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Ambiguity attitudes of individuals and groups in gain and loss domains

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Abstract

This study measures the differences in ambiguity attitudes of groups and individuals in the gain and loss domains. We elicit ambiguity aversion and ambiguity-generated insensitivity for natural temperature events. We do not find significant differences between individuals and groups in our main sample, yet higher ambiguity aversion and ambiguity-generated insensitivity result for groups in the gain domain when constraining the sample to groups and individuals with a better understanding of the experiment. The group effect on the ambiguity-generated insensitivity is sign-dependent.

Keywords Ambiguity attitudes · Group decision making · Gain and loss domain

1 Introduction

Decisions are often made under substantial uncertainties: individuals decide on job opportunities, make investments, select their partners, or just make everyday decisions like selecting clothes depending on weather forecasts. Many important decisions, however, are taken in groups. Spouses need to decide on educational prospects for their children, search committees collectively choose prospective job market candidates, society needs to decide on policies, e.g., on climate policy.

This paper compares individual to group decisions on ambiguous natural events when facing potential losses vs. gains. With this, we investigate to what extent

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individuals' and groups' ambiguity attitudes are sign-dependent. Specifically, we elicit preferences on weather-related events, i.e. on temperature ranges. Considering ambiguity-attitudes towards temperature events has the advantage that most individuals are familiar with weather-related decisions (cf. von Gaudecker et al., 2022, who compare ambiguity attitudes in relation to stock markets and temperature rises; Minnich et al., 2024).

A large and vital literature has dealt with decision-making under uncertainty, originating prominently from Knight (1921). Besides a larger theoretical literature on ambiguity preferences and decisions (see, e.g. Etner et al., 2012; Bühren et al., 2021), a substantial empirical literature has evolved and suggests potential differences in ambiguity preferences in the gain vs. the loss domain (e.g., Baillon and Bleichrodt, 2015; Kocher et al., 2018; Trautmann and Van De Kuilen, 2015; Bühren et al., 2021). Yet, the literature comparing ambiguity attitudes between individuals and groups in these two domains is underdeveloped. It largely focuses on hypothetical or very abstract decision contexts (e.g., Marquis and Reitz, 1969; Aggarwal et al., 2022).

We employ the method suggested by Baillon et al. (2018) and consider ambiguity attitudes towards weather (temperature) events. We place our work in the larger literature in Sect. 2. In our experiment, groups of three can chat with each other and must reach an unanimous solution. Our results suggests no significant differences between how groups' and individuals' attitudes are formulated on average. Controlling for comprehension of our experiment, we find larger ambiguity aversion among groups than among individuals in the gain domain. The second measure, the so-called ambiguity-generated insensitivity index (Baillon et al., 2018) is also sign-dependent.

Beyond this, our work confirms previous studies that individuals are more ambiguity averse in the gain than in the loss domain. Exploring the mechanisms through which individual attitudes are aggregated into group decisions, we find that the median players in the group appear to be decisive. That is, ambiguity attitudes between individuals and groups may depend on the specific distribution of preferences, i.e. if the expected median preference in a group is below or above the expected mean.

The remaining paper is structured as follows. Section 2 introduces a brief literature review of the differences in ambiguity preferences between groups and individuals. Section 3 is about the experimental design and procedures. Section 4 presents our results. We discuss our results and conclude in Sect. 5.

2 Literature review

Our paper on group attitudes towards ambiguity complements the extensive literature aggregation of risk attitudes in groups (e.g., Zhang and Casari, 2012; Baillon et al., 2016; Fukutomi et al., 2022). This literature uses related experimental designs. Baillon et al. (2016), for example, also use groups of three and allow for communication. They find stronger aggregation and communication (group) effects of an unanimity rule compared to the majority rule which guided our design choice.

Previous findings on differences in ambiguity preferences between individuals and groups are rather inconclusive.¹ A first (and often overlooked) study on risk and ambiguity preferences between individuals and groups was conducted by Marquis and Reitz (1969). They find that groups show more risk/ambiguity-loving choices in the gain domain and more ambiguity/risk-averse behavior occur in the loss domain. Keck et al. (2014) find higher ambiguity neutrality in group decisions. In contrast, Keller et al. (2007) find stronger ambiguity aversion in groups of two compared to individual decisions but rely on hypothetical statements. Lloyd and Döring (2019) examine the risk and ambiguity attitudes of male adolescents and find more ambiguity seeking in groups. Other studies do not find significant group effects on ambiguity attitudes (Brunette et al., 2015; Levati et al., 2017). Simon (2017) deals with decisions regarding ambiguous gambles and stock investments and finds that groups with communication become more ambiguity neutral, while group formation without communication tends to lead to more ambiguity aversion. Carbone et al. (2019) investigate inter-temporal individual and group decisions on consumption and saving and find that groups perform worse in risky outcomes and better in ambiguous outcomes. Aggarwal et al. (2022) rely on hypothetical statements and find more ambiguity seeking decisions at the individual level in the loss domain, while more ambiguity seeking results in group decisions in the gain domain. Thus, the effects of groups on ambiguity preferences could be sign-dependent (Marquis and Reitz, 1969; Aggarwal et al., 2022; cf. Lahno, 2014).

By comparing individual and group decisions following a chatting opportunity among group members, our study also relates to literature that examines effects of social interactions on individual ambiguity preferences: individual ambiguity attitudes may change (i) if decisions are subsequently disclosed to other persons (e.g., Curley et al., 1986; Muthukrishnan et al., 2009; Trautmann et al., 2008) or observed by peers (Tymula & Whitehair, 2018), (ii) if participants observe other decisions (e.g., Cooper and Rege, 2011; Delfino et al., 2016; Lahno, 2014), or (iii) due to direct social interactions (e.g., Charness et al., 2013; Engle et al., 2011; Engle-Warlick et al., 2020; Ahsanuzzaman et al., 2022).

In our study, we explicitly compare ambiguity attitudes in a gain and a loss domain. Extant literature suggests that ambiguity attitudes at the individual level can be sign-dependent (e.g., Baillon and Bleichrodt, 2015; Kocher et al., 2018; Abdellaoui et al., 2016). The review by Trautmann and Van De Kuilen (2015) suggests a fourfold pattern of ambiguity attitudes, that is, ambiguity aversion for larger probabilities in the gain domain and for small probabilities in the loss domain, ambiguity seeking for low probabilities in the gain domain and for larger probabilities in the loss domain. Baillon and Bleichrodt (2015) additionally find higher ambiguity-generated insensitivity for losses.

Our study contributes to the literature by explicitly comparing group and individual decisions under ambiguity in both loss and gain domains. Our study is the first to compare ambiguity preferences of individuals and groups using the method of Baillon et al. (2018). This method has the advantage that two distinct components

¹ A detailed overview of previous literature findings can be found in Table 4 in the Appendix.

of ambiguity attitudes can be measured: a first index measures ambiguity aversion (ranging from ambiguity seeking behavior to ambiguity indifference to ambiguity aversion), a second index refers to ambiguity-generated insensitivity. The latter index measures the over- or underestimation of small and large probabilities and is also interpreted as a perceived level of ambiguity (Dimmock et al., 2015). We are unaware of any study that measures the difference in perceived levels of ambiguity in groups and individuals.

3 Experimental design and procedures

This section presents our method for eliciting ambiguity attitudes first, before describing the experimental treatments and procedures and discussing hypotheses.

3.1 Ambiguity measurement

We use the method of Baillon et al. (2018) for the elicitation of ambiguity preferences for natural events. It relies on assessing the matching probabilities on single success events (E_1, E_2, E_3) which partition the full state space and the corresponding composite success events (E_{12}, E_{13}, E_{23}). Here, E_{ij} denotes $E_i \cup E_j$ ($j \neq i$).

The matching probabilities are denoted by m_i for the single and m_{ij} for the composite events ($i, j \in \{1, 2, 3\}$). They correspond to the winning probability of a lottery at which the decision maker is indifferent between the lottery or betting on the natural event E (e.g. Dimmock et al., 2016).

As single events are mutually exclusive, their matching probabilities add up to 1 for ambiguity-indifferent decision-makers.

