delta(weights^{CL},\ weights^{CR}) = \Delta(weights^{FL},\ weights^{FR})$$

Research hypothesis 3 states that subjects with domain-related experience show different decisions under ambiguity in comparison with less-experienced subjects. As frequent buyers are more experienced with customer ratings and its visualization with histograms, we hypothesize the following:

Hypothesis 3. *Experienced buyers perceive less ambiguity in the domain of customer ratings and, hence, deviate less from decision making under risk.*

$$\Delta(weights^{CL},\ weights^{CR}_{Experienced}) < \Delta(weights^{CL},\ weights^{CR}_{Non-experienced})$$

4. Results

Here we describe our sample of subjects in Table 1. We find significant differences in the number of semesters (Kruskal-Wallis: $z = 7.006$, $p = 0.0717$). Otherwise, we do not find significant differences between treatment groups in the sample.[3] In FR and CR, we collect data on experience in online shopping to test for Hypothesis 3. Every subject has experience in online shopping. In FR and CR, 34 subjects (31.8%) reported that they shop online at least on a weekly basis, while 73 subjects (68.2%) state shopping only on a monthly basis or less often. Customer reviews therefore range from rather important to important [3.64 (0.98) on a likert scale from 0 to 5] in purchasing decisions.

Table 1: Sample of subjects in the four treatments.

		Fuzzy Ratings (n=53)	Clear Ratings (n=54)	Fuzzy Lotteries (n=55)	Clear Lotteries (n=56)
male		32.1%	37.0%	40.0%	34.4%
age		22.15 (2.69)	22.13 (2.89)	23.29 (6.50)	22.80 (5.57)
studies	economics	39.6%	33.3%	40.0%	42.9%
	education	43.4%	42.6%	32.7%	42.9%
	engineering	7.6%	13.0%	9.1%	5.4%
	humanities	7.5%	9.3%	16.4%	8.9%
semester		4.55 (3.18)	3.34 (3.16)	3.78 (2.43)	3.57 (3.06)
risk	general	5.83 (1.99)	6.20 (2.00)	6.13 (1.77)	5.55 (1.63)
	trust people	5.57 (2.57)	5.00 (2.58)	5.31 (2.33)	5.16 (2.74)
	finances	4.45 (2.54)	4.52 (2.46)	4.55 (2.40)	3.86 (2.17)

4.1. *Treatment effects*

This section reports the estimator results for the four treatments.[4] An overview of estimates for treatments CL, CR, FL, and FR is shown in Table 2. Detailed information on the estimates are reported in the Appendix in Tables C.6 to C.9.[5] To assess the quality of estimates, we compare the category weights with expected value theory (-1/3; -1/6; 0; 1/6; 1/3). Results are also provided in Table 2.

[3] Test results are as follows: general risk attitude (Kruskal-Wallis: $z = 5.292$, $p = 0.1516$), risk attitude with regard to trusting other people (Kruskal-Wallis: $z = 1.307$, $p = 0.7275$), financial risk attitude (Kruskal-Wallis: $z = 2.634$, $p = 0.4515$), gender ($\chi^2 : z = 1.9006$, $p = 0.593$), age (Kruskal-Wallis: $z = 0.934$, $p = 0.8172$), field of studies ($\chi^2 : z = 6.1128$, $p = 0.729$).

[4] The discrete ranking decisions are provided in the Appendix in Table A.4 for the four treatments.

[5] Convergence rates are: 56 subjects (100%) in CL, 52 subjects (96.3%) in CR, 51 subjects (96.2%) in FR, 54 subjects in FL (98.2%). Overall, estimates of five subjects do not converge and are thus excluded from further analysis.

Table 2: Median category weights and their deviations from expected utility (EU) category weights in four treatments. Asterisks indicate deviations from expected value weights. Test statistics are provided in the Appendix in Table C.10.

	Clear Lotteries		Clear Ratings		Fuzzy Lotteries		Fuzzy Ratings	
Category	Median	Diff EU	Median	Diff EU	Median	Diff EU	Median	Diff EU
w_1	-.338	.005	-.306	-.027***	-.326	-.007	-.312	-.021**
w_2	-.121	-.046***	-.178	.011	-.161	-.006*	-.160	-.007*
w_3	.027	-.027***	.006	-.006	.016	-.016	-.013	.013*
w_4	.171	-.004	.211	-.044**	.186	-.019	.208	-.041***
w_5	.261	.072***	.263	.070***	.263	.070***	.266	.067***

4.2. Test the hypotheses

Existence of Ambiguity Aversion. We test whether there are significant differences in decision-making under ambiguity and under risk. Therefore, we analyze differences between category weights $w_1, ..., w_5$ of treatments CL and CR as well as CL and FL with Mann-Whitney-U tests. Results are provided in Figure 6.[6] Differences are significant for four out of five weights between treatments CL and CR, i.e., between deci-

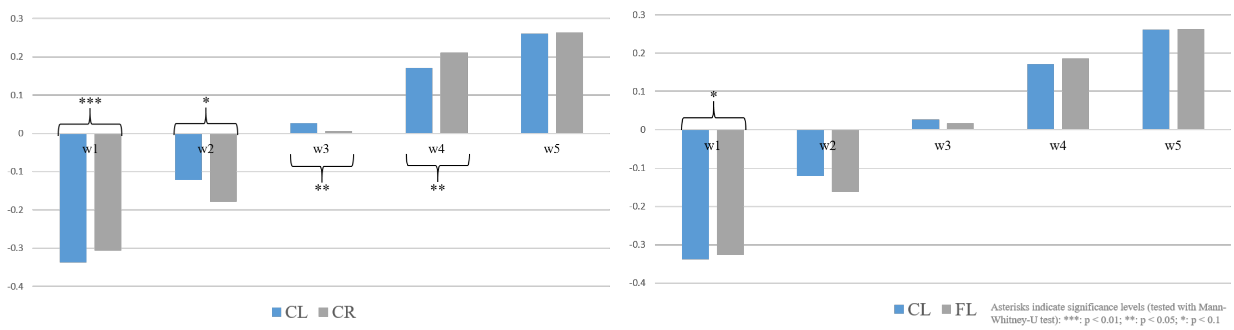

Figure 6: Evidence for ambiguity aversion: Comparison of treatments (risky) CL and (ambiguous) CR (left) and of treatments (risky) CL and (ambiguous) FL (right) over category weighs w_1, ..., w_5 provide significant difference indicating ambiguity aversion.

sions under unknown source credibility and risk. Comparing CL and FL, we find significant differences only for w_1. That is, the fuzziness of information (through the drop of numerical information) changes behavior in only one of five categories. Nevertheless, effect sizes point in the same direction for both sources of ambiguity for all categories.

Result 1. *Differences in category weights for decisions under risk and ambiguity indicate ambiguity aversion. Differences are stronger between CL and CR in comparison with CL and FL. That is, ambiguity by decision domain is*

[6] Test statistics are provided in the Appendix in Table C.11.

perceived stronger than the absence of numerical information in decision processes.

