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Working Paper

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CESifo Working Paper, No. 10783

Provided in Cooperation with:
Ifo Institute – Leibniz Institute for Economic Research at the University of Munich

Suggested Citation: Minnich, Aljoscha; Roggenkamp, Hauke; Lange, Andreas (2023) : Ambiguity Attitudes and Surprises: Experimental Evidence on Communicating New Information within a Large Population Sample, CESifo Working Paper, No. 10783, Center for Economic Studies and ifo Institute (CESifo), Munich

This Version is available at:
https://hdl.handle.net/10419/282471

CESifo WORKING PAPERS

10783
2023

November 2023

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CESifo

Impressum:

CESifo Working Papers
ISSN 2364-1428 (electronic version)
Publisher and distributor: Munich Society for the Promotion of Economic Research - CESifo GmbH
The international platform of Ludwigs-Maximilians University's Center for Economic Studies and the ifo Institute
Poschingerstr. 5, 81679 Munich, Germany
Telephone +49 (0)89 2180-2740, Telefax +49 (0)89 2180-17845, email office@cesifo.de
Editor: Clemens Fuest
https://www.cesifo.org/en/wp
An electronic version of the paper may be downloaded
· from the SSRN website: www.SSRN.com
· from the RePEc website: www.RePEc.org
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CESifo *Working Paper No. 10783*

Ambiguity Attitudes and Surprises: Experimental Evidence on Communicating New Information within a Large Population Sample

Abstract

This paper investigates ambiguity attitudes for natural events (temperatures) and how they are updated following new information. Using a general population sample, we first obtain baseline ambiguity attitudes for future weather events based on real temperatures over several past days. Second, we study the influence of different communication types on updating the ambiguity attitudes: participants are given either point estimators, interval estimators, or the combination of both as weather forecasts. We further vary whether the forecast is surprising or in line with the initially received information. In contrast to claims that ambiguity aversion may increase in response to surprising news, we find that ambiguity attitudes are rather robust to new information and variants of their communication. Yet, different variants of communicating new information significantly change the belief updating process and affect the matching probabilities given to specific events. Our sample allows us to analyze sociodemographic correlates of ambiguity attitudes and the updating of ambiguity attitudes to new information.

JEL-Codes: D810, D830, C930.

Keywords: ambiguity attitude, belief updating, expert forecasts, survey experiment.

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November 13, 2023

1 Introduction

In many decision contexts, objective probabilities are unknown such that decision makers face uncertainties. Substantial evidence suggests that many decision makers do not behave according to expected utility theory, but instead show more general ambiguity attitudes (e.g., Gilboa and Marinacci, 2016). Correspondingly, they may not necessarily incorporate new information according to Bayes rule. Instead, new information may affect both the beliefs as well as ambiguity attitudes (e.g., Gilboa and Schmeidler, 1993; Klibanoff and Hanany, 2007; Baliga et al., 2013; Gilboa and Marinacci, 2016; Hanany et al., 2011; Klibanoff et al., 2009). Most of the literature explores the updating processes under uncertainty from a theoretical angle. Empirical and experimental evidence on how individual ambiguity attitudes change ambiguity attitudes in reaction to new information is rather scarce (cf., Baillon et al., 2018a). This particularly applies for subject samples beyond typical students pools and for decision contexts beyond abstract urn experiments.

In this paper, we investigate how different ways of communicating new information affect the updating of beliefs *and* ambiguity attitudes. We rely on assessing beliefs towards weather (temperature) events within a large general population sample. With this, we mimic the reaction of individuals to weather forecasts, a setting that most individuals are familiar with. We elicit ambiguity attitudes before and after receiving new information based on a forecast. Before the first elicitation, participants receive actual temperature measurements that form their prior. Before the second elicitation, participants receive a weather forecast. We vary both how uncertainty is communicated and whether the forecast is in line (confirmation) with the prior or comes as a surprise (contradiction) (cf., Charness et al., 2021). Our communication treatments differ regarding how uncertainty is recognized: (i) they reflect the forecast's best estimate (a point estimate), (ii) only a confidence interval (interval estimate), or (iii) an asymmetric confidence interval (interval plus point estimate).[1] In the words of Keynes (1921), our study considers how new information affects the "balance of evidence", i.e. the relative weights given to events, and the "weight of evidence" which reflects the extent of ambiguity. Specifically, we consider if ambiguity aversion increases in reaction to surprising news.[2]

Ambiguity attitudes within our experiment are elicited based on the method by Baillon et al. (2018b). They are captured by two indices: the ambiguity aversion index and the ambiguity-generated insensitivity index (sometimes also referred to as perceived ambiguity).[3] The ambiguity aversion index specifies whether a participant is ambiguity-seeking, neutral or averse. The ambiguity-generated insensitivity index reflects whether a participant overweights (underweights) small (large) probabilities, and thus captures the insensitivity toward likelihood changes.

[1] Ho and Budescu (2019) believe that the communication of asymmetric intervals where the lower and upper limits are not equally distant from point estimation can maintain confidence in predictions (see also Viscusi et al. (1991)).

[2] For ambiguous-averse decision-makers, ambiguity aversion may increase or decrease following new information (e.g., Walley, 1991; Li, 2020).

[3] For a recent review of ambiguity preferences, please consider Bühren et al. (2021).

Our study contributes to three areas of research. First, we contribute to the literature that measures ambiguity attitudes for natural events. Specifically, we explore which socio-demographic variables correlate with ambiguity attitudes. We are the first study to apply the indices of Baillon et al. (2018b) to a German general population sample.[4] Second, we study the effects of communicating uncertainty. Specifically, we look at the effects of communication strategies on ambiguity preferences as well as on updated beliefs for specific (weather) events. Compared to previous stated preferences studies, we elicit revealed preferences in an incentivized experimental study. Third, we contribute to the literature on updating ambiguity preferences after receiving new information or learning.

The empirical and experimental evidence on how individual ambiguity attitudes largely relies on abstract urn experiments (e.g., Cohen et al., 2000; Dominiak et al., 2012) or focuses on belief updating (e.g., De Filippis et al., 2017; Georgalos, 2021; Li and Wilde, 2021; Ngangoué, 2021). In Vinogradov and Makhlouf (2021)'s related study, participants decide between an ambiguous urn and a balanced risky urn. In a second stage, the same question has to be answered again but different type of vague news are introduced.[5] Peysakhovich and Karmarkar (2016) research the different effects of favorable and unfavorable partial information in ambiguous financial prospects. They find that favourable information increases the valuation, while unfavourable information has significantly less impact. Baillon et al. (2018a) investigate the effects of learning new information on ambiguity attitudes by eliciting attitudes towards events that depend on returns of initial public offerings on the New York Stock Exchange. Using a sample of university students, they find that subjects perceived ambiguity, but were mostly insensitive to likelihood information. However, they find that new information leads to behavior more in line of subjective expected utility and to less likelihood-insensitivity (in a multiple priors interpretation: ambiguity perception) and minor effects on pessimism (in a multiple priors interpretation: no clear effects on ambiguity aversion). Less evidence is given on actual updating of ambiguity attitudes for natural events based on more general population samples.

Gustafson and Rice (2020) provide a review of the literature on the effects of different strategies to communicate uncertainty in public science communication.[6] They show that technical uncertainty (e.g., ranges, probabilities, confidence intervals) does not seem to have negative effects, while mostly negative effects come from uncertainty communication due to consensus uncertainty (disagreement of relevant stakeholders). Howe et al. (2019) show that acknowledging technical uncertainty can even lead to higher message acceptance and trust in scientists regarding sea level rise due to climate change. A large-scale experimental study by van der Bles et al. (2020) examines how communication strategies on epistemic uncertainty affect public trust. They find that acknowledging uncertainty (technical and verbal) leads to greater perceived uncertainty, a

[4] Previous evidence has been collected with Dutch general population samples (von Gaudecker et al., 2022; Anantanasuwong et al., 2019). Leuker et al. (2021) use a simple ambiguity task in a representative German sample by querying an incentivized measure of participation in an ambiguous bet (yes or no) and a respective Likert scale of participation.

[5] Using a somewhat similar decision task, Aggarwal and Mohanty (2022) study preferences in investment decisions between different types of ambiguity (in terms of outcome, probability, and conflicting information) and risky investments. Brunette et al. (2022) also study and compare different types of ambiguity (outcome, probability, combination) and risks in decision making. They also provide a brief literature review.

[6] Another overview of uncertainty communication is given by Van der Bles et al. (2019).

small decrease in trust in numbers and trust in source (mainly for the verbal format). We add to this literature by considering how different types of uncertainty communication affect people's ambiguity attitudes as well as their updates of beliefs.

Our paper thus adds to the literature by eliciting ambiguity attitudes and the impact of diverse ways of communicating new information within an important natural realm that almost all people relate to: weather events and weather forecast. We find that ambiguity attitudes are rather stable and do not change with information that confirms or contradicts prior beliefs. Neither does the way of communicating the information (best guess, confidence intervals or both) affect the resulting ambiguity attitudes in our general population sample. Yet, we find important effects of uncertainty communication on the updates of the underlying beliefs, i.e. on the matching probabilities assigned to individual temperature events. New information does not only change the beliefs in different ways depending on whether it confirms vs. contradicts initial priors, but also interacts with the impact of acknowledging uncertainty by communicating the confidence interval. Besides affecting the "balance of evidence", the communication also changes the perceived credibility of the information, even though it leaves "weight of evidence" (Keynes, 1921) unaffected.

The remaining paper is structured as follows. Section 2 discusses the experimental design and procedures. We discuss the results in section 3, before concluding in section 4.

2 Experimental and survey design and methods

We first present the method of measuring ambiguity attitudes for natural events by Baillon et al. (2018b), before detailing our experimental and survey design as well as discussing our hypotheses.

2.1 Ambiguity measurement

We measure ambiguity attitudes following the method introduced by Baillon et al. (2018b). This method has two advantages: (i) it delivers meaningful information on ambiguity attitudes under many ambiguity theories (Baillon et al., 2018b) and (ii) it is suitable for measuring ambiguity attitudes for natural events and is relatively easy to implement. While Baillon et al. (2018b) study stock markets, the events refer to temperature ranges, i.e. weather events in our application.

Specifically, a state space is partitioned into mutually exclusive and exhaustive events E_1, E_2, and E_3. The method requires participants to indicate the matching probability for these *single* events as well as for the *composite* events $E_{12} = E_1 \cup E_2$, $E_{13} = E_1 \cup E_3$, and $E_{23} = E_2 \cup E_3$. The matching probability of an event thereby refers to the winning probability of a lottery (paying zero or a fixed monetary amount) that makes the individual indifferent between betting on the realization of the event vs. choosing the lottery (e.g., Dimmock et al., 2016). The probability

equivalents are denoted by m_1, m_2, m_3 for the single and by m_{12}, m_{13}, and m_{23} for the composite events. The average single event matching probability is given by $\overline{m_s} = (m_1 + m_2 + m_3)/3$ and the average composite event matching probability by $\overline{m_c} = (m_{23} + m_{13} + m_{12})/3$.

Following Baillon et al. (2018b), we study two indices capturing ambiguity attitudes:

$$b = 1 - \overline{m_s} - \overline{m_c} \qquad a = 3 \times (\frac{1}{3} - (\overline{m_c} - \overline{m_s})).$$

Index b captures the ambiguity aversion and ranges from -1 to 1. A negative b can be interpreted as ambiguity seeking, while a positive b refers to ambiguity aversion: in fact, for expected utility maximizers, i.e. ambiguity-neutral decision makers, the probability equivalents of an event and its complement adds to 1 such that the index takes value 0.

Index a is referred to as the ambiguity-generating insensitivity index. It measures to what extent the matching probabilities converge towards 50%.[7] Again, it takes value 0 under ambiguity neutrality as $\overline{m_s} = 1/3$ and $\overline{m_c} = 2/3$. Positive values of a indicate overweighted low probabilities and underweighted high probabilities, reflecting relative insensitivity. In contrast, negative values of a indicate underweighted low probabilities and overweighted high probabilities (Anantanasuwong et al. (2019)). Both indices b and a are orthogonal (Baillon et al. (2021)).

2.2 The specific event structure and experimental treatments

In our application, the events relate to temperature events. Both the location and the date are unknown to the participants. Specifically, we elicit the attitudes towards the temperature at 2 p.m. (CET) on a Sunday at a location that is unknown to the participants.[8] The participants were told that the temperature events relate to events in the past and were informed about the specific location after conclusion of the experiment. Event E_1 refers to the temperature being below 8 degrees Celsius, event E_2 to temperature between 8 and 14 degrees Celsius, and event E_3 to temperature being above 14 degrees Celsius.

Participants give their probability assessments twice. First, they see the measured temperatures for Wednesday, Thursday, and Friday at 2 p.m. (CET), which are 12 degrees each. The participants then bet on the temperature at 2:00 p.m. on Sunday (nine days ahead). Second, participants receive their respective information treatment. The treatment is a weather forecast from the same Friday. After the treatment, they have to state probability equivalents for the same six temperature events again.

We used a 3x2 treatment between-subjects design. In the first dimension, we varied the communication strategy, i.e., communicated a weather forecast as point estimator (best guess), interval estimator or the combination point and interval estimator (both). In the second dimension, we

[7] a ranges from -2 ($\overline{m_c} = 1, \overline{m_s} = 0$) to 4 ($\overline{m_c} = 0, \overline{m_s} = 1$), but Baillon et al. (2018b) define the maximum as 1 to satisfy weak monotonicity (with $\overline{m_c} \geq \overline{m_s}$).

[8] We also pointed out that the time zone CET does not automatically mean that the unknown location is in that time zone.

varied if forecasts were surprising and thus contradicted the initial priors or if forecasts where confirming the initial information.

Importantly, the information on the previous temperature trends as well as the weather predictions relate to truly existing locations and dates. For this, we searched for past weather data and locations in which (i) initial temperatures coincided (Wednesday, Thursday, and Friday), but (ii) the forecast on that Friday for Sunday 9 days ahead either matched or disagreed with the initial temperatures. We chose the locations of Ilomantsi Mekrijaervi (Finland) and Weiskirchen (Germany), where 12 degrees Celsius was measured as the temperature at 2 p.m. (CET) for each of three consecutive days (October 7-9, 2020), while the forecasts for nine days ahead (October 18, 2020) at 2 p.m. (CET) were very different. We obtained the temperature measurements and forecasts from the website `kachelmannwetter.com`. We used the ensemble forecasts ECMWF/Global Euro HD. The main runs of the ensemble were used as the point estimator and the 80% confidence intervals were used as the interval estimator. We chose to communicate that 80% confidence interval as very likely because Budescu et al. (2012) showed that a general population sample perceived the term very likely (actually intended for >90%) for communicating uncertainties in IPCC reports as substantially less likely than >90%. The actual temperatures ended up being 3 degrees in Ilomantsi and 9 degrees in Weiskirchen.

The treatments were displayed graphically as well as communicated verbally. The treatment texts always begin identically with "Experts made a forecast on Friday for Sunday 9 days later 14:00 (CET):" and have a text modifications depending on the treatment (see Table 1). The treatments were randomly assigned to participants in a between-subjects design.

	confirmation	contradiction
point (best guess)	They consider a temperature of 12°C as most probable.	They consider a temperature of 4°C as most probable.
interval	They consider it very likely that the temperature at 14:00 will be between 8°C and 14°C.	They consider it very likely that the temperature at 14:00 will be between 2°C and 8°C.
point + interval (both)	They consider it very likely that the temperature at 14:00 will be between 8°C and 14°C. They consider a temperature of 12°C as most probable.	They consider it very likely that the temperature at 14:00 will be between 2°C and 8°C. They consider a temperature of 4°C as most probable.

Table 1 3x2 treatments design and the respective treatment texts.

2.3 Hypotheses

Our experimental design allows to investigate the distribution of ambiguity attitudes across the full sample (based on the first elicitation before randomly allocating participants into the treatments). The second elicitation task then allows investigating the effects of the respective information treatments with subject as well as studying the treatment effects between subjects.

The updating process of ambiguity attitudes or beliefs is an empirical question. Besides a large theoretical literature (e.g., Baliga et al., 2013; Gilboa and Marinacci, 2016; Hanany et al., 2011; Klibanoff et al., 2009), only limited empirical or experimental evidence exist. Baillon et al. (2018a) find that little effects of information on ambiguity aversion, but some effects of

ambiguity perception. Vinogradov and Makhlouf (2021) find that ambiguity-neutral subjects react differently to (vague) news than ambiguity averse subjects. They conjecture that subjects consider if the new information requires the priors to be updated or not. As such vague signals may not reject the prior belief, and thus lead to less updating.

Within our treatments, we thus can expect that the surprising forecasts lead more changes in ambiguity attitudes.

Hypothesis 1: The surprising forecasts are associated with more ambiguity aversion compared to the unsurprising ones.

We assume that the participants become familiar with the historical weather data in the first part of the experiment and thus form a prior. We expect the weather prior to be around 12 degrees Celsius due to the consistency of observable temperature realizations over three past days at 2 pm. We anticipate that weather forecasts confirming this prior will reduce ambiguity among participants, as this additional source of information confirms the previous source of information (realized temperatures). We hypothesize that the weather forecasts contradicting this prior are associated with more ambiguity than the confirming forecast since the additional source of information contradicts the previous source of information (realized temperatures) and thus necessitates larger updates of the priors.

Hypothesis 2: The acknowledgment of uncertainty (reporting intervals) is associated with a higher level of ambiguity aversion in the confirmation treatments, but a lower level of ambiguity aversion in the contradiction treatments.

The second hypothesis relates to the effect difference of the point estimator compared to the interval estimator. The point estimator exactly matches the historical weather realizations (prior) in the confirmation case, while the interval estimator has a larger distance to the prior. Because of the distance to the prior, we assume that the interval estimator induces more ambiguity in the case of confirmation. In the case of surprise, it is the opposite that the interval estimator is closer to the prior in the upper range than the point estimator. Therefore, we hypothesize that the interval estimator induces less ambiguity than the point estimator in the case of surprise.

Hypothesis 3: The combination of the point (best guess) and interval estimators leads to a combined effect and thus lies in the middle of the two individual effects of the forecasts.

In the third hypothesis, we address the effect of the combined treatment (point estimator and interval estimator). Here, we assume that the effects on the ambiguity attitude of the two estimators are averaged. Therefore, we hypothesize that the attitude lies between the ambiguity index values of the point and interval estimators for the confirmation and the contradiction case.

While these hypotheses refer only to ambiguity aversion, we expect similar effects for ambiguity-generated insensitivity as well as to the changes in the underlying probability equivalents.

2.4 Survey design and procedures

The experiment was conducted as an online survey experiment with a general population sample. It was programmed and conducted using oTree (Chen et al. (2016)). The instructions can be found in Online Appendix E. The study was preregistered (Lange et al. (2021)).[9] Initially, we ran a small field test with HamburgPanel, a Hamburg general population sample provided by the WiSo Research Laboratory at University of Hamburg with recruitment via hroot (Bock et al., 2014). Subsequently, the market research institute Respondi conducted a pretest with 51 complete participants, which subsequently transitioned to the field phase due to its functionality.