Baillon et al. (2018) defines two indices that measure ambiguity attitudes:

$$b = 1 - \overline{m}_s - \overline{m}_c \quad a = 3 \times \left(\frac{1}{3} - (\overline{m}_c - \overline{m}_s) \right) \quad (1)$$

where $\overline{m}_s = (m_1 + m_2 + m_3)/3$ and $\overline{m}_c = (m_{23} + m_{13} + m_{12})/3$ refer to the averages of matching probabilities for single and composite events, respectively.

Index b measures ambiguity aversion. It ranges from -1 (minimum aversion or maximum ambiguity seeking) to 1 (maximum ambiguity aversion). Ambiguity indifference is given at a value of 0 . Index a measures the relationship between the matching probabilities of the single and composite events and is labeled as an index of ambiguity-generated insensitivity. It theoretically can range from -2 to 4 , yet a maximum of 1 is possible if preferences satisfy weak monotonicity ($\overline{m}_c \geq \overline{m}_s$). Ambiguity neutrality gives $b = 0$ and $a = 0$ ($\overline{m}_c = 2/3$ and $\overline{m}_s = 1/3$). If participants overweight low probabilities and underweight high probabilities, a will be positive. In the case of underweighted low probabilities and overweighted high probabilities, the index will be negative (Anantanasuwong et al., 2019). The two indices are orthogonal (Baillon et al., 2021).

3.2 Experimental treatments and natural events

The ambiguous bet is about the temperature in an undisclosed city on the known date, October 18, 2020, at 2 pm (CEST). Participants were informed that indicating the CEST time zone does not automatically mean that the city is located in the CEST zone. The events correspond to temperature ranges. E_1 refers to the temperature being below 8 degrees Celsius, E_2 to the temperature range higher than or equal to 8 degrees Celsius and lower than 14, and E_3 to higher than or equal to 14 degrees Celsius. Correspondingly, E_{12} refers to a temperature below 14 degrees, E_{23} to a temperature above or equal to 8 degrees, and E_{13} to temperature below 8 degrees or weakly above 14 degrees Celsius. The order of events was randomized in the experiment for participants or at the group level for group treatments.

The treatments vary the payoff domain between gains and losses. In the gain domain, choosing the temperature bet over a lottery pays 10 euros in case that event E materializes. In the loss domain, the realization of the given event E leads to a loss of 10 euros. Similar to Baillon et al. (2018), we use choice lists to determine the matching probabilities of each single and each composite event. The matching probabilities are given by the probability of a risky lottery in the gain (loss) domain that makes the participants indifferent between the risky lottery and the ambiguous temperature bet.

We consider four different treatments: Individual-gain (IG), group-gain (GG), individual-loss (IL), group-loss (GL). In IG and IL, the individual subjects decide alone. In GG and GL, groups of three subjects have to reach a unified decision on the probability at which they just prefer a risky bet over an ambiguous one.

3.3 Experimental procedures

The experiment was conducted as an online laboratory experiment with a student pool from the WiSo Research Laboratory at the University of Hamburg. Ethical approval was obtained through the WiSo Research Laboratory. The study was pre-registered (Lange & Minnich, 2022). The experiment was programmed with oTree (Chen et al., 2016), and hroot was used for recruitment (Bock et al., 2014). Four sessions were held in February 2022 (9th at 4:00 pm, 15th at 9:00 am, 17th at 9:00 am, 21st at 12:00 pm), and 382 participants took part, of whom 367 completed the experiment.² At all four sessions, all treatments ran at the same time, and treatment affiliation was randomized. In the last session, two groups of the group-loss

² Two groups of the group-gain and three groups of the group-loss treatment did not complete the experiment. Since four groups in the group-loss and two groups in group-gain treatments did not arrive at common solutions in at least one of the six ambiguity decisions, our final data set includes 349 participants. The sample size was informed by the number of independent observations in previous studies (e.g., Keck et al., 2014), instead of being based on an explicit power test as initial evidence on the effect size and standard errors using the method by Baillon et al. (2018) were missing.

Table 1 Experimental setup in the respective treatments

Sequence	Treatments			
	Group-gain	Individual-gain	Group-loss	Individual-loss
Phase 1	Explanation of the experiment, Control questions			
Phase 2	Ambiguity task			
	+10 euros or 0		-10 euros or 0	
Phase 3	Cognitive reflection test (5 questions) to balance the payouts			
	-2 euros per wrong answer		+2 euros per right answer	
Phase 4	Questionnaire and payout			
Participants	129	47	126	47
Independent observations	43	47	42	47

treatment were also run separately to equalize the number of observations for each treatment.³

In the following, we describe the timeline of the experiment, which can also be found in Table 1. The instructions of our experiment are based on Baillon et al. (2018), Li (2017), and Anantanasuwong et al. (2019), and an example of the instructions of the treatment group-loss is given in Online Appendix A.

First, the participants get a description of the ambiguity task. They then have to correctly answer two control questions about the ambiguity task. Participants had to stay in the instructions for at least 15 seconds per page and at least three minutes in total.

Second, the individual and group decisions concerning the ambiguity take place for the three single and three composite events. The order of the six events was randomized at the individual level or at the group level for group treatments. Following Baillon et al. (2018), participants face choice lists for six temperature events in an undisclosed city. The groups can chat together, while the individuals can only chat alone. The groups have three chances per choice list to reach a common unanimous solution (Zhang and Casari, see 2012). The groups are informed that they will automatically receive the worst payout (0 in the gain domain and – 10 euros in the loss domain) if a choice list of an event without a common solution is randomly selected for their payout. Figure 5 in the Appendix shows that the groups need fewer attempts to reach unanimity over time. Afterward, there was a one-minute break.

Third, subjects answer five questions of a cognitive reflection task. They get paid (additional/ less 2 euros per right/wrong answer in loss vs. gain domain) to balance out the payouts (see Kocher et al. (2018) for a similar payment procedure). The cognitive reflection test has the advantage of being relatively quick. It also has already

³ We use the control variables to check the randomization of our treatments (see Table 5 in the Appendix). We do not find systematic differences between treatments. Only minor differences exist in some demographic variables (gender, parenthood, income, previous experiment participation, faculty) and comprehension tasks.

been used as a control variable for ambiguity preferences in Li (2017). The five questions are based on Frederick (2005) and Li (2017).

Fourth, subjects fill out a questionnaire concerning demographic variables and behavioral attitudes, before the payouts are carried out. The questions include age, gender, faculty, number of semesters, number of previous participation in experiments at the University of Hamburg, income, vaccination status (Covid-19), parentship, comprehension of the ambiguity tasks, four survey questions about ambiguity preferences (Cavatorta & Schröder, 2019),⁴ a survey measure of risk attitudes (Dohmen et al., 2011), a weather-related risk attitude and the ten-item personality inventory (Gosling et al., 2003; Muck et al., 2007). We decided to collect the big five inventory using the ten-item personality inventory because Zhang and Casari (2012) found effects of the big five inventory on how groups reached a decision under risk. In addition, participants of groups answered two more questions about how they arrived at the group decision and how their own preferences contributed to the group decision.

We used a randomized incentive scheme to pay for the ambiguity task, i.e. the decision one of the six events mattered for final payments for which one random line of the decision table (lottery vs. ambiguous bet) was selected. For the natural events, participants or groups were randomly assigned to one of 30 cities which then determined the payoff.⁵ The respective city was only revealed after the experiment on the payment screen. Payments from this task thus were either plus 10 euros (gain treatments), minus 10 euros (loss treatment) in case of realization of the assessed event or 0 euro otherwise.

The payment of the participants consists of a starting amount of 10 Euro, the payment based on randomly selected ambiguity tasks (10, − 10, or 0), and the payoff from the cognitive reflection tasks (adding (loss treatments) or subtracting (gain treatments) 2 Euro per right/wrong answer). Participants can thus earn between 0 and 20 euros in every treatment.

The average payment to participants who completed the experiment was 12.72 euros (IG = 12.47, GG = 11.88, IL = 12.43, GL = 13.74).⁶ The average completion time of these participants was 38.5 min (IG = 21, GG=43, IL=21, GL=46).