Effect of Multiple Sources of Ambiguity. Identifying evidence for ambiguity aversion, we next test whether an amplifying effect of multiple sources of ambiguity exists. Therefore, we test for differences between treatments CL and CR, and between treatments FL and FR. An amplifying effect should result in similar effects between the domains of risk and ambiguity through unknown source credibility. Results are depicted in Figure 7.[7]

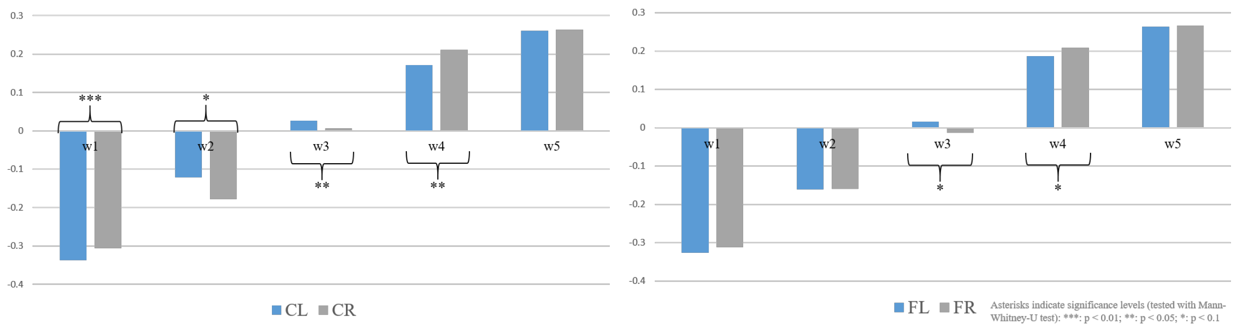

Figure 7: No evidence for an amplifying effect of multiple sources of ambiguity: Comparing the test results pairwise for $w_1, ..., w_5$ between $\Delta(CL, CR)$ (left) and $\Delta(FL, FR)$ (right), we observe that effect sizes shrink between decision-making under risk and ambiguity when fuzziness of information is included.

Comparing effect sizes by introducing a fuzziness of information as a second source of ambiguity, we observe different effects on decisions under risk and decisions under ambiguity. This is evidence against the amplifying effect of ambiguity. In contrast, we observe that category weights converge as effect sizes decrease when fuzziness is introduced. Box plots of category weights are depicted in Figure 8. Tests results of Hypothesis 1 and Hypothesis 2 are marked with asterisks. We conclude the following:

Result 2. *The introduction of fuzziness of information leads to different reactions in decision-making under risk and ambiguity. That is, we find no evidence of an amplifying effect of multiple sources of ambiguity. Moreover, there is convergence in category weights under risk and ambiguity when fuzziness is introduced as another source of ambiguity.*

Effect of Experience on Category Weights. We classify subjects to be more-experienced when they state shopping online at least on a weekly basis (n=34, 31.8%; CR: 29.5%; FR: 34.0%). Less-experienced subjects (n=73, 68.2%; CR: 70.4%; FR: 66.0%) state shopping on a monthly basis or less often. The estimates of more-experienced and less-experienced subjects are summarized in the Appendix in Tables D.13 and D.14. In the

[7] Test statistics of Mann-Whitney-U tests are provided in Table C.12.

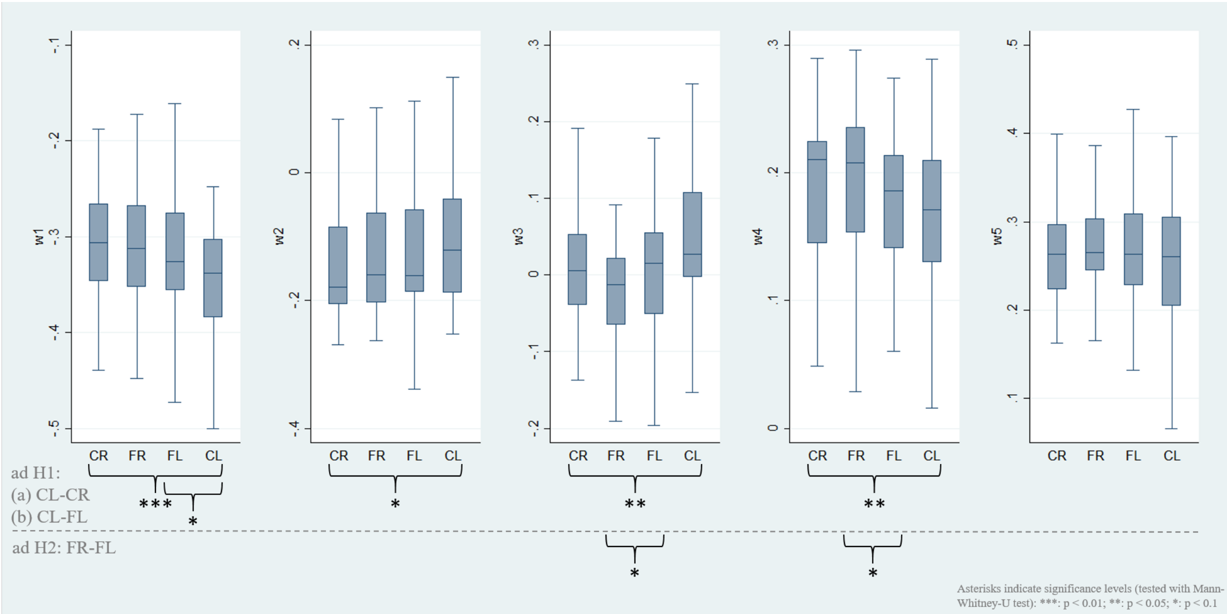

Figure 8: Box plots of category weighs $w_1 ... w_5$ in the four treatments CR, FR, FL, and CL. Ad H1: The effect of the decision domain (customer ratings or lotteries, i.e., CL and CR) is stronger than introducing a fuzziness of information (i.e., CL and FL). Ad H2: Differences between decision domains shrink when a fuzziness of information is included (in FL and FR), demonstrating evidence against an amplifying effect of multiple sources of ambiguity. In contrast, in comparing differences between $\Delta(CL, CR)$ and $\Delta(FL, FR)$, category weights seem to converge when a fuzziness of information is introduced.

following analysis we test whether more-experienced and less-experienced subjects are affected differently by the introduction of ambiguity (Hypothesis 3).

We test for differences between $\Delta(CL, CR_{more-exp})$ and $\Delta(CL, CR_{less-exp})$ with Mann-Whitney-U tests (cf. Figure 9). Test statistics (cf. Table D.15 in Appendix) indicate that less-experienced subjects deviate more from behavior of subjects in CL treatment, as we find significant differences for three categories. In comparison, more-experienced subjects deviate in only one category. That is, we find evidence that ambiguity is indeed perceived stronger by subjects that are less-experienced in the domain of customer ratings. The results are also illustrated in Figure 10.