The full study took place between September 2, 2021 and September 14, 2021 and includes a total of 1505 completed surveys.[10]

Participants were invited representatively for Germany according to quotas that considered gender (male and female), age (18-69 years, cohorts of 10 years) and regions. The median completion time was 15.5 minutes. Participants received two euros as a fixed payout and either zero or ten euros as variable payout. The average variable payment was 5.85 euros. The payment structure was a randomized incentive scheme in which each event (from part 1 and part 2) and each lottery probability could be drawn with the same chance.

The survey experiment was structured as follows: first, participants received instructions for the ambiguity aversion elicitation tasks. They had to answer two comprehension questions correctly at the end of the instructions to progress to the ambiguity attitudes elicitation tasks. Second, participants had to state the matching probabilities for the six events (E_1, E_2,E_3,E_{12},E_{13},E_{23}). The sequence of the six events was randomized on the participant level. Third, the six information treatments were randomly assigned to the participants[11] and they had to submit the matching probabilities for the six events again (same order as before). Fourth, subjects answered several survey questions.

For the elicitation of the matching probabilities, participants state how many green balls (winning color) must be at least in a lottery urn (with 100 balls), so that they prefer the lottery over the bet on the temperature event. Participants are presented with a graph that shows the proportion of green balls in the lottery pot depending on their input.[12] Participants can specify

[9] Compared to our preregistration, we made two short-term changes to the secondary outcomes and also introduced further robustness checks that seemed useful. Instead of the number of children, we only asked whether one has children or not. In addition, the vaccination status was queried. As additional robustness checks (see also Section 3.3), we excluded different variants of non-monotonicity, see below.

[10] Several participants dropped out of the survey experiment before and during the instructions, yet only 17 dropouts occurred *after* the treatments were introduced such that we can rule out attrition bias affected the treatments. See also Figure OA.2a in Online Appendix A.

[11] Since we had too few observations of one treatment due to the randomization (point (best guess), contradiction, see also Table 1), we decided to remove the randomization at the end of the survey period (September 13 (evening) and September 14, 2021) and only collect data from the missing treatment (49 participants). The resolution of randomization at the end of the survey period has no effects with regard to our treatment effects.

[12] The graph is shown from the beginning without the participants having entered anything. Since we want to avoid a middle bias, the graph starts at 34 green balls for single events and 67 green balls for composite events. This procedure resembles Baillon et al. (2018b) who also adjust their choice lists to avoid middle bias depending on whether the event is a single event or a composite event.

values between 0 and 101 in steps of one.[13] The value 0 means that the lottery is always preferred over the bet on the ambiguous event, while the value 101 means that the lottery is never chosen. As the stated number of winning balls indicates the minimum number of balls such that the lottery is preferred, we subtract 0.5 from the selected values to specify the matching probability (indifference point). Zero remains coded as zero, and 101 is coded as 100.

The final survey part elicited socio-demographic characteristics of subjects (age, gender, education, income, family status, children) as well as answers on risk attitudes, credibility and accuracy (of information treatment texts), personal weather forecast usage, and current temperature (at the location of the participant).[14]

We use the survey answers to create dummy variables for age(18-34), age(35-52), age(53-69), gender (female), high education, high income, family (married or same sex union), parentship, high general risk attitude (median), high weather risk attitude (median), high credibility (median), high accuracy (median), high weather forecast usage (median), and high temperature (median). For their definition, see Table A.2 in Appendix A.

Our dataset contains only fully completed questionnaires. Our result section reports the results from the full sample, before we conduct several robustness checks: (i) we exclude participants who self-reported not understanding the experiment well or rather well (Question: "Did you understand the tasks well?"), (ii) we exclude participants with at least one wrong answer in the control questions, (iii) we exclude participants who completed the experiment excessively fast or slow,[15] and (iv) we exclude participants violating the weak monotonicity condition based on the averages of the matching probabilities for composite and single events, i.e. we exclude agents with $\overline{m_c} < \overline{m_s}$ in the first or second elicitation task.

2.5 Regression method and empirical strategies

Our empirical approach for investigating the treatment effects combines non-parametric tests (Wilcoxon signed rank test for comparing first and second elicitation within subject; Mann Whitney U tests for treatment comparisons) as well as regression analyses that control for the diverse socio-demographic characteristics of participants. Besides the ambiguity indices b and a, we also consider the treatment effects on the matching probabilities of the underlying single and composite events.

[13] Allowing the value 101 seems counterintuitive at first glance. However, similar to other ambiguity tasks in tabular form, we also wanted to give participants the option to prefer the ambiguous bet even if 100 green balls are present in the risky lottery. However, the participant's choice of 100 means that the ambiguous bet will be chosen if there are 99 or fewer green balls in the risky lottery. Therefore, we also allowed for 101 as an answer.

[14] For the general risk attitude question, we used the measurement method of Dohmen et al. (2011). We have constructed a weather-related risk question related to Dohmen et al. (2011). For our query on the credibility of our treatment texts, we were inspired by Appelman and Sundar (2016) and used Likert scales to ask about accuracy in addition to credibility.

[15] Here we use only participants between the 10th and the 90ies percentiles of completion time. The response time of the ambiguity tasks provides an indication that participants engaged with our treatments. For the distribution, see Figure OA.1 in Online Appendix A.

We use the following regression equation:

$$y_{it} = \alpha_{baseline} + \sum_{treat} \alpha_{treat} treat_i + \beta_{baseline} part2_t + \sum_{treat} \beta_{treat} treat_i \times part2_t + \gamma X_i + \epsilon_{it}. \quad (1)$$

where y is the dependent variable (b, a, and matching probabilities for E_1, E_2, E_3, E_{23}, E_{13}, E_{12}). i refers to the individual participant, while t refers to the temporal level (first and second elicitation task). $treat_i$ are dummy variables that take value 1 when the individual is in the respective treatment arm. The coefficient β_{treat} thus captures the treatment effect. ϵ represents the clustered standard errors at the individual level. We also use control variables X that we add stepwise, starting with none, then demographic variables, and finally further control variables.

For the test of hypothesis 1, we pool across the different information treatments (interval, best guess, both) and only consider the effect of contradiction vs. confirmation. That is, in (1) *treat* refers to contradiction while confirmation is used as the baseline.

For hypothesis 2 and 3, we then test the effects of the different information treatments (interval, best guess, both) separately for confirmation and contradiction treatment arms. That is, the best guess information treatment serves as the baseline and *treat* in (1) refers to the information treatments interval or both.

Furthermore, we exploratively test for heterogeneous treatment effects by adding interaction terms of treatment dummies with dummy variables defined by high education, gender (female), high credibility (median), high accuracy (median), high weather forecast usage (median), and high temperature (median).

3 Results

To get a first impression of our main variables and treatments, Table 2 shows an overview of the ambiguity indices and the matching probabilities of all events split by treatments and parts.

Overall, we observe almost ambiguity neutrality on average. In the first elicitation task (before treatment variations), the average value for index b is -0.07. In fact, 35% percent of participants show a positive, while 65% show a negative b index in this task ($b = 0$ holds for only 4 players). The average value of index a is 0.72, thereby indicating a relatively large insensitivity to the generating ambiguity. The ambiguity aversion as measured by index b is thus very similar in our general population sample to the values obtained among students in Baillon et al. (2018a). Yet, the insensitivity index is substantially larger.

Table 2 Descriptive statistics: Average values per treatment and standard deviations for part 1 and 2

		Pooled	**confirmation**			**contradiction**		
Treatment			point	point + interval	interval	point	point + interval	interval
	Part	mean	mean	mean	mean	mean	mean	mean
Variables		(sd)	(sd)	(sd)	(sd)	(sd)	(sd)	(sd)
b	1	-0.07	-0.05	-0.09	-0.07	-0.04	-0.08	-0.08
		(0.30)	(0.27)	(0.30)	(0.29)	(0.31)	(0.31)	(0.31)
	2	-0.08	-0.09	-0.09	-0.08	-0.04	-0.10	-0.07
		(0.32)	(0.31)	(0.32)	(0.32)	(0.31)	(0.34)	(0.34)
a	1	0.72	0.71	0.78	0.73	0.71	0.68	0.69
		(0.49)	(0.50)	(0.47)	(0.51)	(0.49)	(0.44)	(0.51)
	2	0.71	0.73	0.73	0.73	0.69	0.70	0.69
		(0.54)	(0.54)	(0.51)	(0.56)	(0.54)	(0.53)	(0.56)
E1	1	47.41	46.65	49.08	47.98	45.16	46.65	48.93
		(20.96)	(19.05)	(20.32)	(21.74)	(20.53)	(21.02)	(22.84)
	2	50.19	47.61	46.58	46.35	52.63	56.24	51.57
		(25.46)	(25.00)	(25.10)	(24.46)	(24.79)	(26.81)	(25.24)
E2	1	50.06	50.11	51.67	50.28	48.61	51.05	48.70
		(20.80)	(19.95)	(20.49)	(21.62)	(20.08)	(20.78)	(21.84)
	2	50.75	54.34	55.01	53.28	45.51	48.63	47.89
		(23.38)	(22.15)	(23.46)	(24.48)	(21.29)	(24.14)	(23.23)
E3	1	48.43	46.28	51.09	48.48	47.51	48.47	48.83
		(20.34)	(19.22)	(20.01)	(20.58)	(21.53)	(19.36)	(21.11)
	2	46.70	48.44	49.31	48.47	42.09	45.72	46.27
		(24.49)	(22.04)	(23.08)	(23.55)	(25.44)	(26.34)	(25.70)
E12	1	58.13	57.13	58.80	59.20	57.57	58.02	58.11
		(20.00)	(19.64)	(19.76)	(19.23)	(20.24)	(21.17)	(20.00)
	2	61.94	60.22	61.48	58.80	62.03	66.30	62.72
		(24.17)	(22.64)	(21.98)	(23.39)	(26.61)	(25.07)	(24.54)
E13	1	55.60	55.41	55.89	54.06	52.73	57.07	58.31
		(20.11)	(19.15)	(20.00)	(21.15)	(20.07)	(19.93)	(20.09)
	2	55.93	54.08	52.53	54.12	56.94	59.55	58.19
		(23.45)	(23.73)	(24.57)	(23.32)	(21.92)	(24.11)	(22.41)
E23	1	60.42	59.32	59.63	60.04	59.58	62.71	61.24
		(22.37)	(23.18)	(22.24)	(22.48)	(23.51)	(21.38)	(21.38)
	2	58.37	62.63	63.52	62.12	52.01	54.40	55.77
		(24.38)	(24.44)	(23.92)	(23.02)	(24.71)	(24.54)	(23.29)
Observations		1,505	255	247	243	252	250	258

3.1 Determinants of ambiguity attitudes

In order to gain further insights into the determinants of ambiguity attitudes, we examine correlations between the ambiguity indices and our control variables. Table 3 shows the results.[16] Here, we use the demographic control variable set in regression (1) and (3), the complete control variable set in regressions (2) and (4). Considering index b, we observe that females are less ambiguity averse. Similarly, large age tends to reduce ambiguity aversion as well as does higher education. For index a, larger age appears to generate a larger insensitivity, while gender or ed-

[16] Overall, we find a low R-squared and thus a low explanatory power of our control variables on ambiguity attitudes. However, this is a typical result for ambiguity attitudes (e.g., l'Haridon et al., 2018; von Gaudecker et al., 2022).

ucation do not affect this measure. Furthermore, a high temperature reduces the insensitivity.[17] This result is in line with the proposed orthogonality of the two indices which indeed capture different moments of ambiguity attitudes.

We also note that the risk aversion measures (both individual risk as well as weather risk) do not affect the ambiguity attitudes as measured in both indices. These results are largely robust to replacing the dummy variables based on the median responses with the original value responses. However, we find a positive significant effect for the general risk attitude on index b with the original values.[18]

3.2 Treatment effects

We first consider non-parametric Wilcoxcon signed-rank tests to compare the first and second parts of the experiment and Wilcoxon-Mann-Whitney tests for the treatment comparisons of the second part. The p-values are reported in Figure 1 for index b and Figure 2 for index a, respectively. Both figures show that treatment differences occur for neither index b nor a. There is only one exception, namely a significant difference between the best guess and both treatment in the contradiction treatment arm (see Figure 1c), which may be due to differences in the first part. Yet, we observe a significant decrease in the ambiguity aversion as measured by index b between the first and the second elicitation part, if the information is confirmatory and communicated solely in terms of a best guess (see Figure 1b).

These non-parametric results of null treatment effects are confirmed by a series of regression analyses. Table 4 and 5 report the main regressions for index b and a respectively. Figure 3 displays the corresponding treatment effect estimators and the associated 95% confidence intervals, controlling for different sets of socio-demographics. While the ambiguity index b is reduced in the confirmation treatment, this effect is exclusively driven by the best guess information treatment. No changes to the ambiguity indices occur when communicating the confidence interval instead of or in addition to the best guess. Concentrating on the point prediction of the best guess, we see a significant difference between communicating a confirmatory or a contradictory report (in partial support of hypothesis 1, see Table 4, regression (4)). However, none of the treatment effects comparing the best guess communication and other communication styles (interval, both) are significant.

Further details on the distribution of the indices is given in Online Appendix C where we report a set of scatterplots that relate the measured ambiguity indices b and a from the two elication tasks *before* and *after* the information treatments are given (cf., Baillon et al., 2018b). These display the indices for the confirmation and contradiction treatments pooled across the information treatments (best guess, interval, both) as well as for the six individual treatments separately.

We thus find that ambiguity attitudes as measured by the two indices are highly robust to

[17] This effect appears because the high temperature significantly increases the matching probabilities of the composite events E13 and E23.

[18] Since we see the median version as a more conservative measure, we have decided to continue using it in our main specifications.

Table 3 Linear regressions: Explanatory analysis of Ambiguity Indices b and a

	Dependent variable:			
	b	b	a	a
	(1)	(2)	(3)	(4)
age(35-52)	−0.004	−0.001	0.065*	0.050
	(0.021)	(0.021)	(0.037)	(0.036)
age(53-69)	−0.047**	−0.043*	0.149***	0.139***
	(0.023)	(0.023)	(0.038)	(0.037)
gender(female)	−0.064***	−0.055***	0.037	0.040
	(0.017)	(0.017)	(0.027)	(0.027)
high education	−0.071***	−0.072***	0.022	0.025
	(0.018)	(0.018)	(0.028)	(0.028)
high income	0.024	0.019	0.018	0.027
	(0.017)	(0.017)	(0.030)	(0.031)
family (married or same sex union)	−0.019	−0.017	−0.056*	−0.059*
	(0.019)	(0.019)	(0.032)	(0.033)
parentship	0.020	0.016	−0.054*	−0.052*
	(0.020)	(0.020)	(0.030)	(0.030)
high temperature (median)		−0.022		−0.074***
		(0.016)		(0.027)
high weather forecast usage (median)		−0.016		−0.008
		(0.016)		(0.026)
high general risk attitude (median)		0.028		−0.010
		(0.018)		(0.027)
high weather risk attitude (median)		0.025		−0.028
		(0.018)		(0.028)
high accuracy (median)		−0.025		−0.010
		(0.022)		(0.035)
high credibility (median)		0.007		−0.046
		(0.017)		(0.029)
Constant	0.013	0.017	0.656***	0.759***
	(0.023)	(0.034)	(0.039)	(0.053)
Observations	1,361	1,361	1,361	1,361
R^2	0.028	0.036	0.015	0.024
Adjusted R^2	0.023	0.026	0.009	0.015
Residual Std. Error	0.289	0.289	0.480	0.479
F Statistic	5.550***	3.835***	2.845***	2.542***

Note: *p<0.1, **p<0.05, ***p<0.01; heteroscedasticity consistent standard errors ("HC1") in parentheses and estimated with the R package sandwich (Zeileis, 2004; Zeileis et al., 2020).

information being given. Even if the new information is contradictory, no significant changes to measured ambiguity aversion can be observed.

These null results may put doubts on the experimental technique to elicit the ambiguity measures as they may suggest that individuals do not respond to information at all. Yet, our data clearly shows that this is not the case. The elicitation of matching probabilities for the single and composite events allows to investigate how information affects the "balance of the evidence" rather than its weight (cf., Keynes, 1921).

Figure 4a summarizes the treatment effects on the matching probabilities of the respective events.

It is seen that the matching probabilities in the contradiction treatments differ significantly from those in the confirmation treatments, exactly as expected (in line with the forecasts): events E_1, E_{12}, and E_{13} receive a significantly larger weight in the contradiction treatments where the forecast suggests a temperature of 4 degrees Celsius which is included in event E_1. Figures 4b and 4c separate these effects for both confirmation and contradiction treatments by the style in which the information is communicated.

In the contradiction case (see Figure 4c), participants state significantly smaller matching probabilities for events E_1 and E_{13} when the interval is communicated relative to communicating only the best-guess. That is, acknowledging the uncertainty of the forecast while not communicating the best guess reduces the extent to which beliefs are updated. This is different in the confirmation case: here communicating the interval (8-14 degrees) in addition to the best guess tends to lead participants to further lower the matching probability of events E_1 and E_3, i.e. the events that are outside this confidence interval. This differential effects of communicating the uncertainty around the best guess for confirmation vs. contradiction treatments is in line with acknowledging uncertainty in the contradiction treatment leading to a lesser need to update the priors while having the opposite effect in the confirmation treatment. For event E_{12}, the interval communication tends to decrease the matching probability in the confirmation case and the communicating the best guess and the interval tends to increase the matching probability in the contradiction case.

These treatment effects are confirmed by series of non-parametric tests that are reported in Online Appendix B and regression analysis reported in Appendix B. Additionally, we again report further details on the distribution of the matching probabilities in Online Appendix C where we report a set of scatterplots that relate the matching probabilities from the two elicitation tasks *before* and *after* the information is given.

An alternative way of analyzing the effects of information on changes of prior is reported in Table 6. Here, the dependent variable is the Euclidian distance between the vector of matching probabilities before and after receiving the information. Consistent with the changes in the individual events discussed above, we observe that a larger belief change follows contradicting information, yet this is no longer the case if only the confidence interval is communicated.