⁴ Due to for temporal conciseness, we decided against the fifth measurement of Cavatorta and Schröder (2019), namely the dynamic Ellsberg two-color urn thought experiment measurement. Accordingly, for the calculation of the ambiguity score we only use the conversion of the Likert scales and do not use the constant of 130.

⁵ Unknowingly to participants, cities were selected such that each single success event being true for ten cities and each composite event being true for 20 cities correspondingly. The number of cities is set so high that no useful information can be exchanged between the participants between the different sessions.

⁶ Participants who could not finish the experiment because a team member had dropped out were paid a kind of hourly wage depending on their time commitment.

3.4 Coding the data

As described, we use choice lists to determine the matching probabilities. The choice lists contain 28 rows and are adjusted to avoid middle bias.⁷ For consistency of answers, participants may only indicate a single switching point from when they prefer the risky lottery. The matching probability (indifference point) is coded as the midpoint between the two values of the risky lottery where they switched preferences with two exceptions at the extremes: in the gain (loss) domain, we set the matching probability to 0 (100) if the lottery is always preferred and 100 (0) if the ambiguous bet is always preferred.⁸

Based on the matching probabilities, the ambiguity indices b and a are calculated (Baillon et al., 2018). Yet, the interpretation of b values differ in the gain vs. loss domains. A positive b reflects ambiguity aversion in the gain domain yet ambiguity seeking in the loss domain. In order to facilitate the interpretation of results, we multiply b as calculated with the matching probabilities with -1 in the loss domain.⁹

The variables from the survey were used to code control variables, see Table 6 in the Appendix which also gives the summary statistics of these variables. For example, we coded dummy variables based on demographic variables, risk and uncertainty preferences, as well as experiment-specific variables (cognitive reflection test, control questions errors, comprehension). We mostly use a median split for the control variables, creating dummy variables as independent variables.¹⁰ We code the statements on groups' decision-making and the inclusion of own preferences in the group decision as categorical variables.

In our main analyses, we removed participants who did not complete the experiment. This was the case for groups when one person dropped out of the experiment.¹¹ Next, we removed the groups that did not find a common solution in at least one of the six decisions of the ambiguity task.¹²

⁷ If participants choose option B in the gain and loss domain from row 15 onwards, they have a matching probability of 32.5 for individual success events and 67.5 for composite success events.

⁸ The choice lists run from 0 to 100% in the gain domain and from 100 to 0% in the loss domain to ensure the similarity of treatments (deciding when to prefer a risky lottery).

⁹ Intuitively, losing in case of event E in the loss domain corresponds to winning if the event does not occur (payoff 0 instead of -10). Accordingly, the matching probabilities in the gain domain can be converted into the loss domain by calculating the matching probabilities of the counter events $\bar{m}_s = 1 - \bar{m}_c$ and $\bar{m}_c = 1 - \bar{m}_s$. Thus $b = 1 - (1 - \bar{m}_c) - (1 - \bar{m}_s) = -1 * (1 - \bar{m}_s - \bar{m}_c)$. The ambiguity-generated insensitivity stays the same $a = 3 \times (\frac{1}{3} - ((1 - \bar{m}_s) - (1 - \bar{m}_c))) = 3 \times (\frac{1}{3} - (\bar{m}_c - \bar{m}_s))$

¹⁰ For the calculation of the medians, we only used the data where groups reached a common solution for every decision and only data from participants in group treatments.

¹¹ There is one exception, as one participant in the group-gain treatment did not have time to complete the questionnaire at the end of the experiment due to a follow-up appointment.

¹² This applied to a total of only 6 groups across gain (2) and loss (4) domain. Including these groups does not make any difference to our results when using the median value of the last decision round in which no common solution was found.

3.5 Hypotheses and concept of analysis

We formulated two hypotheses in our preregistration (Lange & Minnich, 2022). While our initial hypotheses only mentioned the dimension of ambiguity attitude relating to index b (aversion, indifference, seeking), we expected similar effects for the ambiguity-generated insensitivity (index a).

Hypothesis 1 Group decisions are more ambiguity neutral than individual decisions.

Hypothesis 2 The domain (gain or loss) has an impact on the difference in ambiguity attitudes (w.r.t. aversion, indifference, seeking as well as insensitivity) between groups and individual decisions.

Hypothesis 1 is consistent with the findings for gains by Simon (2017) and Keck et al. (2014). The tendency towards ambiguity-neutrality would typically already result via the aggregation of individual preferences within a group if this is based on the median preference. Yet, Keck et al. (2014) show that groups make more ambiguity-neutral choices beyond this pure aggregation effect and thus show fewer violations of the expected utility paradigm. We thus expect both indices b and a to be closer to 0 in groups than for individual decisions. Given the fourfold patterns of individual ambiguity attitudes (e.g., Trautmann and Van De Kuilen, 2015), the same aggregation logic leads us to hypothesize that the effects of groups on ambiguity preferences is sign-dependent. This is formulated in hypothesis 2. In line with this hypothesis, Aggarwal et al. (2022) and Marquis and Reitz (1969) provide preliminary evidence that the effects of groups compared to individuals depend on being in a gain vs. loss domain. We therefore expect an interaction effect between the group and the loss domain for both index b and a .

In order to test hypothesis 1, we use non-parametric and parametric tests to analyze. We examine both ambiguity indices and all six matching probabilities. We thereby separate the sample into gain and loss domains for the analyses. Furthermore, we run the following cross-sectional regression:

$$y = \beta_0 + \beta_1 \text{group} + \epsilon \quad (2)$$

We use the ambiguity indices b and a and all six matching probabilities as dependent variables y . Our main variable of interest is the independent variable *group*, which becomes 1 if a group makes a decision. The model also has an intercept and an error term, where we use heteroscedasticity consistent standard errors. Again, we separate the analysis for both domains gain and loss.¹³

For hypothesis 2, we use the following regression equation:

$$y = \beta_0 + \beta_1 \text{group} + \beta_2 \text{loss} + \beta_3 \text{group} \times \text{loss} + \epsilon \quad (3)$$

¹³ Contrary to our preregistration, we do not use control variables in our regressions since we do not consider comparing control variables of individuals to three-person groups appropriate.

Here, we add the two dummy variables *loss* and the interaction term $group \times loss$. The interaction term is our main variable of interest to test our second hypothesis.

In addition, we perform an exploratory analysis in order to better understand how groups reach their decisions. That is, we specifically investigate mechanisms that are behind potential differences between group and individual ambiguity attitudes.

First, we bootstrap the individual decisions on matching probabilities into groups of three to derive the minimal, the median, and the maximal matching probability. We then derive the ambiguity indices based on these measures and compare their distribution with the distribution of probability indices arising from the actual group treatments. This way, we can study if groups are more likely to follow in their decision the least or most ambiguity-averse group member or if the median player is more relevant.

Second, we exploit our survey measures on individual assessments on how groups arrive at decisions (unanimity, majority, imposition of one person) and how their own preference played a part in the group decision on average (adjusted, not, imposition of their own preference). We study how different control variables correlate with the dependent variables on group decision-making in the following multinomial logistic regression model:

$$\ln\left(\frac{P(\text{answer} = k_1)}{P(\text{answer} = k_3)}\right) = \beta_1 + \beta_2 \text{loss} + \beta_3 X \quad (4)$$

$$\ln\left(\frac{P(\text{answer} = k_2)}{P(\text{answer} = k_3)}\right) = \beta_4 + \beta_5 \text{loss} + \beta_6 X \quad (5)$$

In the regressions with the dependent variable about the group decision method, we use $k_3 = \text{unanimity}$ as a baseline and $k_1 = \text{majority}$, $k_2 = \text{person}$. In the regressions with the dependent variable about the imposition of their own preference, we use $k_3 = \text{adjusted}$ as a baseline and $k_1 = \text{no}$, $k_2 = \text{own}$. In each regression, we use the dummy variable *loss*. As control variables X , we use different sets, namely demographic variables, risk and uncertainty preferences, the ten-item personality inventory, and experiment-specific variables (cognitive reflection test, control questions errors, comprehension).