Result 3. *More-experienced subjects deviate less from decisions under risk than less-experienced subjects in the domain of customer rating distributions. This might be explained by a perceived lower ambiguity aversion.*

4.3. Appropriateness of the estimator and goodness-of-fit of the estimates

We assess the suitability of the estimator by comparison with estimates that fix the weights $w_1, ..., w_5$ to arithmetic mean weights and are thus a reasonable benchmark. The likelihood-ratio statistics are summa-

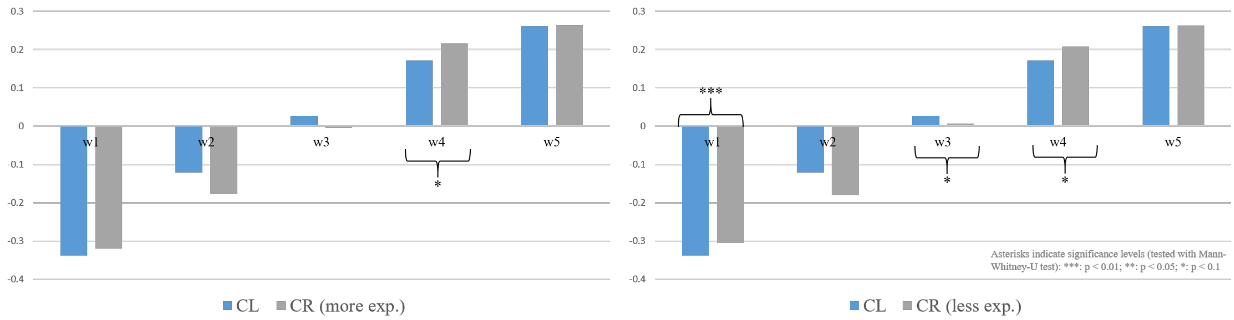

Figure 9: Evidence for more ambiguity aversion of less-experienced subjects: Test results of Mann-Whitney-U tests for differences between more-experienced and less-experienced subjects in *CR* treatment. Comparing the test results pairwise for $w_1, ..., w_5$ between $\Delta(CL, CR_{more-exp})$ and $\Delta(CL, CR_{less-exp})$, we observe that the absolute effect sizes are stronger for less-experienced subjects.

rized in Table 3.[8] Overall, 86.9% of the estimates with variable weights perform better than the benchmark

Table 3: Summary of likelihood-ratio tests. Frequencies are based on the available test results in each treatment.

CL			CR			FL			FR		
$p < 0.1$	$p < 0.05$	$p < 0.01$	$p < 0.1$	$p < 0.05$	$p < 0.01$	$p < 0.1$	$p < 0.05$	$p < 0.01$	$p < 0.1$	$p < 0.05$	$p < 0.01$
85.7%	76.8%	69.6%	88.5%	84.6%	65.4%	83.3%	70.4%	57.4%	90.2%	78.4%	60.8%

estimates with fixed weights.[9]

Comparing the estimates of category weights within the 213 subjects, in 119 subjects (55.9%) we observe strictly increasing weights (i.e., $w_1 < w_2 < w_3 < w_4 < w_5$) that are consistent with the ordinal scale (in CR and FR) and cardinal scale (in CL and FL), respectively. For 65 subjects (30.5%) we see one violation: namely, subject 189 weights categories 4 and 5 with 0.258 resp. 0.242, thus violating the inequality $w_5 > w_4$.[10] There are two violations for 25 subjects (11.7%)[11], three violations for 3 subjects (1.4%), and one subject with all four inequalities violated.[12] Considering no or one violation (and those with two violations not) to be reasonable, a conservative share of 86.4% showed consistent decision-making.[13]

8 Information on individual level is provided in Appendix E.

9 At the 10% level. At 5% (1%) level the respective frequencies are 77.5% (63.4%).

10 However, these weights seem reasonable since they can be interpreted as weighting the best and the second-best options similarly.

11 e.g., subject 147 seems quite reasonable, whereas subject 43 does not (cf. Appendix E).

12 e.g., category weights of subject 186 are: $w_1 = 0.267$; $w_2 = -0.023$; $w_3 = 0.233$; $w_4 = -0.152$; $w_5 = -0.324$. These violations are incomprehensible as they mean giving only positive weights on categories 1 and 3 and minimizing categories 4 and 5.

13 The number of violations are independent of the treatment ($\chi^2 : p = 0.853$).

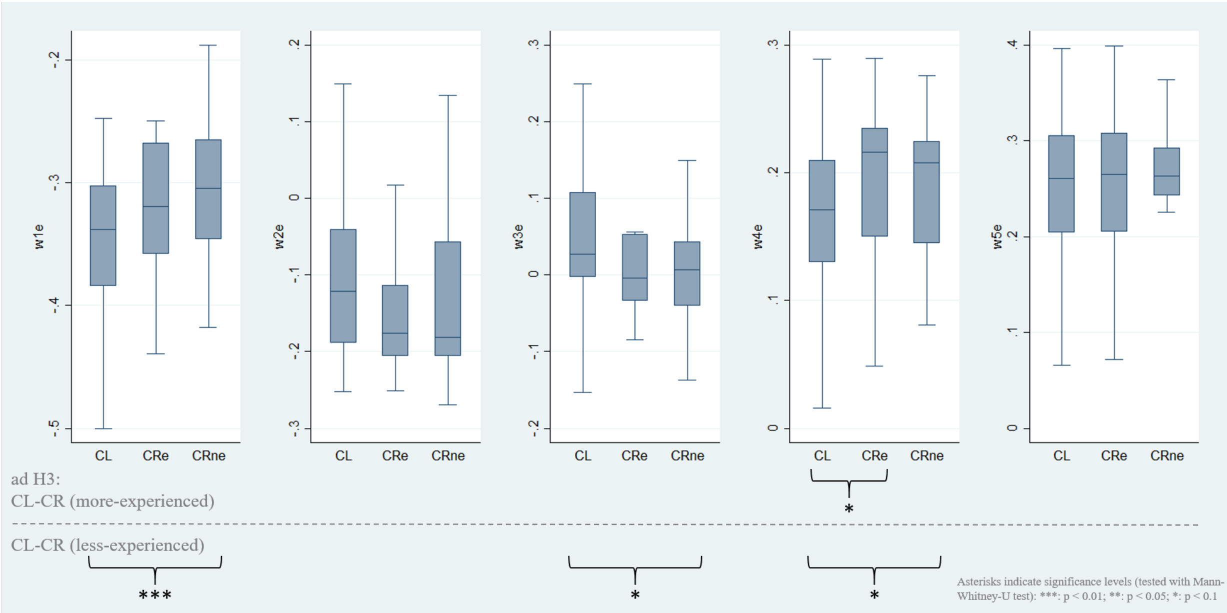

Figure 10: Category weights of more-experienced and less-experienced subjects under one source of ambiguity in comparison with category weights of risky decisions.