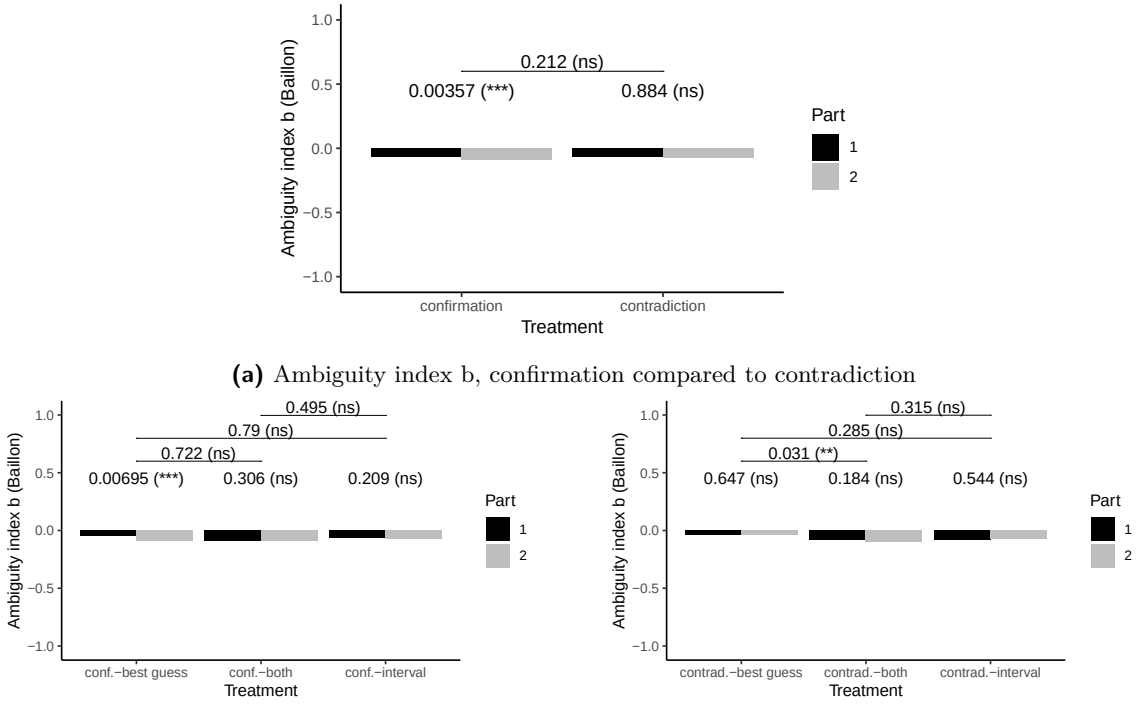
We thus have a clear indication that the way the information is communicated affects the belief updating process. While the matching probabilities change, the ambiguity attitudes as measured in the two indices suggested by Baillon et al. (2018b) are rather stable.

3.3 Robustness Checks

The elicitation method for ambiguity attitudes requires some understanding of probabilities. While our experimental instructions were designed to be rather comprehensible, the application of the rather sophisticated method in a general population sample may potentially be more complex than in a typical students sample (e.g., Baillon et al., 2018a).

In order to check the robustness of these result, we therefore conduct a several robustness checks which rely on specific subsamples: (i) we only use participants who self-reported understanding the experiment well or rather well, (ii) we only use participants who answered all control questions correctly on their first attempt, (iii) we only use participants between the 10th and the 90ies percentiles of completion time. We finally only use participants who satisfy the weak monotonicity condition based on the averages of the matching probabilities for composite and single events ($\overline{m_c} \geq \overline{m_s}$).

These are reported in Online Appendix D. For all subsamples, the non-result on treatment effects for the ambiguity attitudes as well as the results on the updated matching probabilities for the individual events remain robust.[19] We are thus confident that the results are not driven by limited understanding of the elicitation method for ambiguity attitudes.



(a) Ambiguity index b, confirmation compared to contradiction

(b) Ambiguity index b, confirmation treatments

(c) Ambiguity index b, contradiction treatments

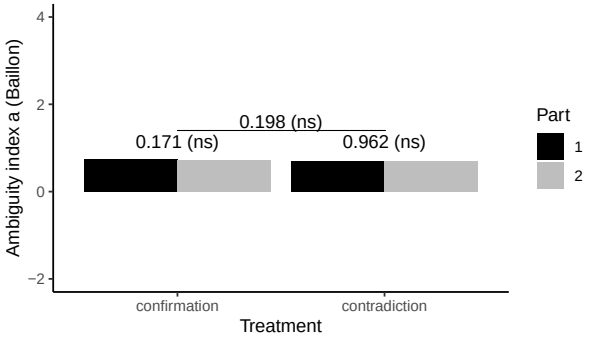
Figure 1 Means of ambiguity index b separated by treatments and part 1 and part 2. P-values of Wilcoxon signed-rank test comparing part 1 and 2 directly above the mean values. P-values of Wilcoxon–Mann–Whitney test comparing part 2 of different treatments at the top. Note: *p<0.10, **p<0.05, ***p<0.01, ns: not significant

3.4 Heterogeneous treatment effects

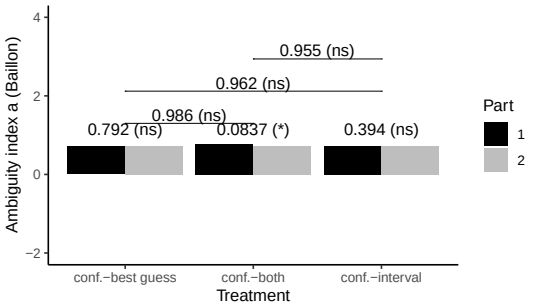
We now look at the treatment effects in more detail. Section 3.1 had shown that gender and high education affect the ambiguity attitudes. We now explore if these determinants also affect the updating in response of new information.

The results are reported in Appendix C. We find no significant differences comparing the confir-

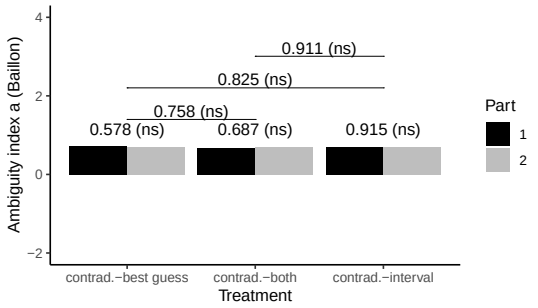
[19] There are some slight differences regarding the significance of the communication effects (interval and both compared to best guess).



(a) Ambiguity index a, confirmation compared to contradiction

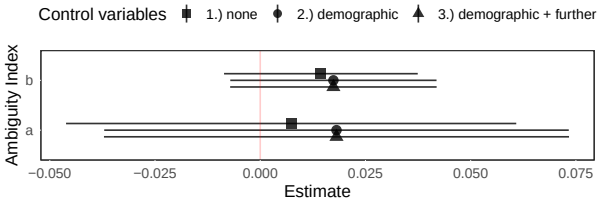


(b) Ambiguity index a, confirmation treatments

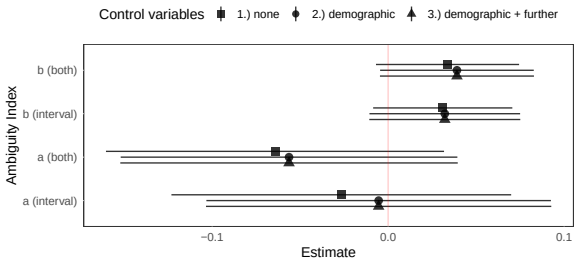


(c) Ambiguity index a, contradiction treatments

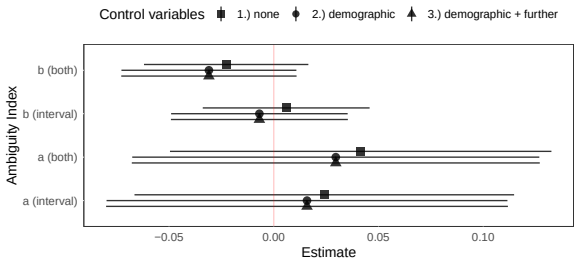
Figure 2 Means of ambiguity index a separated by treatments and part 1 and part 2. P-values of Wilcoxon signed-rank test comparing part 1 and 2 directly above the mean values. P-values of Wilcoxon–Mann–Whitney test comparing part 2 of different treatments at the top. Note: *p<0.10, **p<0.05, ***p<0.01, ns: not significant



(a) Effect of contradiction (relative to confirmation).



(b) Effect of information treatments (both, interval) relative to best guess, confirmation treatments



(c) Effect of information treatments (both, interval) relative to best guess, contradiction treatments

Figure 3 Treatment effects of regression equation (1) with dependent variables b and a. Estimators with 95% confidence intervals. The underlying standard errors ("HC1") are clustered at the individual level and estimated with the R package sandwich (Zeileis, 2004; Zeileis et al., 2020).

mation and control treatments when controlling for these socio-demographics (see Figure C.1).

Yet, one may expect that the extent of updating priors as well as the effect on ambiguity attitudes may depend on whether subjects are used to read weather forecasts as well as on

Table 4 Linear regressions: Treatment effects on ambiguity index b

	Dependent variable: b					
Sample	full	confirmation	contradiction	point	interval	both
	(1)	(2)	(3)	(4)	(5)	(6)
contradiction	0.002			0.012	−0.014	0.007
	(0.015)			(0.026)	(0.027)	(0.027)
both		−0.038	−0.043			
		(0.025)	(0.027)			
interval		−0.017	−0.043			
		(0.025)	(0.027)			
part2	−0.020**	−0.041***	−0.0002	−0.041***	−0.010	−0.008
	(0.008)	(0.014)	(0.014)	(0.014)	(0.014)	(0.015)
contradiction×part2	0.014			0.041**	0.016	−0.015
	(0.012)			(0.020)	(0.020)	(0.020)
both×part2		0.034	−0.023			
		(0.021)	(0.020)			
interval×part2		0.031	0.006			
		(0.020)	(0.020)			
Constant	−0.068***	−0.050***	−0.037*	−0.050***	−0.067***	−0.087***
	(0.010)	(0.017)	(0.019)	(0.017)	(0.019)	(0.019)
Observations	3,010	1,490	1,520	1,014	1,002	994
R^2	0.001	0.003	0.006	0.005	0.0003	0.001
Adjusted R^2	-0.0002	-0.001	0.002	0.003	-0.003	-0.002
Residual Std. Error	0.310	0.300	0.320	0.299	0.317	0.315
F Statistic	0.770	0.819	1.694	1.851	0.083	0.244

Note:*p<0.1; **p<0.05; ***p<0.01. The underlying standard errors ("HC1") are clustered at the individual level and estimated with the R package sandwich (Zeileis, 2004; Zeileis et al., 2020)

their view on the credibility of these forecasts. We observe that those who more frequently use forecasts become more insensitive to ambiguity-generation (index a) under confirmation when the forecasts involves the confidence interval rather than the best guess only. The opposite effect occurs under contradiction. This finding is in line with the determinants of increasing the weights on the single events E_2 under confirmation and E_1 under contradiction that we discussed above. It thus appears that the information leads to larger updates among subjects with larger expertise in forecast use.

Similarly, the perceived credibility of the information matters: if subjects consider the information as highly credible, communicating the interval instead of the best guess leads to lower ambiguity aversion (index b) in the contradiction treatment, while higher ambiguity aversion results for those who deem information as having low credibility (see Figure C.1b).

3.5 Additional effects of communicating information

We have seen that the way the information is communicated affects the updating process. Depending on whether the new information confirms or contradicts the initial prior, communicating a best-guess vs. additionally or exclusively communicating the confidence interval affects the extent of updating of the prior.

Table 5 Linear regressions: Treatment effects on ambiguity index a

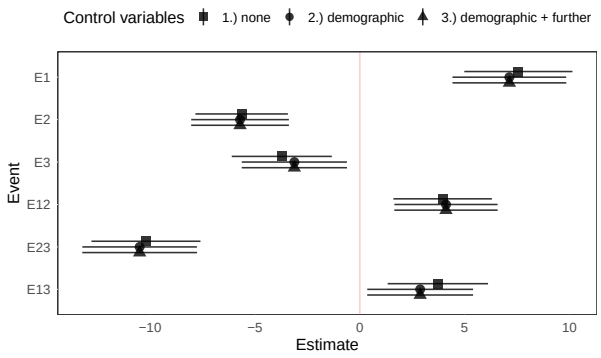
	Dependent variable: a					
Sample	full	confirmation	contradiction	point	interval	both
	(1)	(2)	(3)	(4)	(5)	(6)
contradiction	−0.045*			0.002	−0.046	−0.092**
	(0.025)			(0.044)	(0.045)	(0.041)
both		0.063	−0.030			
		(0.043)	(0.041)			
interval		0.023	−0.026			
		(0.045)	(0.044)			
part2	−0.007	0.023	−0.022	0.023	−0.004	−0.041
	(0.020)	(0.036)	(0.033)	(0.036)	(0.033)	(0.033)
contradiction×part2	0.007			−0.044	0.006	0.061
	(0.027)			(0.049)	(0.046)	(0.046)
both×part2		−0.064	0.042			
		(0.049)	(0.046)			
interval×part2		−0.027	0.024			
		(0.049)	(0.046)			
Constant	0.740***	0.712***	0.714***	0.712***	0.734***	0.775***
	(0.018)	(0.031)	(0.031)	(0.031)	(0.033)	(0.030)
Observations	3,010	1,490	1,520	1,014	1,002	994
R^2	0.002	0.001	0.0004	0.001	0.002	0.005
Adjusted R^2	0.001	-0.002	-0.003	-0.002	-0.001	0.002
Residual Std. Error	0.513	0.516	0.512	0.515	0.535	0.490
F Statistic	1.647	0.405	0.123	0.285	0.549	1.639

Note:*p<0.1; **p<0.05; ***p<0.01. The underlying standard errors ("HC1") are clustered at the individual level and estimated with the R package sandwich (Zeileis, 2004; Zeileis et al., 2020)

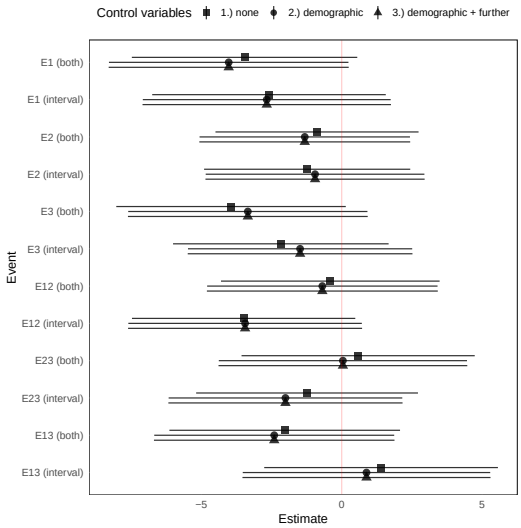
Table 6 Linear regressions: Treatment effects on Euclidian distance between vector of matching probabilities in part 1 vs. part 2.

	Dependent variable: : Euclidian distance part 2 vs. part 1					
Sample	full	confirmation	contradiction	point	interval	both
	(1)	(2)	(3)	(4)	(5)	(6)
contradiction	6.824***			10.120***	2.423	8.023**
	(1.775)			(3.029)	(3.033)	(3.158)
both		1.195	−0.902			
		(2.991)	(3.194)			
interval		0.701	−6.996**			
		(2.933)	(3.126)			
Constant	44.941***	44.316***	54.436***	44.316***	45.017***	45.511***
	(1.224)	(2.001)	(2.274)	(2.001)	(2.144)	(2.223)
Observations	1,505	745	760	507	501	497
R^2	0.010	0.0002	0.008	0.022	0.001	0.013
Adjusted R^2	0.009	-0.002	0.005	0.020	-0.001	0.011
Residual Std. Error	34.441	33.445	35.337	34.076	33.956	35.205
F Statistic	14.768***	0.081	2.966*	11.180***	0.637	6.453**

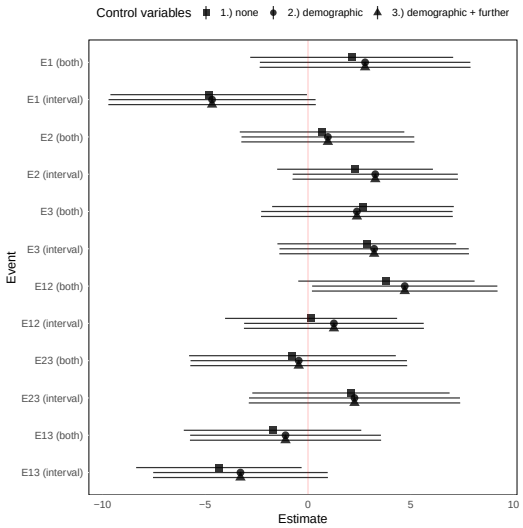
Note: *p<0.1, **p<0.05, ***p<0.01; heteroscedasticity consistent standard errors ("HC1") in parentheses and estimated with the R package sandwich (Zeileis, 2004; Zeileis et al., 2020).



(a) Effect of contradiction (relative to confirmation).



(b) Effect of information treatments (both, interval) relative to best guess, confirmation treatments



(c) Effect of information treatments (both, interval) relative to best guess, contradiction treatments

Figure 4 Treatment effects of regression equation (1) with matching probabilities for all events as dependent variables. Estimators with 95% confidence intervals. The underlying standard errors ("HC1") are clustered at the individual level and estimated with the R package sandwich (Zeileis, 2004; Zeileis et al., 2020).

Yet, the different communication treatments can affect the updating process through another channel: we asked participants how credible and accurate they found the particular text of their treatment. Figure D.1 and Figure D.2 in Appendix D show how these perceptions depend on the information treatments.

We observe that the confirmation treatments have significantly higher credibility and accuracy scores than the contradiction treatments. We interpret this as participants less trusting contradictory news. Importantly, credibility and accuracy scores are larger when both the confidence interval and the best guess are communicated compared to the best guess treatment. This result is similar to Howe et al. (2019) who find higher message acceptance and trust in scientists by combining point and interval estimators. In the contradiction case, the perceived accuracy of the both treatment is even significantly larger than in the interval treatment (see Figure D.2).

We thus conclude that communicating information more completely, i.e. combining best guess and confidence interval, may generate higher credibility of the information and, consequently, may lead to different and potentially improved updating behaviors.

4 Conclusion

In this paper, we studied ambiguity attitudes towards natural (weather) events within a general population sample. We investigated whether ambiguity attitudes are influenced by the ways that uncertainty is communicated within forecasts. Understanding the impact of packaging new information is particularly crucial as, outside of the scientific community, incentives to communicate uncertainty are rather weak. One reason is that acknowledging uncertainty may have adverse effects, as it possibly signals incompetence or dispute within the scientific community (Johnson and Slovic, 1995; Johnson, 2003).

We find that ambiguity attitudes are rather stable with respect to receiving new information. Importantly, surprises do not affect ambiguity attitudes differently than receiving confirmatory information. Yet, the way of communicating new information crucially affects the weight given to individual events. We thus can rule out information avoidance as an explanation for the lack of treatment effects on ambiguity attitudes. New information is thus found to affect the "balance of evidence", rather than the weight given to the evidence (Keynes, 1921).

Furthermore, our results show that ambiguity matters: the average subject's response is not in line with additive probability measures. Specifically, age, gender and education affect ambiguity aversion and ambiguity-generated insensitivity. This shows how important it is to study more population samples beyond the typical students population.