4 Results

This section deals with the descriptive and regression analysis of our treatments, an exploratory analysis of the group decisions, and the robustness checks. We report the test statistics (W) of the Wilcoxon–Mann–Whitney tests and the corresponding p-values (p) as well as the estimators of the regressions (β), the t-values with the degrees of freedom ($t(\text{degrees of freedom})$) and the corresponding p-values (p).

Table 2 presents the means and standard deviations of both ambiguity indices and the matching probabilities of each treatment. Considering the ambiguity aversion index b , we observe slightly ambiguity averse attitudes in the gain domain (GG and IG), while decisions in the loss domain (GL, IL) show slight ambiguity loving

Table 2 Summary Statistics for ambiguity indices and matching probabilities in treatments group-gain (GG), individual-gain (IG), group-loss (GL), individual-loss (IL). Observation in GG and GL at group level

Treatment	GG	IG	GL	IL
	Mean	Mean	Mean	Mean
Variables	(sd)	(sd)	(sd)	(sd)
Index b	0.10 (0.20)	0.04 (0.26)	-0.06 (0.22)	-0.08 (0.37)
Index a	0.50 (0.41)	0.38 (0.57)	0.50 (0.46)	0.58 (0.46)
Event E_1	37.19 (15.39)	33.65 (19.73)	39.76 (16.23)	36.86 (24.65)
Event E_2	39.21 (16.64)	40.53 (22.45)	40.63 (17.85)	39.94 (21.04)
Event E_3	34.42 (13.91)	38.30 (21.31)	36.07 (14.57)	40.05 (20.55)
Event E_{12}	54.65 (19.41)	59.62 (21.25)	57.82 (16.17)	48.41 (23.71)
Event E_{13}	52.17 (21.79)	55.72 (20.91)	52.79 (18.08)	53.21 (23.81)
Event E_{23}	53.86 (14.11)	59.21 (22.16)	56.31 (18.10)	57.29 (23.87)
Observations	43	47	42	47

attitudes. The averages of index a across all treatments suggest that overweighting of probabilities of single events relative to the weight given to composite events. The former are assigned matching probabilities reaching from 34–41%, while the latter receive weights 48–60%.

4.1 Treatment comparisons

A first look at Table 2 suggests only minor differences between treatments. This is confirmed by a series of non-parametric Wilcoxon–Mann–Whitney tests comparing ambiguity indices and matching probabilities between the group and the individual treatments. Figure 1 presents these for the gain domain. The results for the loss domain are in Fig. 2.¹⁴ No significant differences result with two minor exceptions: individuals indicate a higher matching probability for E_{23} in the gain domain ($W=796.5$, $p=0.082$), while groups in the loss domain have a higher matching probability for the composite event E_{12} ($W=1253.5$, $p=0.028$) (see also Tables 7 and 8). Comparing the gain and loss domain (see Table 3 as well as Figure OB.1 and Figure OB.2 in Online Appendix B), we find a significantly larger ambiguity aversion index b in the gain domain ($\beta_2 = -0.12$, $t(175) = -1.87$, $p = 0.063$). This result is

¹⁴ The results are robust to using parametric Welch's t-tests as a robustness check for the non-parametric tests except that the difference of the composite event E_{23} is no longer significant in the gain domain.

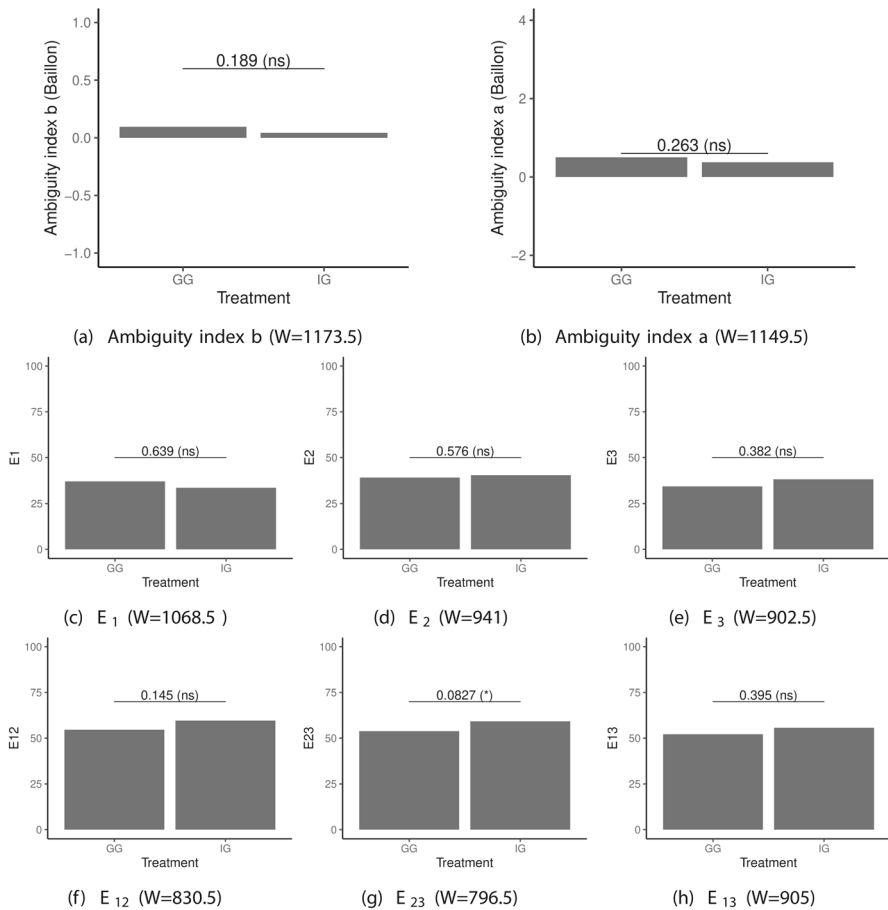


Fig. 1 Means of ambiguity indices and matching probabilities in the gain domain separated by treatments. P-values of Wilcoxon–Mann–Whitney test comparing the treatments group-gain (GG) and individual-gain (IG) above the mean values. Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, ns: not significant

significant for groups ($W = 1330.5$, $p < 0.001$) and for individual decision making ($W = 1362.5$, $p = 0.052$). For individuals, we find a significant lower index a in the gain domain ($W = 817$, $p = 0.030$).

We formulate the following result:

Result 1 Individuals and groups do not show significantly different ambiguity attitudes. Both groups and individuals are more ambiguity seeking in the loss domain than in the gain domain.

In order to investigate Hypothesis 2, we consider regressions allowing for interaction effects $group \times loss$. The results are again reported in Table 3. The interaction effect as our main variable of interest is not significant for the