5. Conclusion

This study provides novel insights into decision-making under uncertainty. The design of our experiment allows us to compare decisions under risk with decisions under different levels of ambiguity while controlling for risk aversion. In doing this, we do not change the provided information so we can therefore directly compare the effects of various decision domains. In the domain of customer rating distributions, subjects deal with decisions under an unknown source credibility (i.e., ambiguity) as they do not have information about the authors of the customer reviews and their evaluation of the products. In the lottery domain, subjects choose between histograms of different lotteries and therefore make decisions under risk. Employing a maximum likelihood approach on individual level, we find that differences are present in decisions under risk and ambiguity. This is evidence for the existence of ambiguity aversion and against the comparative ignorance hypothesis (Fox and Tversky 1995).

Varying the presentation of information on subjects' choices, we implement a second source of ambiguity. In particular, the pure graphical presentation of the histograms and the absence of numerical information generates fuzziness about the options. When we introduce this fuzziness, differences between decision domains shrink. That is, under risk the implementation of ambiguity has a stronger effect, whereas a second source of ambiguity has a rather small effect on decisions under another source of ambiguity. This is evidence against an amplifying effect of different sources of ambiguity. On the individual level, we observe that subjects with more experience in the domain of customer rating distributions deviate less from decisions under risk in comparison with less-experienced subjects. That is, more-experienced subjects might perceive less ambiguity due to unknown source credibility or, at least, behave less averse to ambiguity than less-experienced subjects.

Our study has some limitations. We implemented customer rating distributions as ambiguous prospects and assume ambiguity due to an unknown source credibility to be the most prominent characteristic that affects decision-making. Even though this is reasonable from our perspective, the validity of our design and our results depend on this assumption. Furthermore, we did not discuss the data exhibit heterogeneity in category weights (i.e., decision-making, cf. Figure 8) in detail. Accounting for this heterogeneity, we use non-parametric tests for rank data that are robust to test our hypotheses. However, the test results should not be interpreted quantitatively but considered as directional test results. We also want to stress this point, as our hypothesis tests are conducted indirectly by comparing effect sizes of test statistics.

Nevertheless, this study has important implications because ambiguous options often are more efficient from an economic perspective although subjects shy away from them due to ambiguity aversion. For instance, many people stay with private pension insurance policies for their pension funds instead of investing in stocks because of the preference for risky prospects over ambiguous prospects. Our results point out an alternative approach to deal with ambiguity in decision-making. The biases driven by ambiguity aversion might be diminished when a second source of ambiguity, e.g., visualization instead of numerical information, is provided in decision processes for all options, both risky and ambiguous.

We see our study as a starting point for reconsidering multiple sources of ambiguity as a promising empirical research field. The effect of ambiguity aversion on decision-making is explored well. However, remedies for biases and inefficiencies through ambiguity aversion (except increasing experiences and knowledge) are still scarce.

Acknowledgements

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Appendix A. Discrete-ranking Decisions Across Treatments

The discrete ranking decisions are provided in Table A.4. See Table B.5 for a list of options. There is heterogeneity in decision-making between treatments. This heterogeneity seems to depend on the underlying lotteries and customer rating distributions, since differences in ranking behavior differ strongly between categories. For example, in category 3 there is almost no difference whereas in category 8 differences are large.

Table A.4: Ranking decisions in four treatments. R1 is the ranking with options, i.e. lotteries and customer rating distributions, being ranked in accordance with the arithmetic mean (1st, 2nd, 3rd). R2 is the ranking (2nd, 1st, 3rd). R3 is the ranking (1st, 3rd, 2nd). R4 is the ranking (3rd, 1st, 2nd). R5 is the ranking (2nd, 3rd, 1st). R6 is the ranking (3rd, 2nd, 1st).

Decision	Treatment	R1	R2	R3	R4	R5	R6
1 (Options 1-3)	CL	21	1	29	1	2	2
	CR	23	2	21	2	0	6
	FL	26	1	22	6	0	0
	FR	19	1	25	4	0	4
2 (Options 4-6)	CL	48	2	4	1	1	0
	CR	45	0	8	0	0	1
	FL	49	2	4	0	0	0
	FR	43	1	6	1	2	0
3 (Options 7-9)	CL	36	8	7	3	1	1
	CR	39	3	3	5	1	3
	FL	27	6	14	4	1	3
	FR	27	4	13	5	2	2
4 (Options 10-12)	CL	24	14	9	5	2	2
	CR	21	13	11	4	3	2
	FL	14	11	13	10	4	3
	FR	21	18	4	5	1	4
5 (Options 13-15)	CL	34	7	8	3	3	1
	CR	31	9	3	2	3	6
	FL	23	6	12	0	8	6
	FR	22	13	6	3	4	5
6 (Options 16-18)	CL	28	8	1	4	10	5
	CR	24	7	5	1	10	7
	FL	20	13	6	5	3	8
	FR	23	4	9	2	5	10
7 (Options 19-21)	CL	13	5	11	12	8	7
	CR	8	8	20	11	3	4
	FL	8	8	15	15	3	6
	FR	16	6	15	6	4	6
8 (Options 22-24)	CL	29	15	4	7	1	0
	CR	13	32	2	3	3	1
	FL	23	19	5	3	3	2
	FR	17	27	4	1	2	2
9 (Options 25-27)	CL	35	9	6	1	3	2
	CR	22	17	7	2	6	0
	FL	26	14	3	4	7	1
	FR	24	15	3	2	6	3
10 (Options 28-30)	CL	32	21	1	1	0	1
	CR	11	37	1	0	3	2
	FL	25	18	9	1	0	2
	FR	18	28	2	1	2	2
11 (Options 31-33)	CL	44	9	1	2	0	0
	CR	29	20	5	0	0	0
	FL	30	16	3	3	2	1
	FR	29	17	3	1	3	0
12 (Options 34-36)	CL	20	25	1	1	6	3
	CR	21	23	2	2	5	1
	FL	20	23	3	3	5	1
	FR	25	17	8	2	1	0

Appendix B. Histogram Options

Table B.5: Triples of lotteries to rank.