Additionally, the communication strategies have a direct impact on perceived forecast credibility and accuracy. Thus, a more complete communication of the information may have benefits beyond the direct impact on updating the priors. Nonetheless, the differential views on the credibility of confirmatory vs. contradictory information require further investigation.

Further research should be devoted to the robustness of the results to other ambiguous domains. While we focused on weather events, it would be desirable to study additional contexts and to study interaction effects induced by confirmation biases (see also Su, 2022). An important application related to the temperature events in our study is the reaction to climate predictions. Besides affecting individual attitudes, the public support for policies (e.g., climate, criminal justice, education, and public health) policies can be expected to depend on how these uncertainties are perceived and communicated (e.g., Manski, 2015, 2019). It is thus important to better understand how different ways of communicating forecasts may impact the populations' attitudes towards uncertainty and how heterogeneous ambiguity attitudes and the different extents of belief updating translate into support of policy measures.

Acknowledgments

We would like to thank the WiSo Research Laboratory of the University of Hamburg for conducting the pilot and Respondi for conducting the main study. In addition, we would like to thank the participants of the EAERE conference 2022, the AERE conference 2023, and seminar participants at the University of Hamburg for their valuable comments. Special thanks goes to

Grischa Perino, Dallas Murphy and Stefan Traub for their valuable comments.

Technical Note: The statistical analysis and the visualizations were mostly carried out with the help of R and extensions (R 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).

Funding: Funded by the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) under Germany's Excellence Strategy – EXC 2037 'CLICCS - Climate, Climatic Change, and Society' – Project Number: 390683824, contribution to the Center for Earth System Research and Sustainability (CEN) of Universität Hamburg

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Appendices

Appendix A

Table A.1 Descriptive statistics (control variables): Mean values per treatment

	pooled		confirmation						contradiction					
Treatment			point		point + interval		interval		point		point + interval		interval	
Variable	N	Mean	N	Mean	N	Mean	N	Mean	N	Mean	N	Mean	N	Mean
age(18-34)	1503	0.335	255	0.325	247	0.296	243	0.309	251	0.386	249	0.345	258	0.345
age(35-52)	1503	0.306	255	0.31	247	0.3	243	0.313	251	0.299	249	0.313	258	0.302
age(53-69)	1503	0.359	255	0.365	247	0.405	243	0.379	251	0.315	249	0.341	258	0.353
gender (female)	1503	0.49	255	0.463	246	0.48	243	0.444	251	0.542	250	0.528	258	0.484
high education	1505	0.618	255	0.616	247	0.575	243	0.687	252	0.643	250	0.612	258	0.578
high income	1363	0.525	230	0.552	227	0.498	220	0.564	225	0.547	227	0.471	234	0.517
family (married or same sex union)	1505	0.396	255	0.427	247	0.421	243	0.379	252	0.389	250	0.356	258	0.403
parentship	1505	0.429	255	0.4	247	0.482	243	0.395	252	0.44	250	0.404	258	0.45
high temperature (median)	1505	0.591	255	0.557	247	0.543	243	0.613	252	0.575	250	0.668	258	0.589
high weather forecast usage (median)	1505	0.511	255	0.518	247	0.526	243	0.494	252	0.548	250	0.516	258	0.465
high general risk attitude (median)	1505	0.54	255	0.561	247	0.514	243	0.506	252	0.512	250	0.552	258	0.589
high weather risk attitude (median)	1505	0.633	255	0.6	247	0.587	243	0.588	252	0.679	250	0.66	258	0.678
high accuracy (median)	1505	0.786	255	0.8	247	0.81	243	0.819	252	0.698	250	0.836	258	0.756
high credibility (median)	1505	0.503	255	0.49	247	0.615	243	0.56	252	0.369	250	0.504	258	0.484
comprehension	1505		255		247		243		252		250		258	
... no	32	2.1%	5	2%	5	2%	8	3.3%	3	1.2%	5	2%	6	2.3%
... rather not	254	16.9%	44	17.3%	40	16.2%	38	15.6%	50	19.8%	43	17.2%	39	15.1%
... rather yes	739	49.1%	132	51.8%	114	46.2%	125	51.4%	112	44.4%	131	52.4%	125	48.4%
... yes	480	31.9%	74	29%	88	35.6%	72	29.6%	87	34.5%	71	28.4%	88	34.1%
temperature	1505	20.1	255	19.9	247	19.5	243	20.3	252	20.1	250	20.5	258	20.1
weather forecast usage	1505	3.35	255	3.41	247	3.35	243	3.35	252	3.39	250	3.31	258	3.28
general risk attitude	1505	4.19	255	4.29	247	3.99	243	4.01	252	4.05	250	4.4	258	4.41
weather risk attitude	1505	5.26	255	5.12	247	4.94	243	4.97	252	5.43	250	5.5	258	5.59
accuracy	1505	2.24	255	2.31	247	2.4	243	2.37	252	1.99	250	2.31	258	2.08
credibility	1505	2.38	255	2.38	247	2.56	243	2.5	252	2.06	250	2.4	258	2.38
Observations	1505		255		247		243		252		250		258	

Since our dummy variables are grouped from multiple different answers, an overview can be found below in Table A.2.

Table A.2 Composition of the control variables (dummy variables)

variable	1	0
age(18-34)	18-34	35-69
age(35-52)	35-52	18-34, 53-69
age(53-69)	53-69	18-52
gender (female)	female	male, diverse
high education*	high-school diploma, college or university degree, technical high-school diploma	finished school without degree, still a student, other diploma, completed apprenticeship lowest high school("Hauptschule") average high school("Realschule")
high income	2.001-3.000 €, 3.001-4.000 €, more than 4.000 €	0-500 €, 501-1.000 €, 1.001-2.000 €
family (married or same sex union)	married, same sex union	distant marriage, single, widowed divorced, distant same sex union
parentship	yes	no
high temperature (median)	median (20 degrees) and above	under 20 degrees
high weather forecast usage (median)	median (4 ("daily")), 5("several times a day")	3("several times a week") 2("weekly"), 1("less"), 0("never")
high general risk attitude (median)**	median (4) -10	0-3
high weather risk attitude (median)**	median (5) -10	0-4
high accuracy (median)**	median (2)-4	0-1
high credibility (median)**	median (3)-4	0-2

*high education=1 for "Abitur, Hochschulreife", "Fachhochschul-/Hochschulabschluss", "Fachabitur, Fachhochschulreife"
*high education=0 for "Schule beendet ohne Abschluss", "Noch Schüler", "Anderer Abschluss", "Abgeschlossene Lehre", "Volks-, Hauptschulabschluss, Quali ", "Mittlere Reife, Realschul- oder gleichwertiger Abschluss"
**The higher the value the the more risk loving, credible, accurate
We declared age as missing value under 18 (assuming careless mistakes). For gender and income, participants were also able to indicate that they did not wish to respond, which is why we declare these entries as missing from the data.
There are four questions not used for our analyses: Two open-ended ones on climate change, vaccination status, and zip code.

Appendix B

Table B.1 Linear regressions: Treatment effects on E1

	Dependent variable:					
	E1					
Sample	full	confirmation	contradiction	point	interval	both
	(1)	(2)	(3)	(4)	(5)	(6)
contradiction	−0.962			−1.492	0.951	−2.435
	(1.080)			(1.760)	(1.993)	(1.855)
both		2.430	1.487			
		(1.759)	(1.856)			
interval		1.331	3.773**			
		(1.836)	(1.923)			
part2	−1.036	0.955	7.468***	0.955	−1.634	−2.504*
	(0.846)	(1.500)	(1.791)	(1.500)	(1.498)	(1.391)
contradiction×part2	7.563***			6.513***	4.269*	12.098***
	(1.315)			(2.336)	(2.232)	(2.251)
both×part2		−3.459*	2.126			
		(2.046)	(2.517)			
interval×part2		−2.589	−4.833**			
		(2.120)	(2.437)			
Constant	47.893***	46.653***	45.161***	46.653***	47.984***	49.083***
	(0.747)	(1.193)	(1.294)	(1.193)	(1.395)	(1.293)
Observations	3,010	1,490	1,520	1,014	1,002	994
R^2	0.014	0.002	0.024	0.015	0.006	0.028
Adjusted R^2	0.013	-0.002	0.021	0.012	0.003	0.025
Residual Std. Error	23.210	22.727	23.652	22.494	23.624	23.473
F Statistic	13.967***	0.530	7.531***	5.226***	2.152*	9.393***

Note:*p<0.1; **p<0.05; ***p<0.01. The underlying standard errors ("HC1") are clustered at the individual level and estimated with the R package sandwich (Zeileis, 2004; Zeileis et al., 2020)

Table B.2 Linear regressions: Treatment effects on E2

	Dependent variable:					
	E2					
Sample	full	confirmation	contradiction	point	interval	both
	(1)	(2)	(3)	(4)	(5)	(6)
contradiction	−1.235			−1.497	−1.578	−0.612
	(1.072)			(1.779)	(1.943)	(1.852)
both		1.558	2.443			
		(1.806)	(1.825)			
interval		0.174	0.092			
		(1.867)	(1.858)			
part2	3.535***	4.227***	−3.103**	4.227***	2.998**	3.348**
	(0.782)	(1.159)	(1.407)	(1.159)	(1.468)	(1.433)
contradiction×part2	−5.636***			−7.331***	−3.812*	−5.768***
	(1.125)			(1.824)	(1.977)	(2.059)
both×part2		−0.879	0.683			
		(1.843)	(2.041)			
interval×part2		−1.230	2.289			
		(1.871)	(1.932)			
Constant	50.681***	50.108***	48.611***	50.108***	50.282***	51.666***
	(0.757)	(1.250)	(1.265)	(1.250)	(1.387)	(1.304)
Observations	3,010	1,490	1,520	1,014	1,002	994
R^2	0.013	0.007	0.005	0.023	0.008	0.010
Adjusted R^2	0.012	0.004	0.002	0.020	0.005	0.007
Residual Std. Error	21.997	22.066	21.941	20.890	22.813	22.276
F Statistic	12.879***	2.214*	1.655	7.827***	2.700**	3.462**

Note:*p<0.1; **p<0.05; ***p<0.01. The underlying standard errors ("HC1") are clustered at the individual level and estimated with the R package sandwich (Zeileis, 2004; Zeileis et al., 2020)

Table B.3 Linear regressions: Treatment effects on E3

	Dependent variable:					
	E3					
Sample	full	confirmation	contradiction	point	interval	both
	(1)	(2)	(3)	(4)	(5)	(6)
contradiction	−0.317			1.231	0.356	−2.623
	(1.049)			(1.814)	(1.864)	(1.767)
both		4.813***	0.958			
		(1.752)	(1.828)			
interval		2.199	1.323			
		(1.787)	(1.889)			
part2	0.148	2.161	−5.425***	2.161	−0.006	−1.779
	(0.818)	(1.477)	(1.635)	(1.477)	(1.283)	(1.469)
contradiction×part2	−3.721***			−7.585***	−2.558	−0.971
	(1.217)			(2.204)	(1.972)	(2.136)
both×part2		−3.940*	2.675			
		(2.083)	(2.253)			
interval×part2		−2.167	2.861			
		(1.956)	(2.217)			
Constant	48.591***	46.278***	47.510***	46.278***	48.477***	51.091***
	(0.733)	(1.204)	(1.357)	(1.204)	(1.321)	(1.274)
Observations	3,010	1,490	1,520	1,014	1,002	994
R^2	0.006	0.004	0.009	0.012	0.002	0.007
Adjusted R^2	0.005	0.001	0.006	0.009	-0.001	0.004
Residual Std. Error	22.475	21.461	23.399	22.160	22.847	22.373
F Statistic	5.563***	1.320	2.815**	4.050***	0.678	2.489*

Note:*p<0.1; **p<0.05; ***p<0.01. The underlying standard errors ("HC1") are clustered at the individual level and estimated with the R package sandwich (Zeileis, 2004; Zeileis et al., 2020)

Table B.4 Linear regressions: Treatment effects on E12

	Dependent variable:					
	E12					
Sample	full	confirmation	contradiction	point	interval	both
	(1)	(2)	(3)	(4)	(5)	(6)
contradiction	−0.453			0.446	−1.087	−0.776
	(1.031)			(1.772)	(1.754)	(1.838)
both		1.672	0.451			
		(1.760)	(1.850)			
interval		2.072	0.539			
		(1.743)	(1.783)			
part2	1.817**	3.090**	4.460***	3.090**	−0.401	2.684*
	(0.828)	(1.365)	(1.611)	(1.365)	(1.499)	(1.440)
contradiction×part2	3.950***			1.370	5.012**	5.592***
	(1.198)			(2.112)	(2.050)	(2.065)
both×part2		−0.406	3.816*			
		(1.984)	(2.187)			
interval×part2		−3.491*	0.150			
		(2.027)	(2.134)			
Constant	58.358***	57.127***	57.573***	57.127***	59.200***	58.800***
	(0.716)	(1.230)	(1.276)	(1.230)	(1.234)	(1.258)
Observations	3,010	1,490	1,520	1,014	1,002	994
R^2	0.010	0.004	0.019	0.008	0.007	0.021
Adjusted R^2	0.009	0.001	0.015	0.005	0.004	0.018
Residual Std. Error	22.155	21.169	23.078	22.444	21.919	22.090
F Statistic	10.599***	1.214	5.751***	2.679**	2.266*	7.149***

Note:*p<0.1; **p<0.05; ***p<0.01. The underlying standard errors ("HC1") are clustered at the individual level and estimated with the R package sandwich (Zeileis, 2004; Zeileis et al., 2020)

Table B.5 Linear regressions: Treatment effects on E23

	Dependent variable:					
	E23					
Sample	full	confirmation	contradiction	point	interval	both
	(1)	(2)	(3)	(4)	(5)	(6)
contradiction	1.513			0.254	1.193	3.086
	(1.154)			(2.075)	(1.963)	(1.959)
both		0.306	3.139			
		(2.028)	(2.006)			
interval		0.722	1.661			
		(2.047)	(1.992)			
part2	3.099***	3.308**	−7.562***	3.308**	2.074	3.893**
	(0.855)	(1.389)	(1.812)	(1.389)	(1.458)	(1.597)
contradiction×part2	−10.200***			−10.869***	−7.545***	−12.211***
	(1.326)			(2.283)	(2.198)	(2.417)
both×part2		0.585	−0.756			
		(2.116)	(2.564)			
interval×part2		−1.234	2.091			
		(2.013)	(2.447)			
Constant	59.658***	59.322***	59.575***	59.322***	60.043***	59.628***
	(0.829)	(1.452)	(1.481)	(1.453)	(1.442)	(1.416)
Observations	3,010	1,490	1,520	1,014	1,002	994
R^2	0.020	0.005	0.027	0.026	0.012	0.024
Adjusted R^2	0.019	0.001	0.023	0.023	0.009	0.021
Residual Std. Error	23.195	23.236	23.167	23.966	22.547	23.058
F Statistic	20.085***	1.441	8.284***	8.939***	3.966***	8.016***

Note:*p<0.1; **p<0.05; ***p<0.01. The underlying standard errors ("HC1") are clustered at the individual level and estimated with the R package sandwich (Zeileis, 2004; Zeileis et al., 2020)

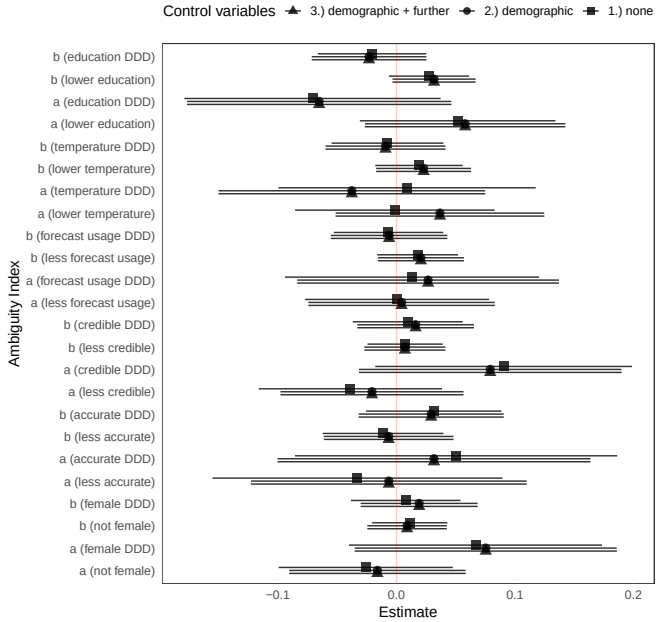
Table B.6 Linear regressions: Treatment effects on E13

	Dependent variable:					
	E13					
Sample	full	confirmation	contradiction	point	interval	both
	(1)	(2)	(3)	(4)	(5)	(6)
contradiction	0.922			−2.686	4.258**	1.173
	(1.037)			(1.743)	(1.846)	(1.792)
both		0.479	4.338**			
		(1.749)	(1.786)			
interval		−1.358	5.586***			
		(1.811)	(1.779)			
part2	−1.549*	−1.333	4.212***	−1.333	0.068	−3.362**
	(0.873)	(1.414)	(1.579)	(1.414)	(1.581)	(1.543)
contradiction×part2	3.721***			5.546***	−0.192	5.848***
	(1.221)			(2.120)	(2.054)	(2.176)
both×part2		−2.029	−1.726			
		(2.093)	(2.201)			
interval×part2		1.401	−4.336**			
		(2.121)	(2.052)			
Constant	55.130***	55.414***	52.728***	55.414***	54.056***	55.893***
	(0.736)	(1.200)	(1.264)	(1.200)	(1.357)	(1.273)
Observations	3,010	1,490	1,520	1,014	1,002	994
R^2	0.006	0.002	0.010	0.005	0.009	0.013
Adjusted R^2	0.005	-0.001	0.007	0.002	0.006	0.010
Residual Std. Error	21.788	22.070	21.473	21.291	21.762	22.259
F Statistic	5.977***	0.717	3.041***	1.812	3.054**	4.266***

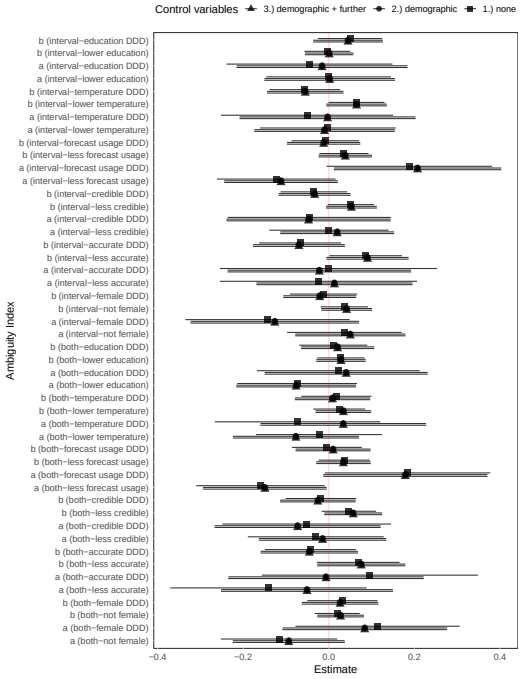
Note:*p<0.1; **p<0.05; ***p<0.01. The underlying standard errors ("HC1") are clustered at the individual level and estimated with the R package sandwich (Zeileis, 2004; Zeileis et al., 2020)

Appendix C

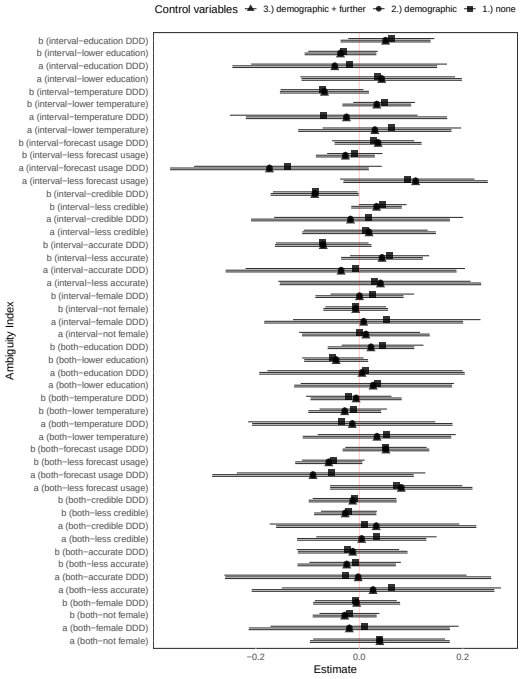
For clarification of the estimators shown in the following graphs, a brief explanation is provided below.