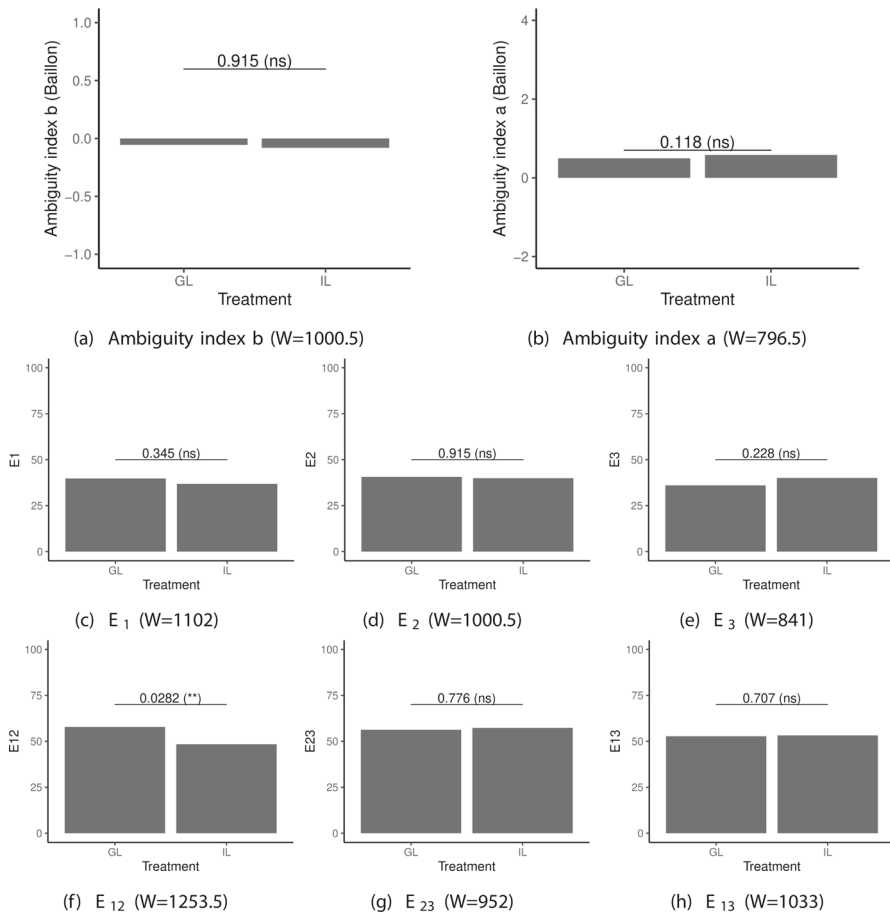


Fig. 2 Means of ambiguity indices and matching probabilities in the loss domain separated by treatments. P-values of Wilcoxon–Mann–Whitney test comparing the treatments group-loss (GL) and individual-loss (IL) above the mean values. Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, ns: not significant

ambiguity indices. A significant effect only arises for the event E_{12} ($\beta_3 = 14.37$, $t(175) = 2.35$, $p = 0.020$). We thus summarize our second result as follows:

Result 2 The domain (gain or loss) does not impact the difference in ambiguity attitudes between groups and individual decisions.

4.2 Exploratory analysis of group decisions

The previous section established that no major differences exist between average individual ambiguity attitudes and group decisions. In the group treatments,

Table 3 Linear regressions: treatment effects

	Dependent variable							
	b	a	E1	E2	E3	E12	E13	E23
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
group	0.052 (0.050)	0.122 (0.105)	3.537 (3.755)	− 1.323 (4.189)	− 3.879 (3.804)	− 4.966 (4.335)	− 3.549 (4.562)	− 5.352 (3.926)
loss	− 0.124* (0.066)	0.200* (0.108)	3.213 (4.655)	− 0.596 (4.536)	1.755 (4.365)	− 11.202** (4.695)	− 2.511 (4.672)	− 1.926 (4.802)
group:loss	− 0.026 (0.081)	− 0.206 (0.144)	− 0.637 (5.808)	2.017 (5.911)	− 0.102 (5.370)	14.372** (6.114)	3.122 (6.411)	4.375 (5.983)
Constant	0.043 (0.039)	0.379*** (0.084)	33.649*** (2.908)	40.532*** (3.310)	38.298*** (3.141)	59.617*** (3.134)	55.723*** (3.084)	59.213*** (3.267)
Observations	179	179	179	179	179	179	179	179
R ²	0.065	0.023	0.012	0.001	0.014	0.044	0.004	0.009
Adjusted R ²	0.049	0.006	− 0.004	− 0.016	− 0.003	0.028	− 0.013	− 0.008
Residual Std. Error	0.273	0.480	19.509	19.747	18.070	20.449	21.318	20.084
F Statistic	4.074***	1.383	0.737	0.048	0.841	2.694**	0.244	0.550

Note: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$; heteroscedasticity consistent standard errors (“HC3”) in parentheses and estimated with the

R package sandwich (Zeileis, 2004; Zeileis et al., 2020)

individuals log in their matching probability only *after* chatting with their fellow group members. As such, we do not have an independent measure of their own ambiguity attitudes.

In this section, we provide an explanatory analysis of decision-making processes within groups. This analysis was not preregistered. We first compare the distribution of ambiguity indices in the group treatments with ambiguity indices that are derived from bootstrapping the decisions in the individual treatments into groups of three and calculate ambiguity indices based on (i) the minimum, (ii) the median, and (iii) the maximum matching probability among the artificially combined group members.

Figure 3 reports the cumulative distribution functions of these ambiguity indices compared with the one derived from the group treatments. For both gain and loss domain, we see that the distribution of the ambiguity index in the group treatment follows closely the distribution based on the median matching probabilities in the simulated groups. We thus conclude that group decisions on matching probabilities in our sample are not driven by the most ambiguity averse or least ambiguity averse agent, but rather are likely based on the intermediate assessments in a group.¹⁵

¹⁵ We note that—lacking an independent measure of individual ambiguity attitudes in the group settings—we cannot identify an additional trend towards ambiguity neutrality beyond the aggregation exercise (cf., Keck et al., 2014).

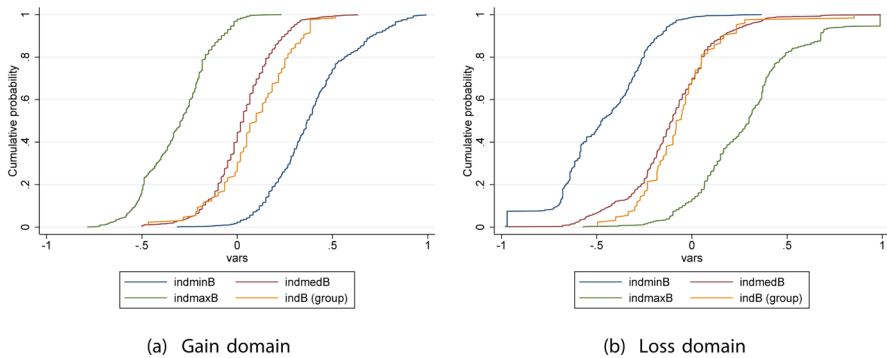


Fig. 3 Ambiguity index b in gain domain (panel (a)) and loss domain (panel (b)). The lines show cumulative distributions based on bootstrapping individual matching probabilities in groups of three (1000 random groups of three). The cdfs correspond to the ambiguity indices b if the bootstrapped groups always chose the minimal, the median, or the maximal matching probability in their group of three. The fourth line displays the actual cdf of index b in the group treatments

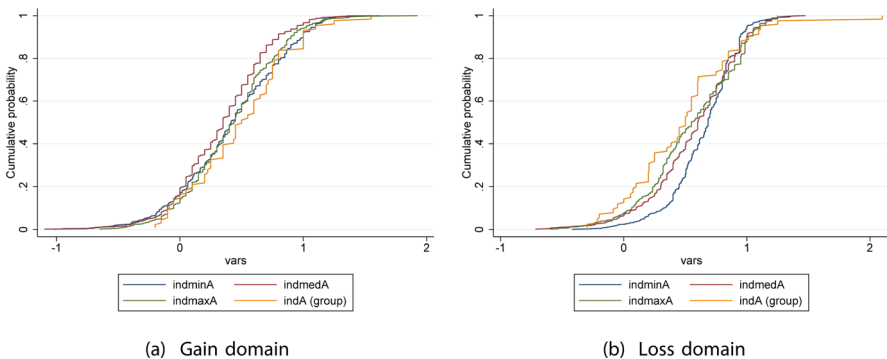


Fig. 4 Ambiguity index a in gain domain (panel (a)) and loss domain (panel (b)). The lines show cumulative distributions based on bootstrapping individual matching probabilities in groups of three (1000 random groups of three). The cdfs correspond to the ambiguity indices a if the bootstrapped groups always chose the minimal, the median, or the maximal matching probability in their group of three. The fourth line displays the actual cdf of index a in the group treatments

For completeness, Fig. 4 shows the corresponding pictures for ambiguity index a . Here, the different lines do not significantly differ: the likely reason is that the *difference* between matching probabilities for composite and single events does not much differ between the individuals with the minimal, median, or maximal matching probability (and hence ambiguity aversion) in a group of three.

Another way to investigate the mechanisms behind group decisions is guided by the survey measures on how participants in the group treatment perceived the decision-making process. On average, most participants reached a group decision through unanimity (169), while 55 reached a solution with majority and 30 with the imposition of one person's preferences in the group. In the process, 177 participants

stated that they adjusted their preferences, 73 participants found that they could enforce their own preferences, and four people subjects assessed that they did not contribute their own preferences to the group decision. Overall, this is consistent with groups finding some middle ground in the assessment of matching probabilities as individuals with the largest or lowest individual preferences are more likely needed to adjust their preferences in order to reach a consistent group decision.