	Chance of winning					
Lottery	1 ECU	2 ECU	3 ECU	4 ECU	5 ECU	Expected Value
1	0.165	0.074	0.057	0.102	0.602	3.90
2	0.255	0.053	0.051	0.119	0.522	3.60
3	0.214	0.071	0.143	0.143	0.429	3.50
4	0.059	0.029	0.029	0.147	0.736	4.47
5	0.097	0.065	0.000	0.129	0.709	4.29
6	0.143	0.024	0.000	0.119	0.714	4.24
7	0.039	0.039	0.066	0.158	0.698	4.44
8	0.097	0.065	0.065	0.065	0.708	4.22
9	0.115	0.082	0.033	0.180	0.590	4.05
10	0.038	0.055	0.066	0.159	0.682	4.39
11	0.027	0.054	0.081	0.257	0.581	4.31
12	0.102	0.082	0.020	0.061	0.735	4.25
13	0.086	0.028	0.044	0.126	0.716	4.36
14	0.074	0.025	0.074	0.222	0.605	4.26
15	0.069	0.080	0.103	0.149	0.599	4.13
16	0.154	0.077	0.115	0.038	0.616	3.89
17	0.149	0.085	0.064	0.213	0.489	3.81
18	0.162	0.030	0.131	0.273	0.404	3.73
19	0.140	0.065	0.061	0.170	0.564	3.95
20	0.021	0.191	0.120	0.291	0.377	3.81
21	0.061	0.087	0.122	0.700	0.030	3.55
22	0.017	0.089	0.400	0.106	0.388	3.76
23	0.056	0.133	0.193	0.346	0.272	3.65
24	0.240	0.111	0.135	0.005	0.509	3.43
25	0.000	0.048	0.504	0.087	0.361	3.76
26	0.195	0.012	0.145	0.259	0.389	3.64
27	0.246	0.150	0.091	0.012	0.501	3.37
28	0.017	0.276	0.208	0.020	0.479	3.67
29	0.175	0.058	0.149	0.293	0.325	3.54
30	0.335	0.012	0.134	0.007	0.512	3.35
31	0.034	0.211	0.256	0.076	0.423	3.64
32	0.249	0.052	0.017	0.367	0.315	3.45
33	0.411	0.012	0.074	0.000	0.503	3.17
34	0.290	0.216	0.000	0.129	0.365	3.06
35	0.262	0.030	0.402	0.164	0.142	2.89
36	0.447	0.000	0.048	0.384	0.121	2.73

Appendix C. Summary of Estimates by Treatments

Table C.6: Estimator results for category weights in the Clear Lotteries treatment (n=56).

Coefficient	Mean	Std.Dev.	Median	25%	75%
w_1	-.334	.146	-.338	-.384	-.303
w_2	-.098	.121	-.121	-.188	-.041
w_3	.042	.091	.027	-.002	.108
w_4	.159	.084	.171	.130	.210
w_5	.232	.135	.261	.204	.305
α	419.08	878.87	89.18	38.71	217.16

Table C.7: Estimator results for category weights in the Clear Ratings treatment (n=52).

Coefficient	Mean	Std.Dev.	Median	25%	75%
w_1	-.303	.106	-.306	-.346	-.266
w_2	-.116	.157	-.178	-.206	-.085
w_3	.019	.107	.006	-.039	.054
w_4	.175	.102	.211	.145	.225
w_5	.224	.149	.263	.223	.297
α	117.83	123.65	67.78	37.30	136.57

Table C.8: Estimator results for category weights in the Fuzzy Lotteries treatment (n=54).

Coefficient	Mean	Std.Dev.	Median	25%	75%
w_1	-.320	.091	-.326	-.356	-.275
w_2	-.124	.129	-.161	-.187	-.057
w_3	.017	.110	.016	-.051	.055
w_4	.173	.066	.186	.141	.213
w_5	.254	.112	.263	.227	.309
α	74.50	68.71	49.58	30.97	86.25

Table C.9: Estimator results for category weights in the Fuzzy Ratings treatment (n=51).

Coefficient	Mean	Std.Dev.	Median	25%	75%
w_1	-.308	.093	-.312	-.353	-.267
w_2	-.118	.136	-.160	-.204	-.063
w_3	-.020	.104	-.013	-.065	.022
w_4	.193	.073	.208	.153	.236
w_5	.252	.129	.266	.244	.303
α	111.10	193.88	58.19	42.53	81.96

Table C.10: Test results of the Wilcoxon signed-rank test for each treatment and coefficient.

	Clear Lotteries		Clear Ratings		Fuzzy Lotteries		Fuzzy Ratings	
	z	p	z	p	z	p	z	p
$w_1 = -1/3$	-1.420	0.1558	2.586	0.0097	1.468	0.1421	1.968	0.0490
$w_2 = -1/6$	3.630	0.0003	0.537	0.5911	1.950	0.0512	1.893	0.0583
$w_3 = 0$	3.149	0.0016	0.519	0.6037	0.779	0.4358	-1.818	0.0690
$w_4 = 1/6$	0.302	0.7628	2.095	0.0362	1.434	0.1517	2.737	0.0062
$w_5 = 1/3$	-5.963	<0.0001	-5.464	<0.0001	-5.351	<0.0001	-5.146	<0.0001

Table C.11: Evidence for ambiguity aversion: Comparing differences between the risky treatment CL and the ambiguous treatments CR and FL, we find evidence for ambiguity aversion.

	$\Delta(CL, CR)$		$\Delta(CL, FL)$	
	z	p	z	p
w_1	2.746	0.0060	1.678	0.0934
w_2	-1.845	0.0651	-1.082	0.2791
w_3	-2.060	0.0394	-1.453	0.1462
w_4	2.158	0.0309	0.945	0.3448
w_5	0.172	0.8633	0.586	0.5579

Table C.12: No evidence for an amplifying effect of multiple sources of ambiguity: Comparing the test results pairwise for $w_1, ..., w_5$ between $\Delta(CL, CR)$ and $\Delta(FL, FR)$, we observe that the effect sizes shrink between decision-making under risk and ambiguity when a fuzziness of information is included.

	$\Delta(CL, CR)$		$\Delta(FL, FR)$	
	z	p	z	p
w_1	2.746	0.0060	0.577	0.5639
w_2	-1.845	0.0651	-0.205	0.8374
w_3	-2.060	0.0394	-1.821	0.0686
w_4	2.158	0.0309	1.789	0.0736
w_5	0.172	0.8633	0.282	0.7779

Appendix D. Estimates for More-experienced and Less-experienced Subjects

Table D.13: Estimator results for category weights in FR treatment for more-experienced (n=17) and less-experienced (n=34) subjects.

Coefficient	Mean	Std.Dev.	Median	25%	75%
w_1 Exp.	-.303	.106	-.323	-.351	-.254
w_2 Exp.	-.136	.092	-.160	-.182	-.095
w_3 Exp.	-.025	.120	-.005	-.029	.034
w_4 Exp.	.182	.072	.177	.132	.201
w_5 Exp.	.281	.114	.300	.253	.347
w_1 Non-Exp.	-.310	.088	-.303	-.353	-.272
w_2 Non-Exp.	-.109	.154	-.157	-.208	-.063
w_3 Non-Exp.	-.017	.096	-.013	-.069	.010
w_4 Non-Exp.	.198	.074	.220	.195	.242
w_5 Non-Exp.	.238	.135	.257	.218	.280

Table D.14: Estimator results for category weights in CR treatment for more-experienced (n=16) and less-experienced (n=36) subjects.