(a) Effect of contradiction (relative to confirmation).



(b) Effect of information treatments (both, interval) relative to best guess, confirmation treatments



(c) Effect of information treatments (both, interval) relative to best guess, contradiction treatments

Figure C.1 Heterogeneous treatment effects of regression equation (1) with dependent variables b and a. Estimators with 95% confidence intervals. The underlying standard errors ("HC1") are clustered at the individual level and estimated with the R package sandwich (Zeileis, 2004; Zeileis et al., 2020).

We examine the heterogeneous effects by estimating a triple interaction effect regression:

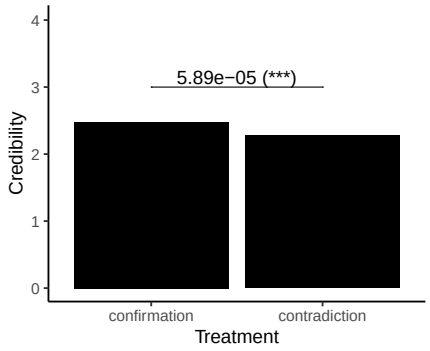
$$\begin{aligned} y_{it} =& \alpha_{baseline} + \sum_{treat} \alpha_{treat} treat_i + \beta_{baseline} part2_t + \sum_{treat} \beta_{treat} treat_i \times part2_t \\ &+ \theta_{baseline}(D_i \times part2_t) + \sum_{treat} \theta_{treat}(D_i \times treat_i \times part2_t) \\ &+ \delta_{baseline} D_i + \sum_{treat} \delta_{treat}(D_i \times treat_i) + \gamma X_i + \epsilon_{it} \end{aligned}$$

The figure C.1a displays the estimators β_{treat} and θ_{treat}. The triple interaction effects θ_{treat} are labelled with education DDD, temperature DDD, forecast usage DDD, credible DDD, accurate DDD, and female DDD in this case. The double interaction effects β_{treat} are labelled with lower education, lower temperature, less forecast usage, less credible, less accurate, and not female in this case. For example, to determine the total treatment effect for female on b , one must add the estimators β_{treat} (b (not female)) and δ_{treat} (b (female DDD)). The same principle can be applied to the other two figures.

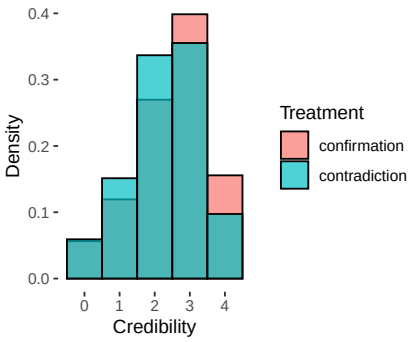
In figure C.1a, we pool across the different information treatments (interval, best guess, both) and only consider the heterogeneous effect of contradiction vs. confirmation. *treat* refers to contradiction while confirmation is used as the baseline.

In figure C.1b and C.1c, we test the heterogeneous effects of the different information treatments (interval, best guess, both) separately for confirmation and contradiction treatment arms. The best guess information treatment serves as the baseline and *treat* refers to the information treatments interval or both.

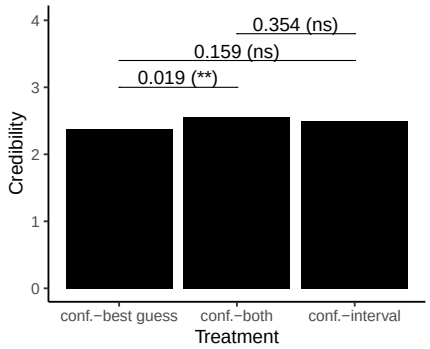
Appendix D



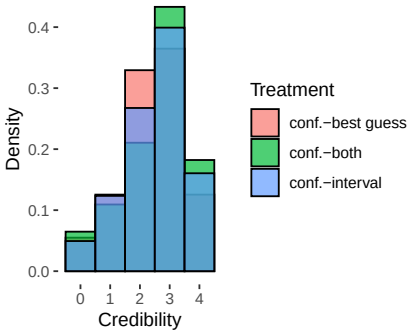
(a) Credibility, confirmation compared to contradiction



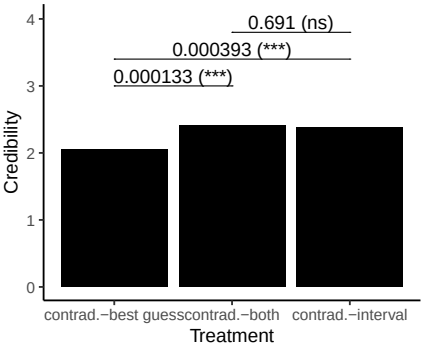
(b) Credibility, confirmation compared to contradiction (density)



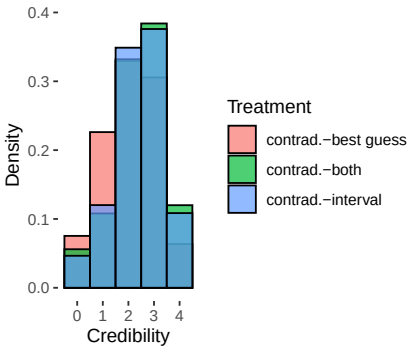
(c) Credibility, confirmation treatments



(d) Credibility, confirmation treatments (density)

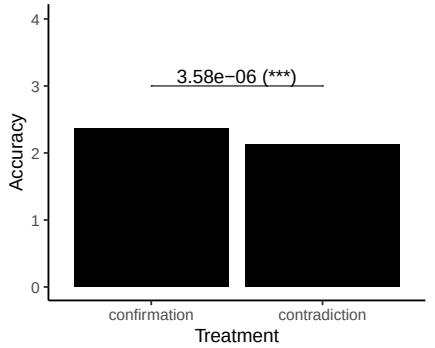


(e) Credibility, contradiction treatments

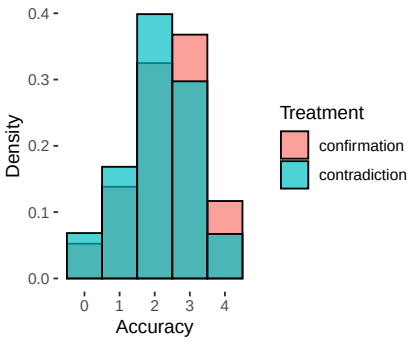


(f) Credibility, contradiction treatments (density)

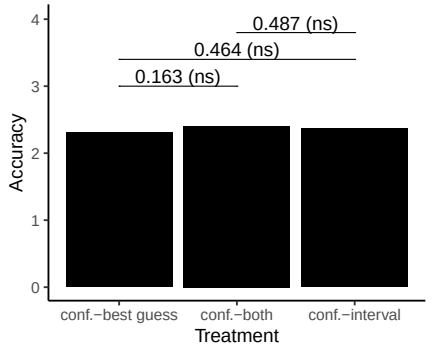
Figure D.1 Means and density of the self-reported credibility of the treatment texts separated by treatments. P-values of Wilcoxon–Mann–Whitney test comparing the different treatments at the top. Note: *p<0.10, **p<0.05, ***p<0.01, ns: not significant



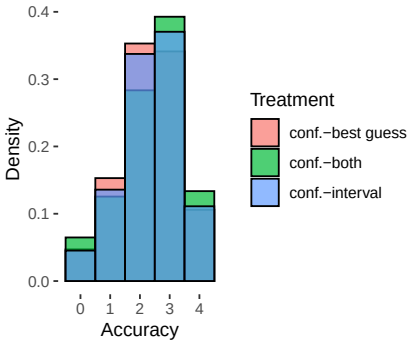
(a) Accuracy, confirmation compared to contradiction



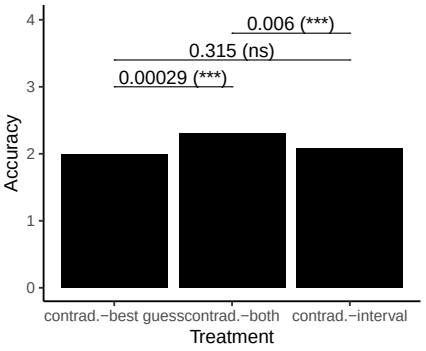
(b) Accuracy, confirmation compared to contradiction (density)



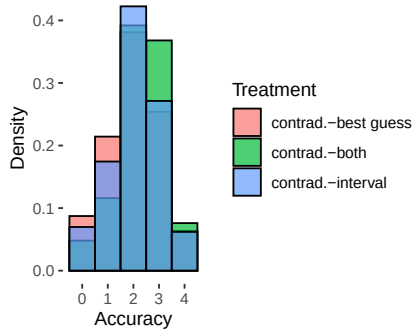
(c) Accuracy, confirmation treatments



(d) Accuracy, confirmation treatments (density)



(e) Accuracy, contradiction treatments



(f) Accuracy, contradiction treatments (density)

Figure D.2 Means and density of the self-reported accuracy of the treatment texts separated by treatments. P-values of Wilcoxon–Mann–Whitney test comparing the different treatments at the top. Note: *p<0.10, **p<0.05, ***p<0.01, ns: not significant

Online Appendices

Manuscript Title: *Ambiguity attitudes and surprises: experimental evidence on communicating new information within a large population sample* **Authors:** Aljoscha Minnich, Hauke Roggenkamp, Andreas Lange

Online Appendix A

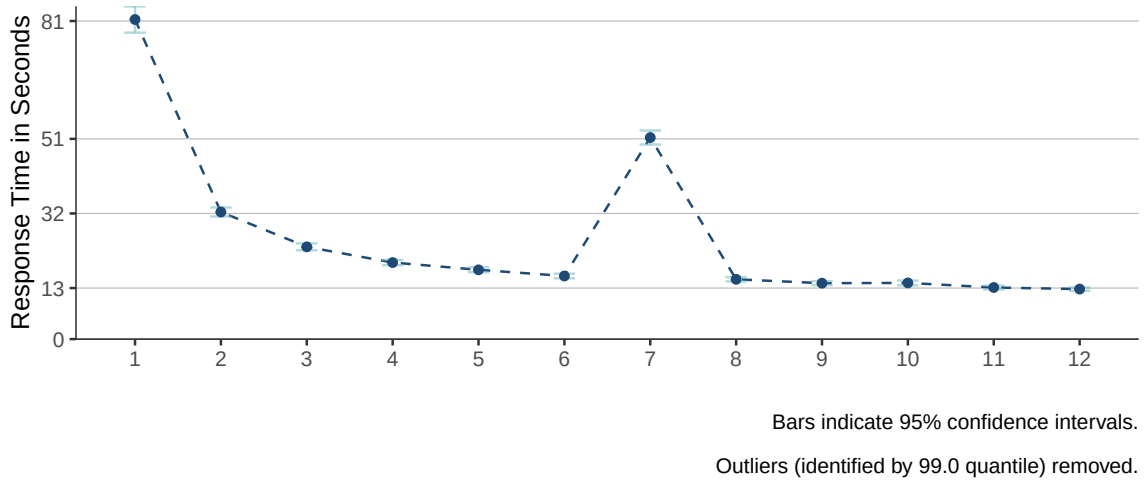
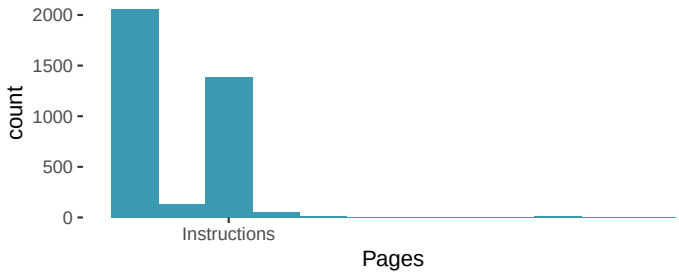
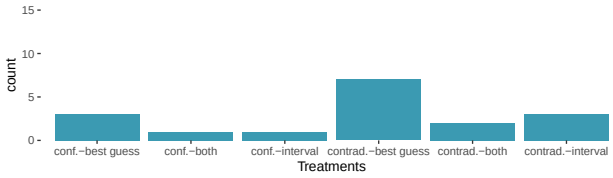


Figure OA.1 Average response time of the 12 ambiguity tasks of the full sample (1505 observations; outliers removed as described in the figure).



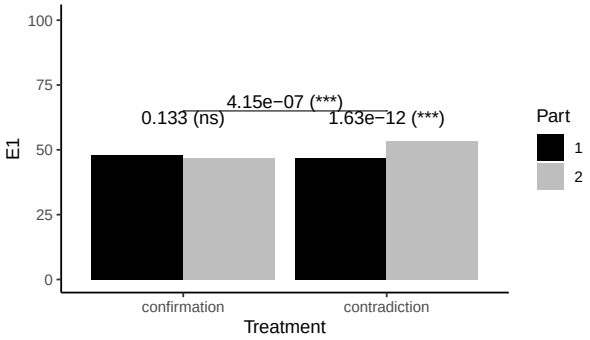
(a) Dropout participants of the experiment by page number. Note that the high number of dropouts on page 0 comes from oTree links that were generated but never clicked.



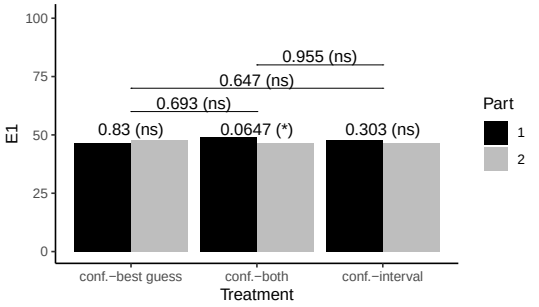
(b) 17 dropout participants separated by treatment after introduction of the treatment (page 9 and following).

Figure OA.2 Dropout participants of the experiment by page number and dropout participants separated by treatment after introduction of the treatment.

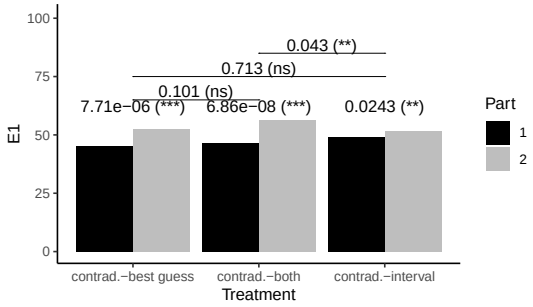
Online Appendix B



(a) E_1, confirmation compared to contradiction

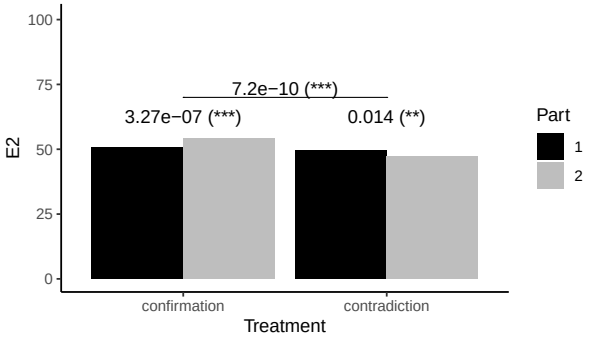


(b) E_1, confirmation treatments

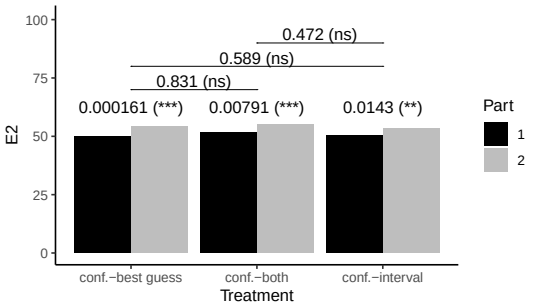


(c) E_1, contradiction treatments

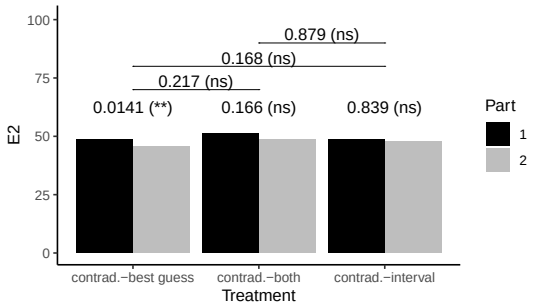
Figure OB.1 Means of the matching probabilities for event E_1 separated by treatments and part 1 and part 2. P-values of Wilcoxon signed-rank test comparing part 1 and 2 directly above the mean values. P-values of Wilcoxon–Mann–Whitney test comparing part 2 of different treatments at the top. Note: *p<0.10, **p<0.05, ***p<0.01, ns: not significant