We now explore if these individual views are driven by some socio-economic characteristics. Table 9 in the Appendix shows the results from multinomial regressions on group strategies, the results of the regressions on the inclusion of own preferences can be found in Table 10. In both tables, two columns always belong to the same underlying regression. The results can always be interpreted in comparison to the baseline response option (unanimity in Table 9 and adjusted in Table 10). Overall, it is noticeable that only very few control variables significantly affect the dependent variables. That is, the views on how the decisions were made in a group do not significantly differ between individuals with different socio-economic characteristics.

4.3 Mechanisms behind group decisions

Figure 5 in the Appendix shows that, on average, the groups agreed more and faster over time, both in terms of gain and loss domains. A significant number of groups reached an agreement in the first round, only a few groups required more than two attempts to reach an agreement.

A total of 4859 text messages were written by the 255 participants in the group treatments (GL, GG). This corresponds to an average of 3.2 text messages written by a participant in one of the six decision tasks. This average number varies from 3.1 in case that participants later stated that the group decision was unanimous, 3.6 if they stated that a majority solution was found, to 3.0 if one person's preferences were imposed on the group. Not surprisingly, the number of messages sent by individuals who stated to not have contributed their own preferences to the group decision was much smaller per decision task (1.5) than if individuals adjusted their preferences (3.2) or if they imposed their preferences (3.1).

A qualitative assessment of the chat messages suggests that decisions may be based on compromises. The messages often involve someone just asking "What do you think?", little exchanges of arguments, and rather someone making a suggestion, a counter suggestion ("going up" or "going down"), before others may agree. In some cases, there are also arguments about the possible locations in the world, the state of day (night in some places), the month of October, and the global average temperature. In some groups, the probabilities of occurrence are discussed or sometimes counter-probabilities are presented. Since the subjects do not know which location is crucial for the temperature event, there is no feasible way for the subject to signal expertise.¹⁶

¹⁶ Given the brevity of most messages, we do not perceive that a machine learning or text analysis approach could provide much deeper insights as we do not have an independent measure of individual ambiguity attitudes. Eliciting those appears beneficial when further investigating the group decision processes in future research by also comparing how different aggregation procedures affect the necessity of (text) exchanges between group members.

4.4 Robustness checks

We preregistered robustness checks to investigate if treatment effects arise for specific subsets of the sample for which one can anticipate better-informed decisions. A first robustness check is based on the comprehension of the experiment participants as self-assessed in the survey (see Online Appendix C). A second robustness check takes the answers to the control question as a criterion for sample quality (see Online Appendix D). In doing so, we compare groups that meet the selection criterion at the median with individuals who meet the criterion.

Restricting the sample on individuals and groups who report a good comprehension (see Online Appendix C), we find difference between groups and individuals in the gain domain: the estimator *group* is positive and marginally significant for index *b* ($\beta_1 = 0.10$, $t(54) = 1.91$, $p = 0.061$), and positive and significant for index *a* ($\beta_1 = 0.36$, $t(54) = 3.21$, $p = 0.002$) (see Table OC.4).¹⁷ Differently, no significant differences between groups and individuals arise in the loss domain (see Table OC.5). In fact, the interaction effect *group* \times *loss* is negative and highly significant for index *a* ($\beta_3 = -0.50$, $t(90) = -2.80$, $p = 0.006$) (see Table OC.6).¹⁸

Similar effects result if we choose the selection criterion of no mistakes in the comprehension questions (see Online Appendix D). In the gain domain, *group* is positive and marginally significant for ambiguity index *b* ($\beta_1 = 0.10$, $t(55) = 1.71$, $p = 0.093$) and positive and significant for ambiguity index *a* ($\beta_1 = 0.24$, $t(55) = 2.29$, $p = 0.026$) (see Table OD.4).¹⁹ In the loss domain, no difference between group and individual ambiguity indices results (see Table OD.5). Consistently, the estimator on the interaction effect of group and loss is negative and marginally significant effect for the ambiguity index *a* ($\beta_3 = -0.29$, $t(115) = -1.81$, $p = 0.073$) (see Table OD.6).

Yet, these results come with a word of caution as the number of observations satisfying good comprehension or no error in the comprehension questions, respectively, is not particularly large.²⁰ Overall, the robustness checks regarding the participants' understanding yield the following result:

Result 3 For subsamples with likely better-informed decisions (good comprehension or no mistakes in control questions), significant differences between individuals and groups arise with respect to ambiguity attitudes in the gain domain, where

¹⁷ This effect is driven by groups assigning a lower matching probabilities to events E_{12} ($\beta_1 = -14.25$, $t(54) = -3.14$, $p = 0.003$) and E_{23} ($\beta_1 = -12.92$, $t(54) = -3.53$, $p = 0.001$) (see Table OC.4).

¹⁸ This effect is driven by the positive interaction effect of *group* \times *loss* on E_{12} ($\beta_3 = 21.89$, $t(90) = 2.83$, $p = 0.006$) and E_{23} ($\beta_3 = 16.20$, $t(90) = 2.02$, $p = 0.047$) (see Table OC.6). Overall, the mean values of E_{12} and E_{23} are in the order $(IG) > (GL) > (GG) > (IL)$

¹⁹ This is again driven by groups assigning a lower matching probabilities to events E_{12} ($\beta_1 = -10.18$, $t(55) = -2.34$, $p = 0.023$) and E_{23} ($\beta_1 = -12.25$, $t(55) = -2.86$, $p = 0.006$) (see Table OD.4).

²⁰ We have also relaxed the criteria for the subsamples. If we consider only groups (median) and individuals with good or rather good understanding (see Table OC.1, OC.2, and OC.3) or groups (median) and individuals with one or less errors on the comprehension questions (see Table OD.1, OD.2, and OD.3), the results point to similar directions.

groups show larger ambiguity aversion and higher ambiguity-generated insensitivity. This group effect for ambiguity-generated insensitivity is domain specific significantly different in the loss domain.

5 Conclusions

We compare ambiguity attitudes of groups and individuals in the gain and loss domain in a between-subject design. Groups of three can chat with each other in order to come to an unanimous decision. We use the method of Baillon et al. (2018) which allows measuring ambiguity attitudes by distinguishing ambiguity aversion (or indifference, or ambiguity seeking behavior) and ambiguity-generated insensitivity for natural events. We apply this method to elicit ambiguity attitudes regarding temperature events.

Comparing gain and loss domains, we find more ambiguity-seeking behavior and a higher ambiguity-generated insensitivity in the loss domain. This result is consistent with literature (e.g., Trautmann and Van De Kuilen, 2015; Baillon and Bleichrodt, 2015) and extends these results to group decisions and to ambiguity attitudes towards naturally occurring temperature events.

In both domains, the matching probabilities for small(er) probabilities (single events) are aggregated above 1, while the corresponding sum for large(r) probabilities (composite events) is aggregated below 2. Without aggregating these matching probabilities into the ambiguity indices à la Baillon et al. (2018), our results are consistent with a fourfold pattern of ambiguity attitudes (Trautmann and Van De Kuilen, 2015): subjects are ambiguity averse for more likely events in the gain domain and for less likely events in the loss domain, while they are ambiguity-seeking for low likelihood events in the gain domain and high likelihood events in the loss domain.

Yet, the differences between groups and individual attitudes are marginal. In our main sample, we do not find significant differences between individual ambiguity attitudes and those that result in group decisions. However, larger ambiguity aversion and ambiguity-generated insensitivity results groups than for individuals in the gain domain when we concentrate on subjects indicating a higher comprehension of the experiment. For those subsamples, the group effect on ambiguity-generated insensitivity appears to be sign-dependent, i.e. individual preferences are aggregated differently into group decisions in the gain vs. the loss domain.