Coefficient	Mean	Std.Dev.	Median	25%	75%
w_1 Exp.	-.328	.072	-.320	-.358	-.268
w_2 Exp.	-.145	.095	-.176	-.206	-.113
w_3 Exp.	.027	.111	-.003	-.034	.054
w_4 Exp.	.200	.083	.216	.150	.235
w_5 Exp.	.246	.100	.265	.205	.308
w_1 Non-Exp.	-.291	.117	-.305	-.346	-.264
w_2 Non-Exp.	-.103	.177	-.181	-.206	-.056
w_3 Non-Exp.	.016	.107	.006	-.040	.043
w_4 Non-Exp.	.164	.108	.208	.145	.224
w_5 Non-Exp.	.215	.167	.263	.243	.292

Table D.15: Evidence for more ambiguity aversion of less-experienced subjects: Test results of Mann-Whitney-U tests for differences between more-experienced and less-experienced subjects in *CR* treatment. Comparing the test results pairwise for $w_1, ..., w_5$ between $\Delta(CL, CR_{more-exp})$ and $\Delta(CL, CR_{less-exp})$, we observe that absolute effect sizes are stronger for less-experienced subjects.

	$\Delta(CL, CR_{more-exp})$		$\Delta(CL, CR_{less-exp})$	
	z	p	z	p
w_1	1.226	0.2201	2.848	0.0044
w_2	-1.598	0.1099	-1.456	0.1454
w_3	-1.246	0.2127	-1.944	0.0519
w_4	1.829	0.0674	1.728	0.0840
w_5	0.095	0.9245	0.168	0.8666

Appendix E. Estimates of subjects

Table E.16: Estimates for subjects in the Fuzzy Ratings treatment. The reference model for likelihood-ratio statistics uses fixed weights corresponding to the arithmetic mean: $w_1 = -1/3$; $w_2 = -1/6$; $w_3 = 0$; $w_4 = 1/6$; $w_5 = 1/3$. Estimates for IDs 10 and 25 did not converge.

ID	w1	w2	w3	w4	w5	alpha	p-value of likelihood-ratio statistic
1	-0.237	-0.061	-0.202	0.132	0.368	58.188	0.001
2	-0.237	-0.263	0.002	0.185	0.314	69.093	0.260
3	-0.191	-0.231	-0.078	0.026	0.474	58.925	0.000
4	-0.304	-0.005	-0.191	0.115	0.385	12.495	0.505
5	-0.401	-0.072	-0.027	0.258	0.242	59.484	0.000
6	-0.172	-0.221	-0.107	0.229	0.271	42.586	0.238
7	-0.353	0.102	-0.147	0.208	0.190	24.259	0.074
8	-0.323	-0.177	0.021	0.166	0.313	62.741	0.006
9	-0.310	-0.190	0.004	0.247	0.248	30.070	0.095
10							
11	-0.321	-0.122	-0.057	0.220	0.280	236.066	0.000
12	-0.448	-0.052	0.063	0.271	0.166	55.437	0.000
13	-0.292	-0.208	0.005	0.240	0.255	79.314	0.002
14	-0.379	-0.089	-0.032	0.253	0.247	78.438	0.000
15	-0.272	-0.216	-0.013	0.207	0.293	328.677	0.000
16	-0.293	-0.056	-0.151	0.234	0.266	35.637	0.032
17	-0.322	-0.178	0.006	0.195	0.299	54.878	0.012
18	-0.415	-0.058	-0.027	0.200	0.300	61.966	0.000
19	-0.196	-0.239	-0.065	0.200	0.300	113.607	0.058
20	-0.338	-0.162	0.057	0.199	0.244	1308.850	0.000
21	-0.299	-0.190	-0.011	0.197	0.303	45.970	0.064
22	-0.271	-0.160	-0.070	0.296	0.204	13.891	0.537
23	-0.351	-0.126	-0.023	0.191	0.309	47.823	0.018
24	-0.340	-0.160	0.003	0.201	0.296	58.696	0.006
25							
26	-0.324	-0.176	0.034	0.213	0.253	491.835	0.000
27	-0.403	0.057	-0.097	0.277	0.166	34.495	0.008
28	-0.318	-0.153	-0.028	0.177	0.323	55.953	0.024
29	-0.300	-0.200	0.282	0.029	0.190	41.542	0.004
30	-0.267	-0.233	0.276	0.124	0.099	24.236	0.033
31	0.008	0.079	-0.382	0.413	-0.118	14.752	0.016
32	-0.256	-0.244	0.024	0.216	0.260	45.269	0.085
33	-0.292	-0.139	-0.069	0.234	0.266	147.959	0.000
34	-0.493	0.273	-0.007	0.071	0.155	14.045	0.092
35	-0.312	-0.182	-0.005	0.236	0.264	149.138	0.000
36	-0.267	-0.204	-0.029	0.153	0.347	100.813	0.002
37	-0.302	-0.198	0.038	0.208	0.254	183.878	0.000
38	-0.280	-0.220	0.034	0.213	0.254	76.810	0.004
39	-0.290	-0.208	-0.002	0.239	0.261	74.134	0.004
40	-0.437	-0.063	0.010	0.243	0.247	172.798	0.000
41	-0.385	-0.095	-0.020	0.208	0.292	43.684	0.010
42	-0.347	-0.153	0.040	0.242	0.218	358.157	0.000
43	-0.002	0.500	-0.062	-0.010	-0.427	38.331	0.037
44	-0.353	-0.099	-0.048	0.253	0.247	42.530	0.010
45	-0.325	-0.162	-0.014	0.220	0.280	148.531	0.000
46	-0.355	-0.145	0.162	0.113	0.225	55.723	0.001
47	-0.253	-0.112	-0.134	0.224	0.276	34.472	0.148
48	-0.413	0.004	-0.087	0.117	0.379	74.065	0.000
49	-0.339	-0.120	-0.041	0.232	0.268	56.411	0.006
50	-0.327	-0.173	0.022	0.140	0.338	64.938	0.003
51	-0.254	-0.246	0.006	0.108	0.386	54.328	0.044
52	-0.253	-0.247	0.041	0.108	0.351	81.957	0.006
53	-0.486	-0.014	0.092	0.156	0.252	48.139	0.000

Table E.17: Estimates for subjects in the Clear Ratings treatment. The reference model for likelihood-ratio statistics uses fixed weights corresponding to the arithmetic mean: $w_1 = -1/3$; $w_2 = -1/6$; $w_3 = 0$; $w_4 = 1/6$; $w_5 = 1/3$. Estimates for IDs 62 and 79 did not converge.