(a) E_2, confirmation compared to contradiction

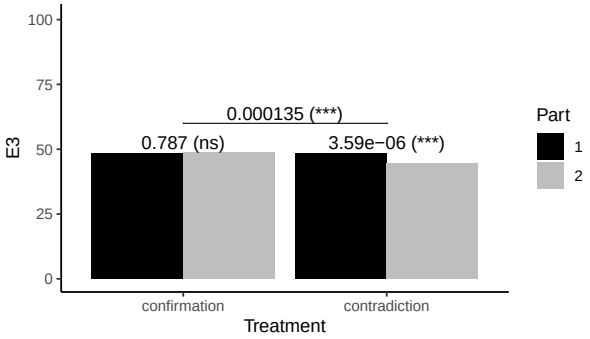


(b) E_2, confirmation treatments

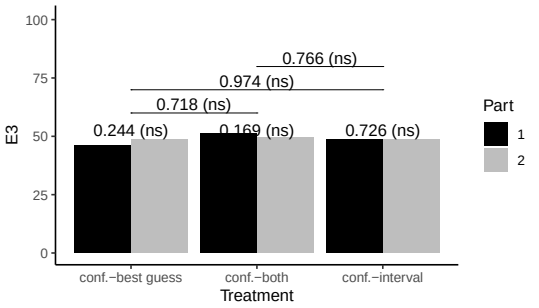


(c) E_2, contradiction treatments

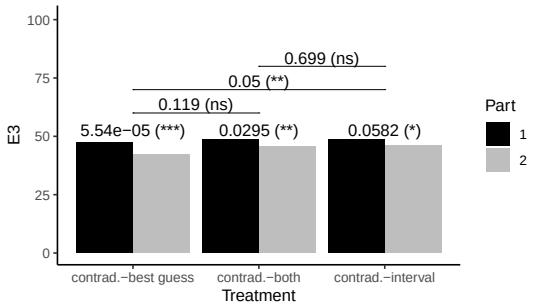
Figure OB.2 Means of the matching probabilities for event E_2 separated by treatments and part 1 and part 2. P-values of Wilcoxon signed-rank test comparing part 1 and 2 directly above the mean values. P-values of Wilcoxon–Mann–Whitney test comparing part 2 of different treatments at the top. Note: *p<0.10, **p<0.05, ***p<0.01, ns: not significant



(a) E_3, confirmation compared to contradiction

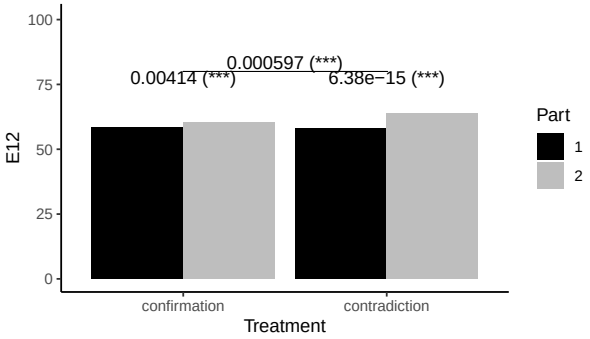


(b) E_3, confirmation treatments

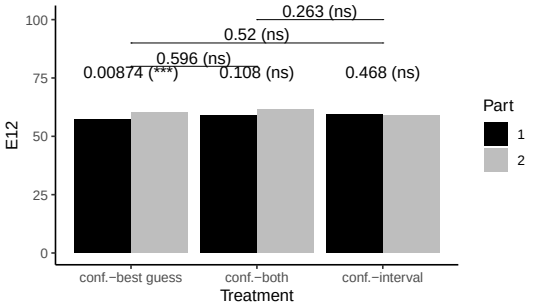


(c) E_3, contradiction treatments

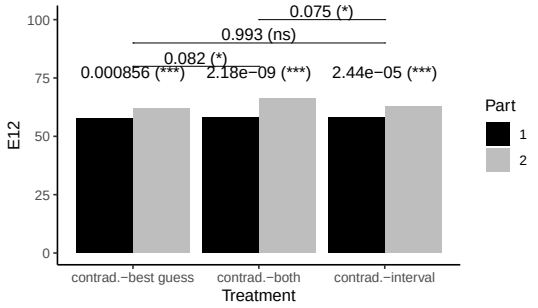
Figure OB.3 Means of the matching probabilities for event E_3 separated by treatments and part 1 and part 2. P-values of Wilcoxon signed-rank test comparing part 1 and 2 directly above the mean values. P-values of Wilcoxon–Mann–Whitney test comparing part 2 of different treatments at the top. Note: *p<0.10, **p<0.05, ***p<0.01, ns: not significant



(a) E_{12}, confirmation compared to contradiction

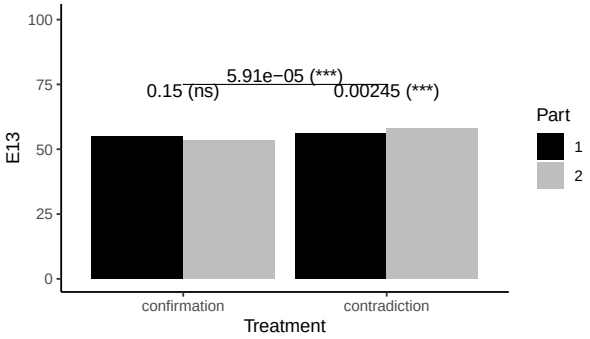


(b) E_{12}, confirmation treatments

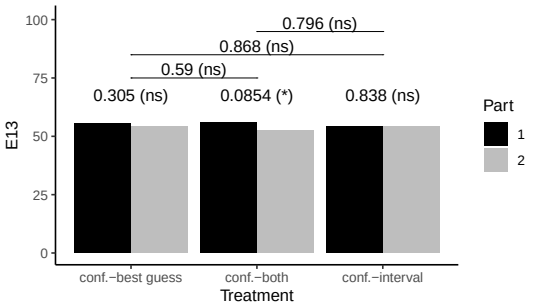


(c) E_{12}, contradiction treatments

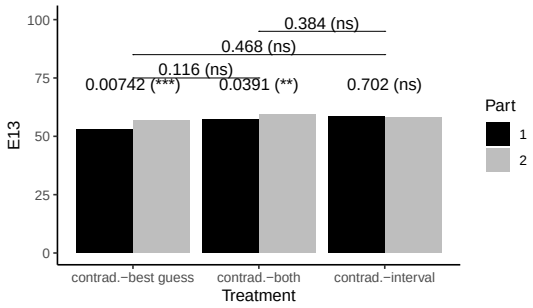
Figure OB.4 Means of the matching probabilities for event E_{12} separated by treatments and part 1 and part 2. P-values of Wilcoxon signed-rank test comparing part 1 and 2 directly above the mean values. P-values of Wilcoxon–Mann–Whitney test comparing part 2 of different treatments at the top. Note: *p<0.10, **p<0.05, ***p<0.01, ns: not significant



(a) E_{13}, confirmation compared to contradiction

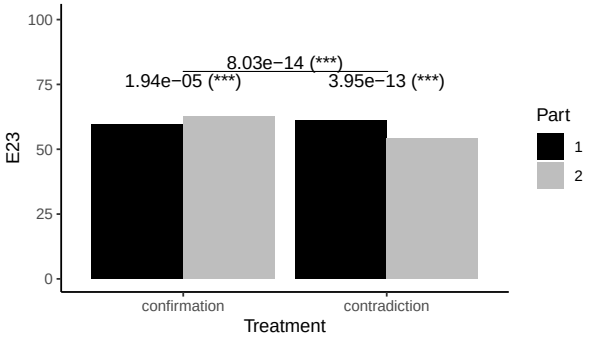


(b) E_{13}, confirmation treatments

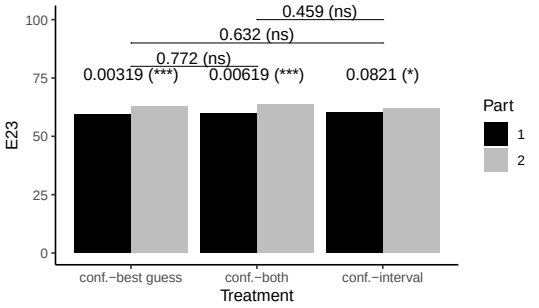


(c) E_{13}, contradiction treatments

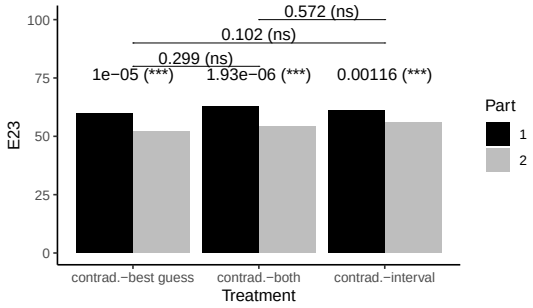
Figure OB.5 Means of the matching probabilities for event E_{13} separated by treatments and part 1 and part 2. P-values of Wilcoxon signed-rank test comparing part 1 and 2 directly above the mean values. P-values of Wilcoxon–Mann–Whitney test comparing part 2 of different treatments at the top. Note: *p<0.10, **p<0.05, ***p<0.01, ns: not significant



(a) E_{23}, confirmation compared to contradiction



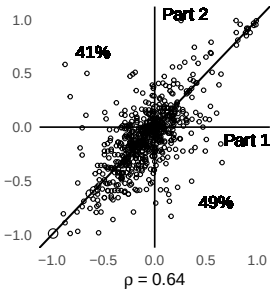
(b) E_{23}, confirmation treatments



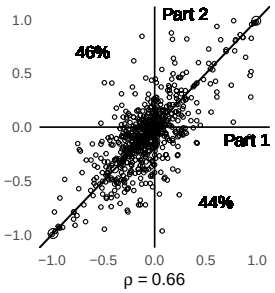
(c) E_{23}, contradiction treatments

Figure OB.6 Means of the matching probabilities for event E_{23} separated by treatments and part 1 and part 2. P-values of Wilcoxon signed-rank test comparing part 1 and 2 directly above the mean values. P-values of Wilcoxon–Mann–Whitney test comparing part 2 of different treatments at the top. Note: *p<0.10, **p<0.05, ***p<0.01, ns: not significant

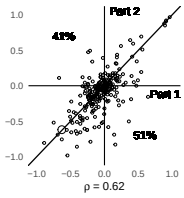
Online Appendix C



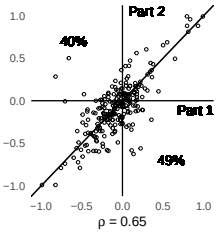
(a) Ambiguity index b, confirmation treatment



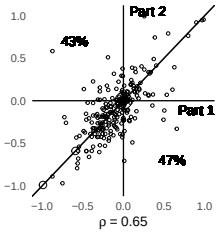
(b) Ambiguity index b, contradiction treatment



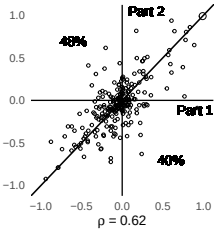
(c) Ambiguity index b, confirmation and point treatment



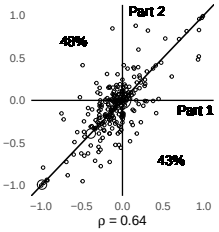
(d) Ambiguity index b, confirmation and interval treatment



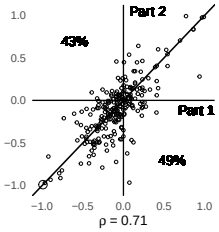
(e) Ambiguity index b, confirmation and point + interval treatment



(f) Ambiguity index b, contradiction and point treatment

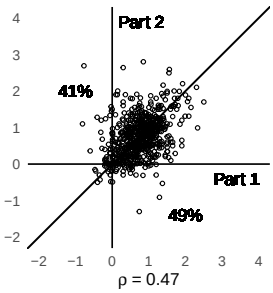


(g) Ambiguity index b, contradiction and interval treatment

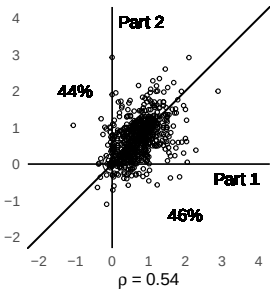


(h) Ambiguity index b, contradiction and point + interval treatment

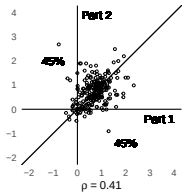
Figure OC.1 Scatterplot of the ambiguity index b. The relationship between part 1 and part 2 separated by treatments with correlation coefficients and percentages above and below the diagonal.



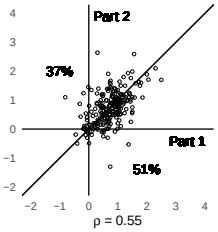
(a) Ambiguity index a, confirmation treatment



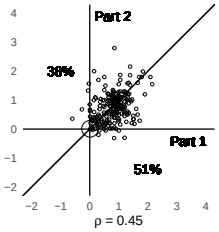
(b) Ambiguity index a, contradiction treatment



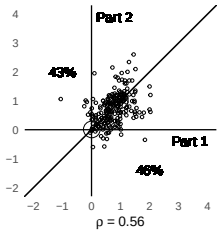
(c) Ambiguity index a, confirmation and point treatment



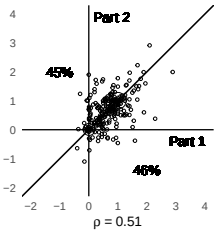
(d) Ambiguity index a, confirmation and interval treatment



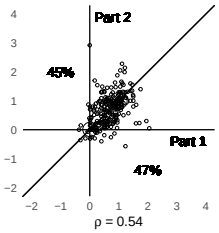
(e) Ambiguity index a, confirmation and point + interval treatment



(f) Ambiguity index a, contradiction and point treatment

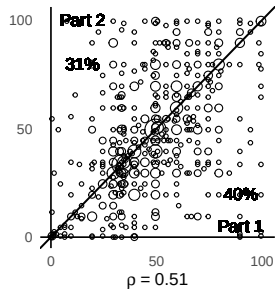


(g) Ambiguity index a, contradiction and interval treatment

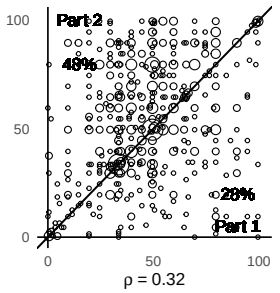


(h) Ambiguity index a, contradiction and point + interval treatment

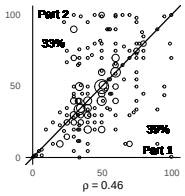
Figure OC.2 Scatterplot of the ambiguity index a. The relationship between part 1 and part 2 separated by treatments with correlation coefficients and percentages above and below the diagonal.



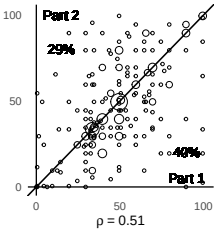
(a) E_1, confirmation treatment



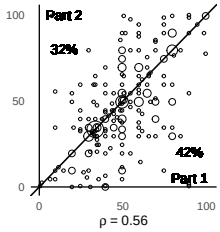
(b) E_1, contradiction treatment



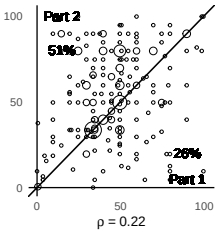
(c) E_1, confirmation and point treatment



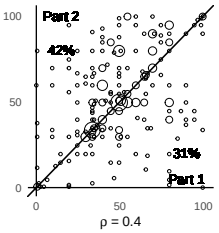
(d) E_1, confirmation and interval treatment



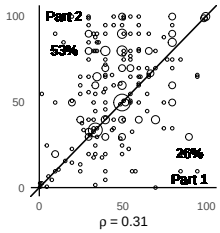
(e) E_1, confirmation and point + interval treatment



(f) E_1, contradiction and point treatment

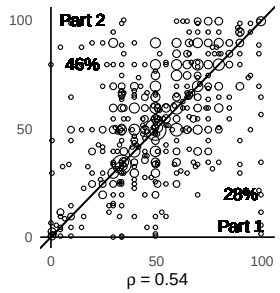


(g) E_1, contradiction and interval treatment

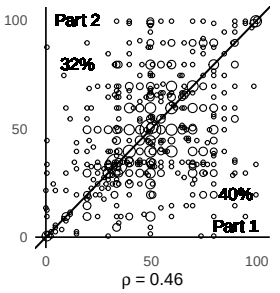


(h) E_1, contradiction and point + interval treatment

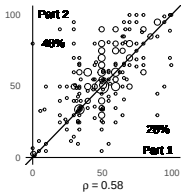
Figure OC.3 Scatterplot of the matching probabilities for event E_1. The relationship between part 1 and part 2 separated by treatments with correlation coefficients and percentages above and below the diagonal.



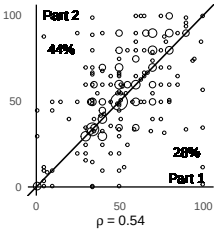
(a) E_2, confirmation treatment



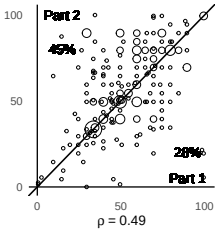
(b) E_2, contradiction treatment



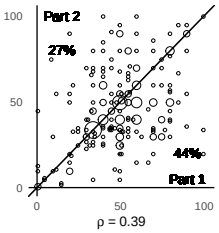
(c) E_2, confirmation and point treatment



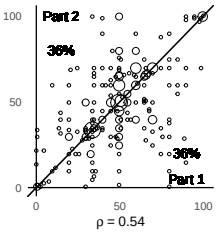
(d) E_2, confirmation and interval treatment



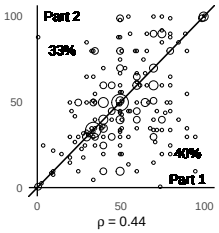
(e) E_2, confirmation and point + interval treatment



(f) E_2, contradiction and point treatment

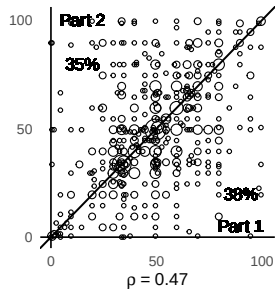


(g) E_2, contradiction and interval treatment

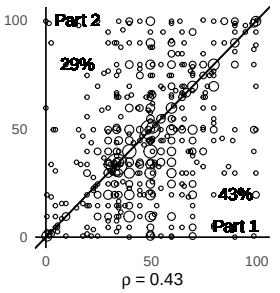


(h) E_2, contradiction and point + interval treatment

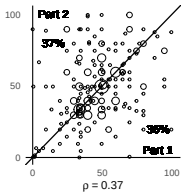
Figure OC.4 Scatterplot of the matching probabilities for event E_2. The relationship between part 1 and part 2 separated by treatments with correlation coefficients and percentages above and below the diagonal.