Appendix

Table 4 Overview of studies with group decisions concerning ambiguity attitudes

Study	Group Size & Set-up	Ambiguity Levels	Communication Decision rule	Domain	Comparison Method	Main Finding Shift to
Marquis & Reitz (1969)	3–7 I–G (Within)	Stake, Probability Winning Price	Discussion Unanimity	Gain, Loss Mixed	Stake size	AA(Loss(–25%))
Keller et al (2007)	2 I–G (Within)	Probability	Discussion –	Gain	WTP (gamble)	AS(Gain, Mixed, Loss (–10%)) AA
Keck et al (2014)	3 I–G, G–I (Within)	Probability	Discussion Majority	Gain	Certainty equivalent to Gamble	AN
Brunette et al (2015)	3 I–G, G–I (Within)	Probability	No communication Unanimity, Majority	Gain	Risk to Ambiguity	No effect
Levati et al (2017)	3 I–G, G–I (Within)	Probability	No communication Majority, Delegate(1,2)	Gain	Risk to Ambiguity	AA (Delegate 1,2)
Simon (2017)	3 I–G (Within); I, G (Between)	Probability	Discussion (Chat:yes/no) Unanimity, Average	Gain	Stock investment; Minimum selling price (Risk to Ambiguity)	AN(discussion) AS (discussion, stock investment)
Carbone et al (2019)	2 I, G (between)	Probability	Discussion (Chat) –	Gain	Consumption/Saving Experiment (inter-temporal)	Better planner under ambiguity
Lloyd & Döring (2019)	2 I, G (Between)	Probability	Discussion –	Gain	Wheel of Fortune task (Ambiguity to Certain)	AS
Aggarwal et al (2022)	5 (partly 4 or 6) I–G (Within)	Probability Winning Price	Discussion Unanimity	Gain, Loss	Lottery choices (Risk to Ambiguity)	AS (gain)

Note: Individual = I, Group=G; AA=Ambiguity Aversion, AS=Ambiguity Seeking, AN=Ambiguity Neutral

Table 5 Summary statistics

treatment Variable	GG			IG			GL			IL		
	N	Mean	Sd	N	Mean	Sd	N	Mean	Sd	N	Mean	Sd
Gender (female)*	128	0.688	0.465	47	0.809	0.398	126	0.587	0.494	47	0.66	0.479
Gender (diverse)*	128	0.00781	0.0884	47	0	0	126	0.0159	0.125	47	0.0213	0.146
Age	128	25.6	4.35	47	24.8	4.17	126	24.9	4.57	47	25.5	4.61
Parentship*	128	0.0469	0.212	47	0.0426	0.204	126	0.0476	0.214	47	0.0851	0.282
Income0 (0–600)*	128	0.234	0.425	47	0.213	0.414	126	0.238	0.428	47	0.319	0.471
Income (600–800)*	128	0.234	0.425	47	0.234	0.428	126	0.246	0.432	47	0.191	0.398
Income (800–1200)*	128	0.375	0.486	47	0.383	0.491	126	0.341	0.476	47	0.362	0.486
Income (1200–1600)*	128	0.102	0.303	47	0.149	0.36	126	0.119	0.325	47	0.0426	0.204
Income (1600–2000)*	128	0.0312	0.175	47	0.0213	0.146	126	0.0159	0.125	47	0.0213	0.146
Vaccinated*	128	0.922	0.269	47	1	0	126	0.937	0.245	47	0.915	0.282
Vaccinated (not)*	128	0.0156	0.125	47	0	0	126	0.0159	0.125	47	0.0213	0.146
Vaccinated (not Yet)*	128	0.00781	0.0884	47	0	0	126	0	0	47	0.0213	0.146
Semesters	128	8.34	6	47	7.85	4.17	126	7.87	4.9	47	8.94	5.89
Experiment participations	128	9.91	13.2	47	10.8	11.6	126	9.94	13.1	47	11	9.23
Faculty (economics, social)*	128	0.445	0.499	47	0.574	0.5	126	0.516	0.502	47	0.468	0.504
Ambiguity index	128	130	17.6	47	131	16.1	126	131	16.6	47	127	18.5
Risk seeking (general)	128	5.73	1.87	47	5.81	2.19	126	5.7	1.99	47	5.45	2.2
Risk seeking (weather)	128	6.48	2.34	47	6.49	2.62	126	6.35	2.43	47	5.96	2.78
Extraversion	128	4.13	1.46	47	4.35	1.29	126	4.15	1.38	47	4.45	1.62
Agreeableness	128	5.1	1.06	47	5.15	1.16	126	5.17	0.976	47	5.05	1.03
Conscientiousness	128	5.46	1.12	47	5.59	1.16	126	5.28	1.19	47	5.36	1.2
Emotional stability	128	4.6	1.24	47	4.31	1.29	126	4.67	1.36	47	4.59	1.12
Openness to experiences	128	5.11	1.14	47	5.06	1.13	126	5.28	1.07	47	5.36	1.12
Cognitive test (correct answers)	129	3.48	1.52	47	3.47	1.33	126	3.96	1.32	47	3.55	1.35

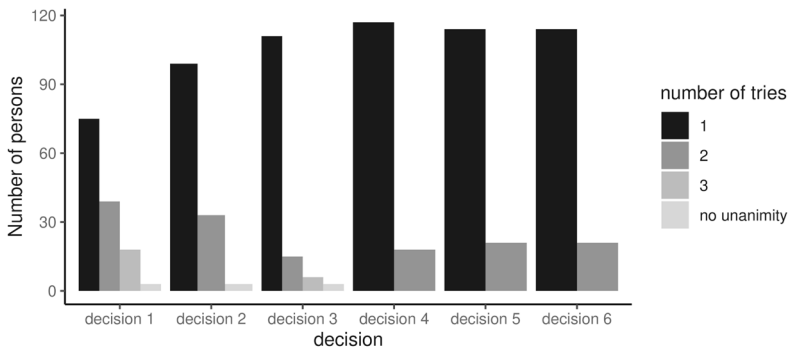
Table 5 (continued)

Variable	GG			IG			GL			IL		
	N	Mean	Sd	N	Mean	Sd	N	Mean	Sd	N	Mean	Sd
Errors (control questions)	129	0.667	1.07	47	1.21	2.15	126	1.11	2.2	47	0.702	1.38
Comprehension (yes)*	128	0.578	0.496	47	0.574	0.5	126	0.429	0.497	47	0.574	0.5
Comprehension (rather yes)*	128	0.398	0.492	47	0.362	0.486	126	0.476	0.501	47	0.34	0.479
Comprehension (rather not)*	128	0.0234	0.152	47	0.0426	0.204	126	0.0794	0.271	47	0.0851	0.282

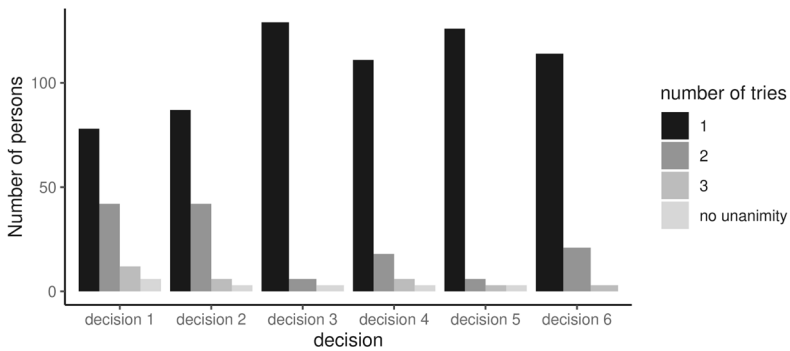
* The variables are dummy variables. For some of the dummy variables, there was another response option, which are listed as follows: Gender (male), income (more than 2000), vaccinated (not specified), comprehension (not)

Table 6 Composition of the dummy variables for the exploratory regressions of group decisions

Variable name	1	0
faculty (economics, social)	business, economics and social sciences	others
age_high	median (24.5) and above	≤ 24
income_high	median (800–1200 €) and above	$\leq 800\text{€}$
semesters_high	median (7) and above	< 7
participation_high	median (6) and above	< 6
risk_1_high (general)	median (6) and above	< 6
risk_2_high (weather)	median (7) and above	< 7
amb_index_high	median (129.5) and above	< 129.5
extraversion_high	median (4) and above	< 4
agreeableness_high	median (5) and above	< 5
conscientiousness_high	median (5.5) and above	< 5.5
emotional_stability_high	median (4.5) and above	< 4.5
openness_to_experience_high	median (5.5) and above	< 5.5
quiz_high	median(4) and above	< 4
error_less	median(0)	> 0
comprehension_high	median (good comprehension)	other options



(a) Number of participants divided according to the number of attempts to achieve unanimity in the group-gain treatment for the six decisions.