ID	w1	w2	w3	w4	w5	alpha	p-value of likelihood-ratio statistic
54	-0.270	-0.180	-0.050	0.167	0.333	123.739	0.001
55	-0.414	-0.086	0.029	0.399	0.072	6.571	0.463
56	-0.474	0.134	0.150	0.216	-0.026	28.376	0.001
57	-0.263	-0.234	-0.003	0.176	0.324	108.748	0.005
58	-0.304	-0.196	0.052	0.216	0.232	138.776	0.000
59	-0.296	-0.204	0.073	0.183	0.243	356.685	0.000
60	-0.263	0.357	0.143	-0.137	-0.100	52.392	0.001
61	-0.418	0.246	-0.040	0.254	-0.042	33.130	0.001
62							
63	-0.322	-0.178	0.007	0.173	0.321	101.660	0.000
64	-0.260	-0.178	-0.062	0.252	0.248	71.708	0.002
65	-0.188	-0.193	0.500	-0.090	-0.030	16.108	0.055
66	-0.306	-0.194	0.029	0.209	0.262	208.343	0.000
67	-0.307	-0.193	0.119	0.136	0.244	34.382	0.049
68	-0.361	-0.139	0.026	0.212	0.262	39.708	0.012
69	-0.261	-0.201	-0.038	0.205	0.295	114.296	0.004
70	-0.283	-0.217	0.061	0.276	0.163	50.650	0.001
71	-0.333	-0.141	-0.027	0.100	0.400	34.882	0.045
72	-0.317	-0.153	-0.029	0.223	0.277	65.703	0.004
73	-0.260	-0.240	0.005	0.216	0.278	447.322	0.000
74	-0.309	-0.191	0.006	0.222	0.271	70.423	0.007
75	-0.290	-0.210	0.016	0.224	0.260	271.441	0.000
76	-0.277	-0.211	-0.012	0.247	0.253	32.671	0.113
77	-0.315	-0.183	-0.002	0.222	0.278	528.000	0.000
78	-0.334	-0.083	-0.083	0.194	0.306	54.470	0.012
79							
80	-0.291	-0.194	-0.014	0.226	0.274	245.295	0.000
81	-0.304	-0.196	0.068	0.206	0.226	77.316	0.001
82	-0.231	-0.269	0.015	0.165	0.320	191.763	0.020
83	-0.267	-0.233	0.057	0.182	0.261	57.272	0.054
84	-0.384	0.084	-0.116	0.174	0.243	10.411	0.559
85	-0.313	-0.157	-0.029	0.214	0.286	214.326	0.000
86	-0.500	0.017	0.364	0.101	0.017	6.608	0.289
87	-0.439	0.080	-0.061	0.049	0.371	23.431	0.035
88	-0.380	-0.120	0.025	0.094	0.381	47.214	0.002
89	-0.301	-0.199	0.021	0.234	0.245	319.083	0.000
90	-0.321	-0.178	-0.001	0.225	0.275	409.762	0.000
91	-0.371	-0.024	-0.105	0.081	0.419	33.187	0.015
92	-0.266	-0.226	-0.008	0.216	0.284	108.692	0.005
93	-0.249	-0.251	0.055	0.245	0.199	52.129	0.004
94	-0.338	-0.119	-0.043	0.231	0.269	134.365	0.000
95	-0.336	-0.142	-0.022	0.216	0.284	66.690	0.005
96	-0.227	-0.218	-0.055	0.218	0.282	87.223	0.015
97	-0.326	-0.174	0.056	0.224	0.220	59.330	0.001
98	-0.362	0.037	-0.138	0.126	0.337	50.652	0.003
99	-0.355	-0.030	-0.115	0.136	0.364	198.534	0.000
100	-0.381	-0.034	-0.085	0.290	0.210	41.249	0.003
101	-0.241	-0.259	0.008	0.228	0.264	68.865	0.020
102	-0.265	-0.235	0.191	0.132	0.176	370.854	0.000
103	-0.320	-0.170	-0.010	0.201	0.299	43.785	0.040
104	-0.293	-0.207	0.022	0.153	0.325	91.461	0.002
105	-0.205	0.486	-0.040	0.014	-0.254	12.098	0.363
106	-0.356	-0.144	0.006	0.232	0.262	87.340	0.000
107	0.298	0.121	0.082	-0.201	-0.299	28.265	0.244

Table E.18: Estimates for subjects in the Fuzzy Lotteries treatment. The reference model for likelihood-ratio statistics uses fixed weights corresponding to the arithmetic mean: $w_1 = -1/3$; $w_2 = -1/6$; $w_3 = 0$; $w_4 = 1/6$; $w_5 = 1/3$. Estimates for ID 128 did not converge.

ID	w1	w2	w3	w4	w5	alpha	p-value of likelihood-ratio statistic
108	-0.296	-0.204	0.005	0.203	0.292	47.436	0.059
109	-0.118	0.307	0.097	0.096	-0.382	25.706	0.004
110	-0.275	-0.225	0.020	0.194	0.286	73.629	0.022
111	-0.326	-0.174	0.154	0.153	0.193	104.639	0.000
112	-0.338	-0.052	-0.110	0.262	0.238	21.929	0.154
113	-0.236	-0.187	-0.077	0.162	0.338	132.481	0.002
114	-0.237	-0.165	-0.099	0.073	0.427	30.282	0.078
115	-0.329	-0.071	-0.100	0.234	0.266	74.519	0.001
116	-0.251	-0.241	-0.008	0.195	0.305	21.431	0.854
117	-0.355	-0.123	-0.022	0.236	0.264	27.002	0.086
118	-0.278	-0.222	0.068	0.200	0.232	206.720	0.000
119	-0.483	-0.017	0.044	0.060	0.396	31.692	0.003
120	-0.268	-0.210	-0.022	0.229	0.271	22.744	0.547
121	-0.252	-0.136	-0.112	0.185	0.315	23.769	0.522
122	-0.249	-0.251	0.337	0.031	0.132	78.122	0.000
123	-0.361	-0.134	-0.005	0.213	0.287	46.588	0.016
124	-0.383	0.041	-0.117	0.073	0.386	40.374	0.004
125	-0.295	-0.185	0.312	-0.020	0.188	75.861	0.000
126	-0.308	-0.192	0.007	0.124	0.369	39.371	0.065
127	-0.299	-0.178	-0.022	0.161	0.339	90.265	0.001
128							
129	-0.248	-0.056	-0.196	0.264	0.236	95.900	0.000
130	-0.337	-0.163	0.062	0.183	0.255	360.859	0.000
131	-0.321	-0.179	0.140	0.164	0.196	66.448	0.000
132	-0.396	-0.104	0.084	0.213	0.203	20.734	0.063
133	-0.448	0.023	-0.052	0.198	0.279	28.726	0.024
134	-0.276	-0.224	0.049	0.195	0.255	82.677	0.002
135	-0.331	-0.169	0.075	0.160	0.265	86.249	0.000
136	-0.333	-0.167	0.055	0.183	0.262	59.843	0.004
137	-0.222	-0.278	0.024	0.144	0.332	50.126	0.419
138	-0.322	-0.022	-0.156	0.269	0.231	34.169	0.023
139	-0.331	-0.169	0.223	0.173	0.104	38.815	0.001
140	-0.300	-0.200	0.051	0.193	0.255	85.548	0.002
141	-0.330	-0.124	-0.046	0.186	0.314	46.613	0.027
142	-0.303	-0.057	-0.140	0.260	0.240	49.035	0.004
143	-0.307	-0.137	-0.056	0.209	0.291	40.752	0.090
144	-0.413	-0.043	-0.044	0.191	0.309	39.697	0.008
145	-0.223	-0.277	0.055	0.150	0.294	61.321	0.156
146	-0.004	-0.444	-0.051	0.187	0.313	12.949	0.774
147	-0.500	0.031	0.029	0.274	0.166	30.971	0.002
148	-0.331	-0.169	0.178	0.141	0.181	97.236	0.000
149	-0.326	-0.174	0.020	0.187	0.293	41.677	0.057
150	-0.393	-0.107	0.011	0.229	0.260	78.377	0.000
151	-0.500	0.009	0.025	0.187	0.279	54.156	0.000
152	-0.341	-0.159	0.036	0.236	0.227	273.785	0.000
153	-0.319	-0.181	0.055	0.251	0.195	32.720	0.026
154	-0.473	0.203	-0.027	0.141	0.156	135.584	0.000
155	-0.356	-0.144	0.021	0.230	0.248	211.168	0.000
156	-0.338	0.150	-0.153	-0.009	0.350	164.535	0.000
157	-0.500	0.113	0.012	0.168	0.208	14.435	0.107
158	-0.253	-0.146	-0.101	0.135	0.365	110.519	0.001
159	-0.391	-0.109	0.041	0.222	0.237	210.512	0.000
160	-0.385	-0.086	-0.029	0.121	0.379	30.511	0.035
161	-0.326	-0.174	0.124	0.116	0.260	50.237	0.004
162	-0.161	-0.339	0.232	0.112	0.157	11.750	0.586