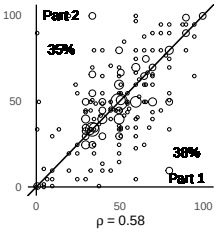
(a) E_3, confirmation treatment



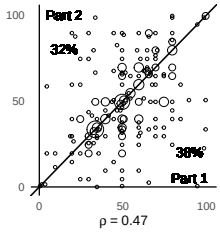
(b) E_3, contradiction treatment



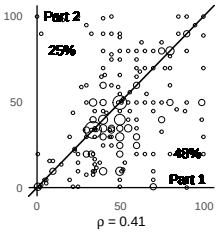
(c) E_3, confirmation and point treatment



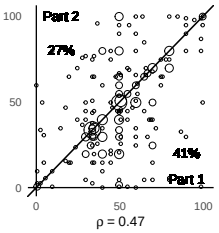
(d) E_3, confirmation and interval treatment



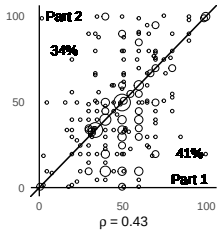
(e) E_3, confirmation and point + interval treatment



(f) E_3, contradiction and point treatment

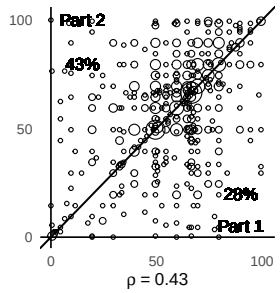


(g) E_3, contradiction and interval treatment

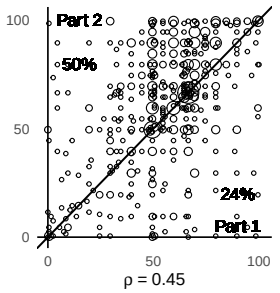


(h) E_3, contradiction and point + interval treatment

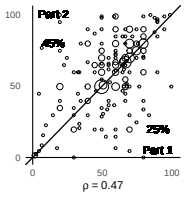
Figure OC.5 Scatterplot of the matching probabilities for event E_3. The relationship between part 1 and part 2 separated by treatments with correlation coefficients and percentages above and below the diagonal.



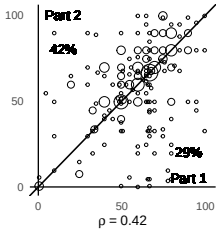
(a) E_{12}, confirmation treatment



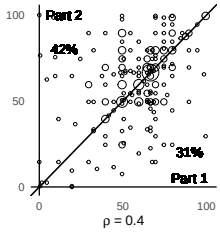
(b) E_{12}, contradiction treatment



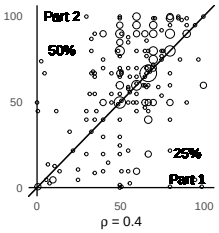
(c) E_{12}, confirmation and point treatment



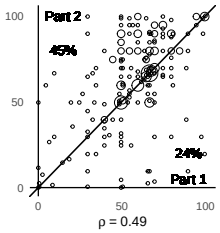
(d) E_{12}, confirmation and interval treatment



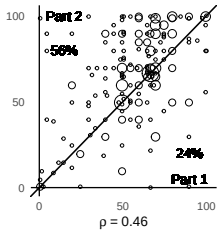
(e) E_{12}, confirmation and point + interval treatment



(f) E_{12}, contradiction and point treatment

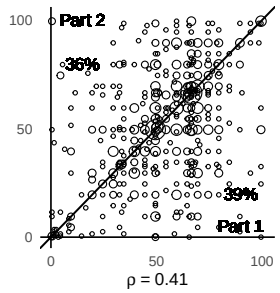


(g) E_{12}, contradiction and interval treatment

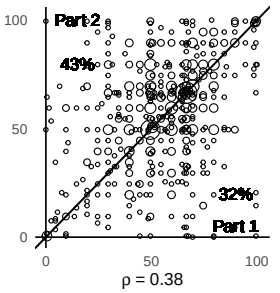


(h) E_{12}, contradiction and point + interval treatment

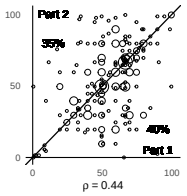
Figure OC.6 Scatterplot of the matching probabilities for event E_{12}. The relationship between part 1 and part 2 separated by treatments with correlation coefficients and percentages above and below the diagonal.



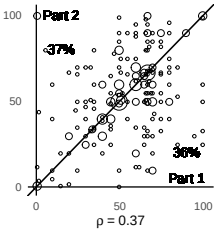
(a) E_{13}, confirmation treatment



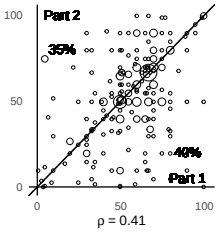
(b) E_{13}, contradiction treatment



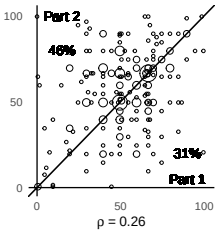
(c) E_{13}, confirmation and point treatment



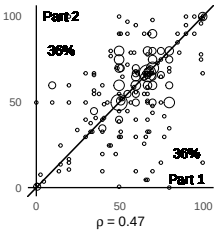
(d) E_{13}, confirmation and interval treatment



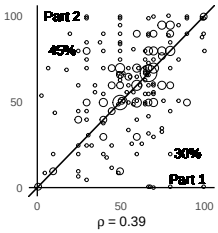
(e) E_{13}, confirmation and point + interval treatment



(f) E_{13}, contradiction and point treatment

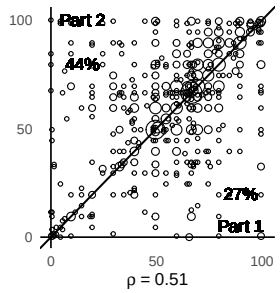


(g) E_{13}, contradiction and interval treatment

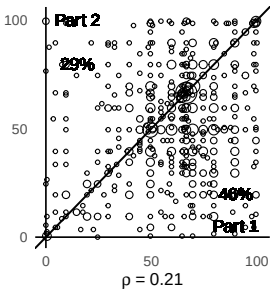


(h) E_{13}, contradiction and point + interval treatment

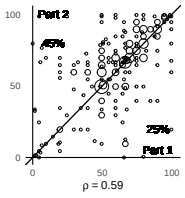
Figure OC.7 Scatterplot of the matching probabilities for event E_{13}. The relationship between part 1 and part 2 separated by treatments with correlation coefficients and percentages above and below the diagonal.



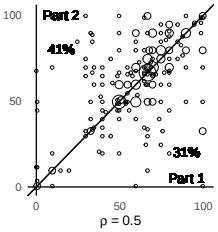
(a) E_{23}, confirmation treatment



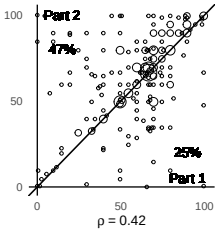
(b) E_{23}, contradiction treatment



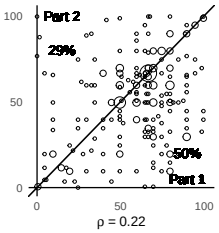
(c) E_{23}, confirmation and point treatment



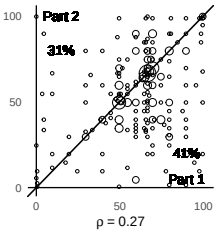
(d) E_{23}, confirmation and interval treatment



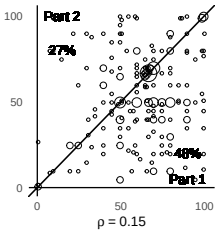
(e) E_{23}, confirmation and point + interval treatment



(f) E_{23}, contradiction and point treatment



(g) E_{23}, contradiction and interval treatment



(h) E_{23}, contradiction and point + interval treatment

Figure OC.8 Scatterplot of the matching probabilities for event E_{23}. The relationship between part 1 and part 2 separated by treatments with correlation coefficients and percentages above and below the diagonal.

Online Appendix D

Subsample 1: Good comprehension (yes or rather yes)

We perceive the tasks as cognitively demanding for the experimental participants. Not understanding the tasks could have led to additional noise in the data set. To exclude this as a factor influencing our results, we excluded participants who self-reported not understanding the experiment well or rather well. In the process, we excluded 286 participants for this robustness check.

Table OD.1 Linear regressions: Treatment effects on ambiguity index b (Subsample 1)

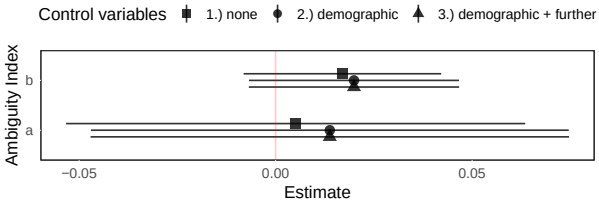
	Dependent variable:					
Sample	full	confirmation	contradiction	point	interval	both
	(1)	(2)	(3)	(4)	(5)	(6)
contradiction	0.005			0.025	−0.021	0.013
	(0.017)			(0.029)	(0.029)	(0.029)
both		−0.035	−0.048			
		(0.028)	(0.030)			
interval		−0.002	−0.048			
		(0.027)	(0.031)			
part2	−0.024***	−0.038**	−0.005	−0.038**	−0.013	−0.022
	(0.009)	(0.016)	(0.018)	(0.016)	(0.015)	(0.015)
contradiction×part2	0.017			0.032	0.008	0.010
	(0.013)			(0.024)	(0.022)	(0.021)
both×part2		0.016	−0.006			
		(0.022)	(0.023)			
interval×part2		0.024	−0.0001			
		(0.022)	(0.023)			
Constant	−0.075***	−0.063***	−0.038*	−0.063***	−0.065***	−0.098***
	(0.012)	(0.019)	(0.022)	(0.019)	(0.020)	(0.021)
Observations	2,438	1,210	1,228	810	820	808
R^2	0.001	0.005	0.006	0.007	0.001	0.002
Adjusted R^2	0.0001	0.001	0.001	0.003	-0.003	-0.002
Residual Std. Error	0.306	0.295	0.317	0.299	0.311	0.309
F Statistic	1.105	1.167	1.360	1.834	0.276	0.442

Note:*p<0.1; **p<0.05; ***p<0.01. The underlying standard errors ("HC1") are clustered at the individual level and estimated with the R package sandwich (Zeileis, 2004; Zeileis et al., 2020)

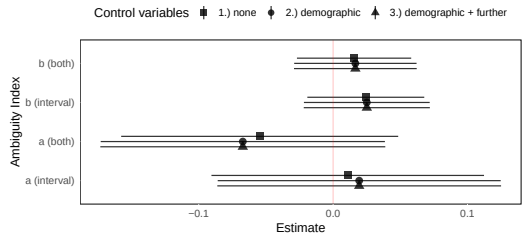
Table OD.2 Linear regressions: Treatment effects on ambiguity index a (Subsample 1)

	Dependent variable:					
	a					
Sample	full	confirmation	contradiction	point	interval	both
	(1)	(2)	(3)	(4)	(5)	(6)
contradiction	−0.044			−0.008	−0.033	−0.091**
	(0.027)			(0.046)	(0.050)	(0.046)
both		0.052	−0.030			
		(0.046)	(0.046)			
interval		0.014	−0.011			
		(0.048)	(0.049)			
part2	−0.001	0.014	−0.009	0.014	0.024	−0.041
	(0.021)	(0.038)	(0.036)	(0.038)	(0.035)	(0.037)
contradiction×part2	0.005			−0.023	−0.003	0.040
	(0.030)			(0.052)	(0.050)	(0.052)
both×part2		−0.055	0.008			
		(0.053)	(0.052)			
interval×part2		0.011	0.030			
		(0.052)	(0.051)			
Constant	0.739***	0.716***	0.708***	0.716***	0.731***	0.769***
	(0.019)	(0.032)	(0.034)	(0.032)	(0.036)	(0.034)
Observations	2,438	1,210	1,228	810	820	808
R^2	0.002	0.001	0.001	0.001	0.002	0.006
Adjusted R^2	0.0005	-0.003	-0.003	-0.003	-0.002	0.002
Residual Std. Error	0.506	0.501	0.512	0.501	0.527	0.491
F Statistic	1.376	0.310	0.214	0.141	0.427	1.642

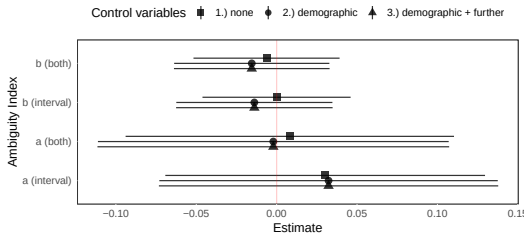
Note:*p<0.1; **p<0.05; ***p<0.01. The underlying standard errors ("HC1") are clustered at the individual level and estimated with the R package sandwich (Zeileis, 2004; Zeileis et al., 2020)



(a) Effect of contradiction (relative to confirmation).

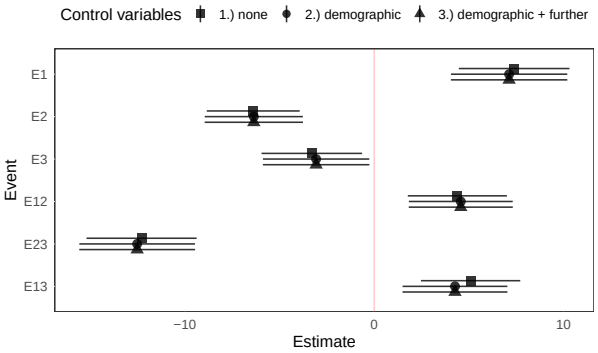


(b) Effect of information treatments (both, interval) relative to best guess, confirmation treatments

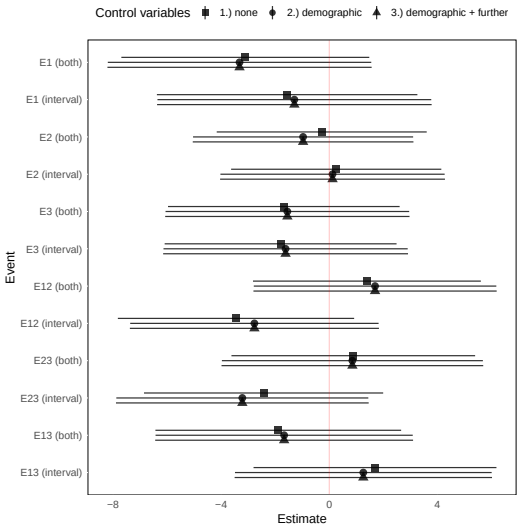


(c) Effect of information treatments (both, interval) relative to best guess, contradiction treatments

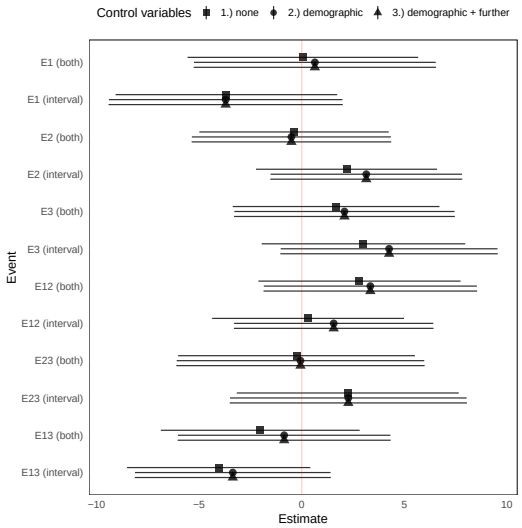
Figure OD.1 Treatment effects of regression equation (1) with dependent variables b and a (Subsample 1). Estimators with 95% confidence intervals. The underlying standard errors ("HC1") are clustered at the individual level and estimated with the R package sandwich (Zeileis, 2004; Zeileis et al., 2020).



(a) Effect of contradiction (relative to confirmation).



(b) Effect of information treatments (both, interval) relative to best guess, confirmation treatments



(c) Effect of information treatments (both, interval) relative to best guess, contradiction treatments

Figure OD.2 Treatment effects of regression equation (1) with matching probabilities for all events as dependent variables (Subsample 1). Estimators with 95% confidence intervals. The underlying standard errors ("HC1") are clustered at the individual level and estimated with the R package sandwich (Zeileis, 2004; Zeileis et al., 2020).

Subsample 2: No wrong answers in the control questions

Using a similar rationale as in subsample 1, we excluded participants who had at least one error in the control questions. In doing so, we removed 321 participants.

Table OD.3 Linear regressions: Treatment effects on ambiguity index b (Subsample 2)

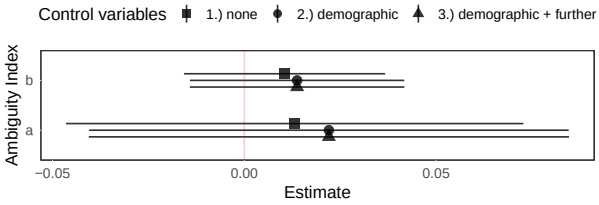
	Dependent variable:					
	b					
Sample	full	confirmation	contradiction	point	interval	both
	(1)	(2)	(3)	(4)	(5)	(6)
contradiction	0.008			0.018	−0.023	0.031
	(0.017)			(0.027)	(0.030)	(0.029)
both		−0.051*	−0.038			
		(0.026)	(0.030)			
interval		−0.019	−0.059**			
		(0.027)	(0.030)			
part2	−0.017*	−0.041**	−0.006	−0.041**	−0.0002	−0.011
	(0.010)	(0.017)	(0.016)	(0.017)	(0.016)	(0.018)
contradiction×part2	0.010			0.034	0.009	−0.012
	(0.013)			(0.023)	(0.022)	(0.025)
both×part2		0.029	−0.018			
		(0.025)	(0.023)			
interval×part2		0.040*	0.014			
		(0.023)	(0.022)			
Constant	−0.089***	−0.066***	−0.049**	−0.066***	−0.085***	−0.117***
	(0.011)	(0.017)	(0.021)	(0.017)	(0.021)	(0.020)
Observations	2,368	1,172	1,196	802	800	766
R^2	0.001	0.005	0.006	0.006	0.001	0.003
Adjusted R^2	-0.0003	0.001	0.002	0.002	-0.003	-0.001
Residual Std. Error	0.302	0.290	0.312	0.288	0.314	0.301
F Statistic	0.782	1.255	1.480	1.654	0.256	0.680

Note:*p<0.1; **p<0.05; ***p<0.01. The underlying standard errors ("HC1") are clustered at the individual level and estimated with the R package sandwich (Zeileis, 2004; Zeileis et al., 2020)

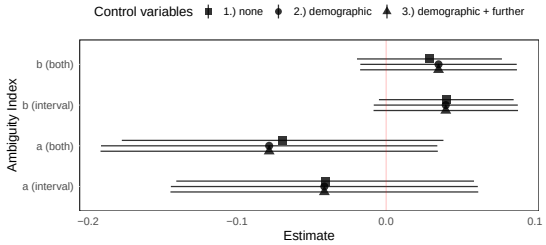
Table OD.4 Linear regressions: Treatment effects on ambiguity index a (Subsample 2)

	Dependent variable:					
	a					
Sample	full	confirmation	contradiction	point	interval	both
	(1)	(2)	(3)	(4)	(5)	(6)
contradiction	−0.024			0.013	−0.022	−0.065
	(0.027)			(0.049)	(0.048)	(0.045)
both		0.062	−0.016			
		(0.047)	(0.046)			
interval		0.039	0.004			
		(0.048)	(0.049)			
part2	−0.005	0.031	−0.002	0.031	−0.010	−0.038
	(0.021)	(0.039)	(0.037)	(0.039)	(0.033)	(0.039)
contradiction×part2	0.013			−0.033	0.011	0.064
	(0.030)			(0.054)	(0.049)	(0.055)
both×part2		−0.070	0.028			
		(0.055)	(0.054)			
interval×part2		−0.041	0.003			
		(0.051)	(0.052)			
Constant	0.734***	0.701***	0.714***	0.701***	0.740***	0.763***
	(0.019)	(0.034)	(0.035)	(0.034)	(0.034)	(0.032)
Observations	2,368	1,172	1,196	802	800	766
R^2	0.0004	0.001	0.0003	0.0005	0.0003	0.002
Adjusted R^2	-0.001	-0.003	-0.004	-0.003	-0.003	-0.002
Residual Std. Error	0.495	0.486	0.505	0.511	0.498	0.477
F Statistic	0.281	0.339	0.063	0.128	0.084	0.605

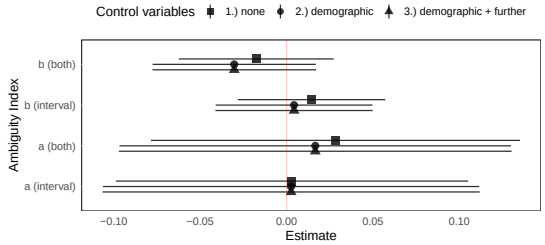
Note:*p<0.1; **p<0.05; ***p<0.01. The underlying standard errors ("HC1") are clustered at the individual level and estimated with the R package sandwich (Zeileis, 2004; Zeileis et al., 2020)



(a) Effect of contradiction (relative to confirmation).