(b) Number of participants divided according to the number of attempts to achieve unanimity in the group-loss treatment for the six decisions.

Fig. 5 Overview of number of attempts to achieve unanimity in the group-gain and group-loss treatments for all six decisions

Table 7 Linear regressions: treatment effects (gain domain)

	Dependent variable							
	b	a	E1	E2	E3	E12	E13	E23
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
group	0.052 (0.050)	0.122 (0.105)	3.537 (3.755)	− 1.323 (4.189)	− 3.879 (3.804)	− 4.966 (4.335)	− 3.549 (4.562)	− 5.352 (3.926)
Constant	0.043 (0.039)	0.379*** (0.084)	33.649*** (2.908)	40.532*** (3.310)	38.298*** (3.141)	59.617*** (3.134)	55.723*** (3.084)	59.213*** (3.267)
Observations	90	90	90	90	90	90	90	90
R ²	0.012	0.015	0.010	0.001	0.012	0.015	0.007	0.020
Adjusted R ²	0.001	0.004	− 0.001	− 0.010	0.0003	0.004	− 0.004	0.009
Residual Std. Error	0.236	0.499	17.789	19.891	18.155	20.394	21.334	18.754
F Statistic	1.085	1.345	0.888	0.099	1.025	1.331	0.621	1.829

Table 8 Linear regressions: treatment effects (loss domain)

	Dependent variable							
	b	a	E1	E2	E3	E12	E13	E23
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
group	0.025 (0.064)	− 0.084 (0.099)	2.900 (4.431)	0.695 (4.170)	− 3.982 (3.789)	9.407** (4.312)	− 0.427 (4.505)	− 0.978 (4.514)
Constant	− 0.081 (0.054)	0.579*** (0.068)	36.862*** (3.635)	39.936*** (3.102)	40.053*** (3.030)	48.415*** (3.496)	53.213*** (3.510)	57.287*** (3.519)
Observations	89	89	89	89	89	89	89	89
R ²	0.002	0.008	0.005	0.0003	0.012	0.051	0.0001	0.001
Adjusted R ²	− 0.010	− 0.003	− 0.007	− 0.011	0.001	0.040	− 0.011	− 0.011
Residual Std. Error	0.306	0.461	21.107	19.600	17.983	20.504	21.301	21.345
F Statistic	0.152	0.733	0.419	0.028	1.087	4.668**	0.009	0.047

Note: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$; heteroscedasticity consistent standard errors (“HC3”) in parentheses and estimated with the

R package sandwich (Zeileis, 2004; Zeileis et al., 2020)

Table 9 Multinomial regressions: group strategy

	Dependent variable							
	Majority (1)	Person (2)	Majority (3)	Person (4)	Majority (5)	Person (6)	Majority (7)	Person (8)
loss	-0.090 (0.319)	0.475 (0.415)	-0.173 (0.313)	0.422 (0.406)	-0.169 (0.317)	0.450 (0.413)	-0.211 (0.322)	0.343 (0.414)
gender (female)	0.408 (0.344)	-0.113 (0.418)						
age_high	0.335 (0.346)	0.647 (0.450)						
income_high	0.265 (0.329)	0.201 (0.421)						
faculty (economics, social)	0.006 (0.322)	0.592 (0.417)						
semesters_high	-0.536 (0.364)	0.247 (0.494)						
participation_high	0.210 (0.332)	0.262 (0.437)						
parentship	-1.409 (1.077)	-1.038 (1.099)						
risk_1_high (general)			0.123 (0.324)	0.203 (0.418)				
risk_2_high (weather)			-0.431 (0.317)	-0.294 (0.406)				
amb_index_high			-0.133 (0.312)	-0.648 (0.411)				

Table 9 (continued)

	Dependent variable							
	Majority (1)	Person (2)	Majority (3)	Person (4)	Majority (5)	Person (6)	Majority (7)	Person (8)
extraversion_high					0.082	-0.027		
agreeableness_high					(0.336)	(0.431)		
					0.043	-0.725*		
conscientiousness_high					(0.338)	(0.411)		
					-0.362	-0.606		
emotional_stability_high					(0.320)	(0.409)		
					-0.373	-0.077		
openness_to_experiences_high					(0.324)	(0.421)		
					-0.349	-0.212		
					(0.319)	(0.409)		
quiz_high							0.143	0.687
							(0.343)	(0.484)
error_less							-0.794**	-0.614
							(0.332)	(0.424)
comprehension_high							0.065	0.040
							(0.335)	(0.424)
Constant	-1.435*** (0.442)	-2.971*** (0.644)	-0.807** (0.360)	-1.628*** (0.476)	-0.514 (0.440)	-1.036* (0.552)	-0.700** (0.340)	-2.059*** (0.503)
<i>n</i>	254	254	254	254	254	254	254	254
Akaike Inf. Crit	455.509	455.509	447.622	447.622	450.679	450.679	444.037	444.037

Note: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 10 Multinomial regressions: own preference

	Dependent variable							
	No (1)	Own (2)	No (3)	Own (4)	No (5)	Own (6)	No (7)	Own (8)
Loss	-0.098 (1.076)	-0.230 (0.284)	-0.037 (1.018)	-0.238 (0.281)	-0.019 (1.035)	-0.207 (0.284)	-0.147 (1.040)	-0.240 (0.287)
Gender (female)	-1.841 (1.221)	0.037 (0.298)						
Age_high	11.834 (161.760)	0.382 (0.310)						
Income_high	-0.629 (1.112)	0.052 (0.292)						
Faculty (economics,social)	-0.140 (1.132)	0.230 (0.286)						
Semesters_high	-0.450 (1.326)	-0.089 (0.326)						
Participation_high	0.773 (1.305)	0.109 (0.296)						
Parentship	1.408 (1.337)	0.155 (0.659)						
Risk_1_high (general)			8.044 (31.400)	0.387 (0.295)				
Risk_2_high (weather)			-0.507 (1.023)	0.152 (0.289)				
amb_index_high			-0.035 (1.023)	-0.065 (0.280)				

Table 10 (continued)

	Dependent variable							
	No (1)	Own (2)	No (3)	Own (4)	No (5)	Own (6)	No (7)	Own (8)
Extraversion_high					0.163 (1.183)	0.097 (0.302)		
Agreeableness_high					-0.787 (1.047)	-0.091 (0.300)		
Conscientiousness_high					-0.344 (1.034)	0.493* (0.298)		
Emotional_stability_high					9.808 (79.792)	0.142 (0.297)		
Openness_to_experiences_high					1.070 (1.177)	-0.243 (0.286)		
Quiz_high							-0.279 (1.042)	-0.041 (0.308)
Error_less							-9.614 (43.224)	-0.430 (0.298)
Comprehension_high							0.751 (1.054)	0.254 (0.299)
Constant	-13.962 (161.762)	-1.152*** (0.396)	-10.961 (31.406)	-1.070*** (0.337)	-13.211 (79.802)	-1.064*** (0.409)	-2.872*** (1.024)	-0.619** (0.314)
<i>n</i>	254	254	254	254	254	254	254	254
Akaike Inf. Crit	365.400	365.400	355.756	355.756	360.272	360.272	352.022	352.022

Note: *p<0.1; **p<0.05; ***p<0.01

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Data availability The data and replication files are available upon request under <https://doi.org/10.25592/uhhfdm.16107>.

Declarations

Conflict of interest All coauthors declare that we have no relevant or material financial interests that relate to the research described in this paper.

Technical Note The data cleaning, the calculations and the visualizations were mostly carried out with the help of R and extensions (Core Team, 2023). In particular, we used the R-package stargazer (to visualize the regression tables) and the R-package ggplot2 (to visualize the graphs) (Hlavac, 2022; Wickham, 2016).

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