Table E.19: Estimates for subjects in the Clear Lotteries treatment. The reference model for likelihood-ratio statistics uses fixed weights corresponding to the arithmetic mean: $w_1 = -1/3$; $w_2 = -1/6$; $w_3 = 0$; $w_4 = 1/6$; $w_5 = 1/3$.

ID	w1	w2	w3	w4	w5	alpha	p-value of likelihood-ratio statistic
163	-0.379	-0.121	0.010	0.159	0.331	1779.055	0.000
164	-0.292	-0.208	0.140	0.164	0.196	40.697	0.016
165	-0.321	-0.179	0.133	0.135	0.231	101.257	0.000
166	-0.305	-0.195	0.096	0.139	0.265	91.016	0.000
167	-0.261	-0.239	0.038	0.175	0.287	131.752	0.001
168	-0.326	-0.118	-0.056	0.128	0.372	114.139	0.000
169	-0.336	-0.161	-0.003	0.228	0.272	294.027	0.000
170	-0.259	-0.241	0.039	0.206	0.256	136.502	0.001
171	-0.303	-0.197	0.017	0.234	0.250	302.082	0.000
172	-0.307	-0.133	-0.060	0.124	0.376	103.801	0.000
173	-0.266	-0.234	0.022	0.200	0.278	220.733	0.000
174	-0.269	-0.231	0.018	0.201	0.281	234.280	0.000
175	-0.378	-0.122	0.031	0.225	0.243	25.642	0.082
176	-0.469	0.011	-0.031	0.155	0.334	1150.503	0.000
177	0.366	-0.013	0.134	-0.171	-0.316	25.907	0.096
178	-0.360	0.132	-0.140	0.223	0.146	10.693	0.479
179	-0.377	-0.084	-0.039	0.220	0.280	35.505	0.029
180	-0.346	0.145	-0.154	0.055	0.301	359.249	0.000
181	-0.388	-0.112	0.019	0.125	0.356	79.363	0.000
182	-0.263	-0.237	0.177	0.140	0.182	76.288	0.000
183	-0.326	-0.174	0.113	0.080	0.307	20.509	0.201
184	-0.376	-0.091	-0.033	0.216	0.284	47.759	0.006
185	-0.289	-0.165	-0.046	0.167	0.333	132.476	0.000
186	0.267	-0.023	0.233	-0.152	-0.324	19.666	0.220
187	-0.302	-0.100	-0.098	0.190	0.310	50.567	0.022
188	-0.410	0.321	0.083	0.096	-0.090	38.045	0.001
189	-0.381	-0.117	-0.002	0.258	0.242	42.672	0.005
190	-0.336	-0.164	0.044	0.231	0.225	107.593	0.000
191	-0.304	-0.196	0.146	0.184	0.170	104.767	0.000
192	-0.474	0.018	-0.026	0.085	0.397	86.214	0.000
193	-0.379	-0.121	0.010	0.159	0.331	1779.055	0.000
194	-0.266	-0.234	0.164	0.128	0.208	148.996	0.000
195	-0.414	-0.086	0.096	0.195	0.209	107.916	0.000
196	-0.500	0.052	0.103	0.131	0.214	4348.457	0.000
197	-0.374	-0.126	0.122	0.114	0.265	28.263	0.042
198	-0.343	-0.157	0.129	0.081	0.290	22.022	0.112
199	-0.312	-0.188	0.061	0.209	0.229	374.204	0.000
200	-0.318	-0.182	0.088	0.156	0.257	81.146	0.001
201	-0.296	-0.105	-0.099	0.202	0.298	88.425	0.001
202	-0.311	-0.188	-0.001	0.197	0.303	81.850	0.004
203	-0.500	0.025	0.093	0.181	0.201	3136.284	0.000
204	-0.379	-0.121	0.010	0.159	0.331	1779.055	0.000
205	-0.500	0.149	0.207	0.016	0.128	59.857	0.000
206	-0.442	-0.058	0.173	0.085	0.242	16.800	0.094
207	-0.340	-0.160	0.005	0.183	0.313	37.943	0.055
208	-0.499	0.002	-0.001	0.289	0.209	53.545	0.000
209	-0.248	-0.252	0.035	0.135	0.330	42.950	0.223
210	-0.376	0.184	-0.124	0.144	0.172	213.584	0.000
211	-0.420	-0.080	0.039	0.218	0.243	192.754	0.000
212	-0.379	-0.121	0.010	0.159	0.331	1779.055	0.000
213	-0.427	-0.073	0.249	0.185	0.066	9.168	0.288
214	-0.306	-0.194	0.140	0.191	0.170	89.928	0.000
215	-0.328	-0.097	-0.076	0.211	0.289	29.389	0.131
216	-0.500	0.009	0.081	0.210	0.200	2954.198	0.000
217	-0.500	0.051	0.002	0.332	0.115	11.234	0.133
218	-0.292	-0.208	0.020	0.211	0.268	39.366	0.082