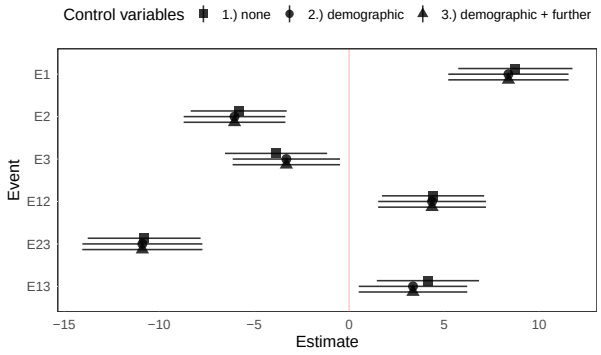


(b) Effect of information treatments (both, interval) relative to best guess, confirmation treatments

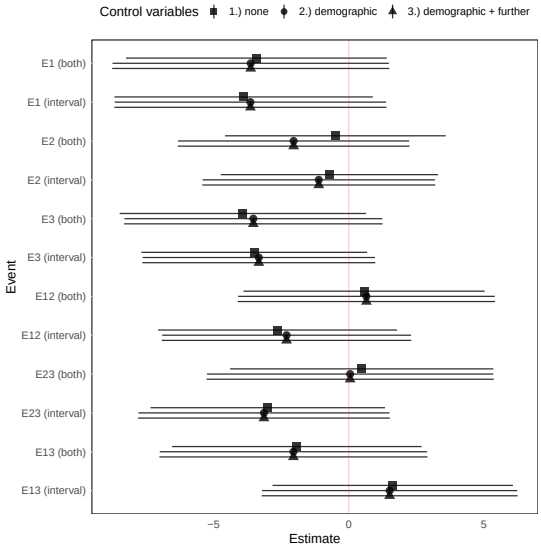


(c) Effect of information treatments (both, interval) relative to best guess, contradiction treatments

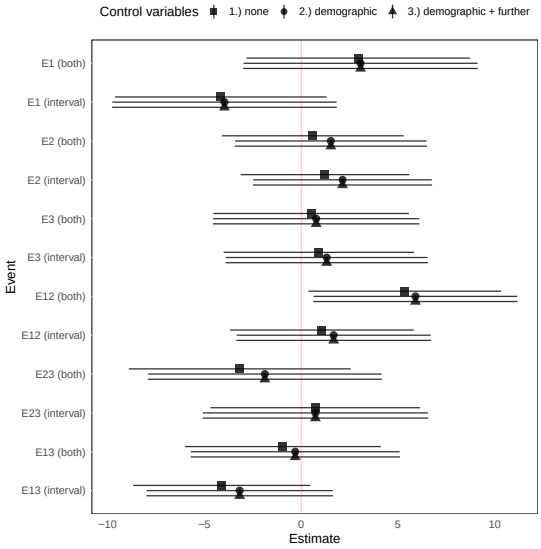
Figure OD.3 Treatment effects of regression equation (1) with dependent variables b and a (Subsample 2). Estimators with 95% confidence intervals. The underlying standard errors ("HC1") are clustered at the individual level and estimated with the R package sandwich (Zeileis, 2004; Zeileis et al., 2020).



(a) Effect of contradiction (relative to confirmation).



(b) Effect of information treatments (both, interval) relative to best guess, confirmation treatments



(c) Effect of information treatments (both, interval) relative to best guess, contradiction treatments

Figure OD.4 Treatment effects of regression equation (1) with matching probabilities for all events as dependent variables (Subsample 2). Estimators with 95% confidence intervals. The underlying standard errors ("HC1") are clustered at the individual level and estimated with the R package sandwich (Zeileis, 2004; Zeileis et al., 2020).

Subsample 3: Survey experiment completion time 10%-90% quantile

We believe that excessively fast participants could introduce additional noise. We also believe that participants doing other things on the side and who may have been very slow in the experiment could cause a similar effect. As a result, we removed participants who took less than 8 minutes 41 seconds (10 percent quantile) and more than 40 minutes 51 seconds (90 percent quantile). This is equivalent to a removal of 303 participants.

Table OD.5 Linear regressions: Treatment effects on ambiguity index b (Subsample 3)

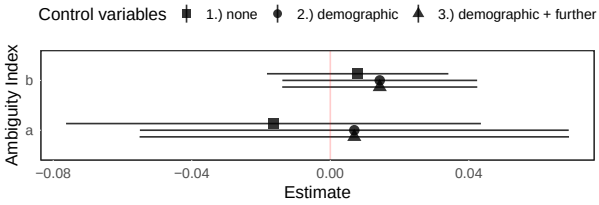
	Dependent variable:					
	b					
Sample	full	confirmation	contradiction	point	interval	both
	(1)	(2)	(3)	(4)	(5)	(6)
contradiction	0.011			0.028	−0.020	0.027
	(0.016)			(0.027)	(0.029)	(0.030)
both		−0.020	−0.020			
		(0.027)	(0.030)			
interval		0.011	−0.037			
		(0.026)	(0.029)			
part2	−0.022**	−0.039**	−0.003	−0.039**	−0.016	−0.008
	(0.010)	(0.016)	(0.016)	(0.016)	(0.017)	(0.017)
contradiction×part2	0.008			0.037	0.006	−0.020
	(0.013)			(0.023)	(0.023)	(0.023)
both×part2		0.031	−0.026			
		(0.024)	(0.022)			
interval×part2		0.023	−0.008			
		(0.024)	(0.023)			
Constant	−0.079***	−0.076***	−0.048**	−0.076***	−0.065***	−0.095***
	(0.011)	(0.016)	(0.021)	(0.016)	(0.021)	(0.021)
Observations	2,404	1,198	1,206	808	800	796
R^2	0.002	0.004	0.004	0.010	0.001	0.002
Adjusted R^2	0.0003	-0.001	0.00002	0.006	-0.002	-0.002
Residual Std. Error	0.297	0.286	0.307	0.277	0.303	0.311
F Statistic	1.277	0.852	1.005	2.589*	0.353	0.497

Note:*p<0.1; **p<0.05; ***p<0.01. The underlying standard errors ("HC1") are clustered at the individual level and estimated with the R package sandwich (Zeileis, 2004; Zeileis et al., 2020)

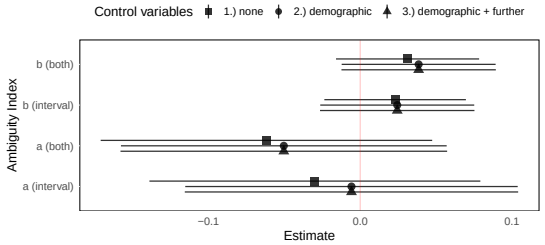
Table OD.6 Linear regressions: Treatment effects on ambiguity index a (Subsample 3)

	Dependent variable:					
	a					
Sample	full	confirmation	contradiction	point	interval	both
	(1)	(2)	(3)	(4)	(5)	(6)
contradiction	−0.015			0.039	−0.011	−0.074*
	(0.028)			(0.048)	(0.051)	(0.045)
both		0.065	−0.048			
		(0.047)	(0.046)			
interval		0.043	−0.007			
		(0.051)	(0.049)			
part2	−0.004	0.026	−0.026	0.026	−0.003	−0.035
	(0.023)	(0.040)	(0.037)	(0.040)	(0.038)	(0.038)
contradiction×part2	−0.016			−0.053	−0.040	0.046
	(0.031)			(0.055)	(0.052)	(0.052)
both×part2		−0.062	0.037			
		(0.056)	(0.051)			
interval×part2		−0.030	−0.017			
		(0.056)	(0.051)			
Constant	0.733***	0.698***	0.736***	0.698***	0.740***	0.763***
	(0.020)	(0.034)	(0.034)	(0.034)	(0.038)	(0.032)
Observations	2,404	1,198	1,206	808	800	796
R^2	0.001	0.001	0.001	0.001	0.002	0.004
Adjusted R^2	-0.001	-0.003	-0.003	-0.003	-0.002	-0.0002
Residual Std. Error	0.513	0.520	0.506	0.517	0.541	0.480
F Statistic	0.560	0.348	0.348	0.213	0.443	0.956

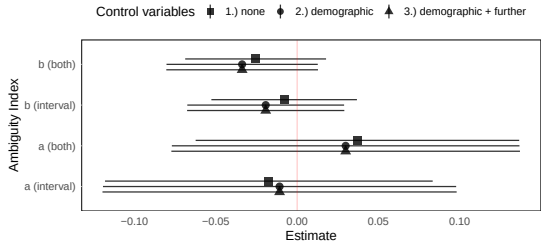
Note:*p<0.1; **p<0.05; ***p<0.01. The underlying standard errors ("HC1") are clustered at the individual level and estimated with the R package sandwich (Zeileis, 2004; Zeileis et al., 2020)



(a) Effect of contradiction (relative to confirmation).

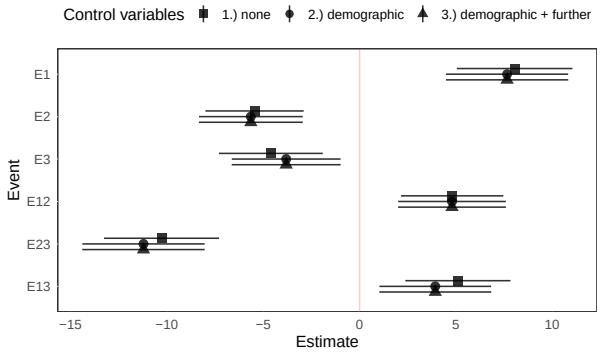


(b) Effect of information treatments (both, interval) relative to best guess, confirmation treatments

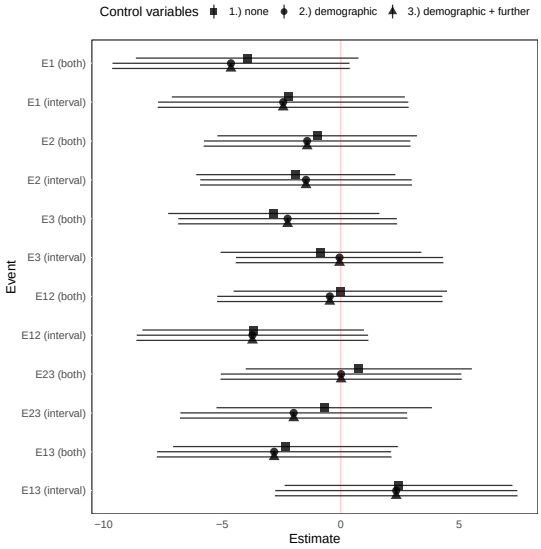


(c) Effect of information treatments (both, interval) relative to best guess, contradiction treatments

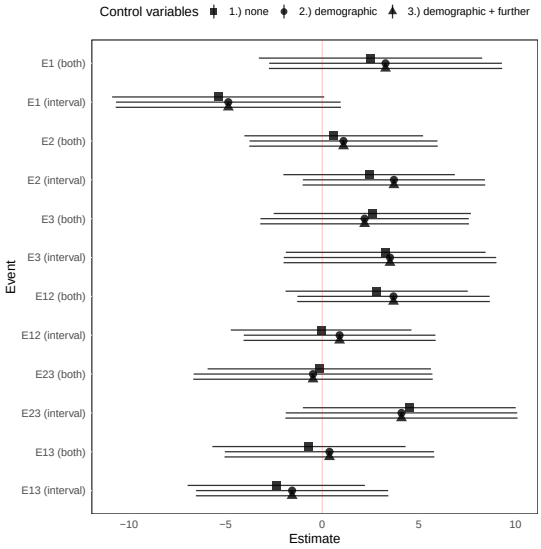
Figure OD.5 Treatment effects of regression equation (1) with dependent variables b and a (Subsample 3). Estimators with 95% confidence intervals. The underlying standard errors ("HC1") are clustered at the individual level and estimated with the R package sandwich (Zeileis, 2004; Zeileis et al., 2020).



(a) Effect of contradiction (relative to confirmation).



(b) Effect of information treatments (both, interval) relative to best guess, confirmation treatments



(c) Effect of information treatments (both, interval) relative to best guess, contradiction treatments

Figure OD.6 Treatment effects of regression equation (1) with matching probabilities for all events as dependent variables (Subsample 3). Estimators with 95% confidence intervals. The underlying standard errors ("HC1") are clustered at the individual level and estimated with the R package sandwich (Zeileis, 2004; Zeileis et al., 2020).

Subsample 4: Weak monotonic answers ($\overline{m_s} \leq \overline{m_c}$)

In this subsample, we removed participants who violated weak monotonicity at least once (either part 1 or part 2). This ensures that index a is 1 or less than 1. Bailloon et al. (2018b) also use this robustness check. We excluded 537 participants.

Table OD.7 Linear regressions: Treatment effects on ambiguity index b (Subsample 4)

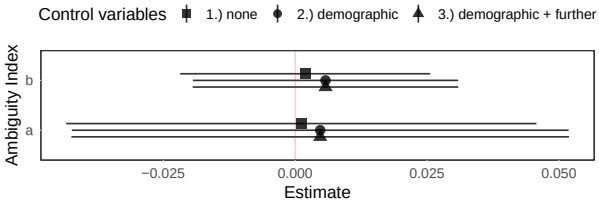
	Dependent variable:					
	b					
Sample	full	confirmation	contradiction	point	interval	both
	(1)	(2)	(3)	(4)	(5)	(6)
contradiction	0.011			0.025	−0.002	0.012
	(0.018)			(0.030)	(0.031)	(0.032)
both		−0.050	−0.063**			
		(0.031)	(0.031)			
interval		0.004	−0.023			
		(0.029)	(0.032)			
part2	−0.017**	−0.027*	−0.013	−0.027*	−0.023	0.0005
	(0.008)	(0.014)	(0.016)	(0.014)	(0.015)	(0.013)
contradiction×part2	0.002			0.014	0.004	−0.013
	(0.012)			(0.022)	(0.021)	(0.020)
both×part2		0.027	−0.00004			
		(0.020)	(0.022)			
interval×part2		0.004	−0.006			
		(0.021)	(0.022)			
Constant	−0.071***	−0.057***	−0.032	−0.057***	−0.053**	−0.106***
	(0.012)	(0.020)	(0.023)	(0.020)	(0.021)	(0.024)
Observations	1,936	926	1,010	650	654	632
R^2	0.001	0.006	0.008	0.005	0.001	0.0003
Adjusted R^2	-0.0004	0.0003	0.003	0.0004	-0.003	-0.004
Residual Std. Error	0.290	0.280	0.298	0.273	0.300	0.296
F Statistic	0.744	1.052	1.614	1.079	0.265	0.069

Note:*p<0.1; **p<0.05; ***p<0.01. The underlying standard errors ("HC1") are clustered at the individual level and estimated with the R package sandwich (Zeileis, 2004; Zeileis et al., 2020)

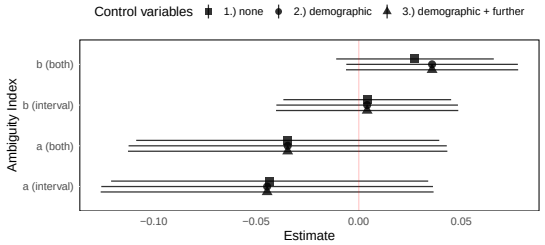
Table OD.8 Linear regressions: Treatment effects on ambiguity index a (Subsample 4)

	Dependent variable:					
	a					
Sample	full	confirmation	contradiction	point	interval	both
	(1)	(2)	(3)	(4)	(5)	(6)
contradiction	−0.033			−0.043	−0.012	−0.046
	(0.024)			(0.040)	(0.042)	(0.041)
both		0.019	0.017			
		(0.043)	(0.038)			
interval		−0.017	0.014			
		(0.043)	(0.039)			
part2	−0.043***	−0.018	−0.050*	−0.018	−0.061**	−0.053*
	(0.016)	(0.025)	(0.028)	(0.025)	(0.030)	(0.028)
contradiction×part2	0.001			−0.032	0.021	0.016
	(0.023)			(0.038)	(0.041)	(0.039)
both×part2		−0.035	0.013			
		(0.038)	(0.039)			
interval×part2		−0.043	0.010			
		(0.039)	(0.040)			
Constant	0.538***	0.537***	0.494***	0.537***	0.520***	0.557***
	(0.018)	(0.029)	(0.027)	(0.029)	(0.031)	(0.031)
Observations	1,936	926	1,010	650	654	632
R^2	0.005	0.006	0.004	0.009	0.004	0.006
Adjusted R^2	0.003	0.001	-0.001	0.004	-0.001	0.001
Residual Std. Error	0.383	0.386	0.380	0.374	0.402	0.372
F Statistic	3.169**	1.126	0.772	1.900	0.880	1.298

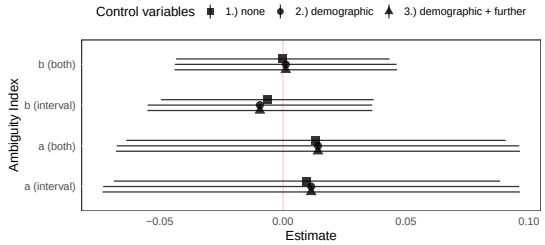
Note:*p<0.1; **p<0.05; ***p<0.01. The underlying standard errors ("HC1") are clustered at the individual level and estimated with the R package sandwich (Zeileis, 2004; Zeileis et al., 2020)



(a) Effect of contradiction (relative to confirmation).

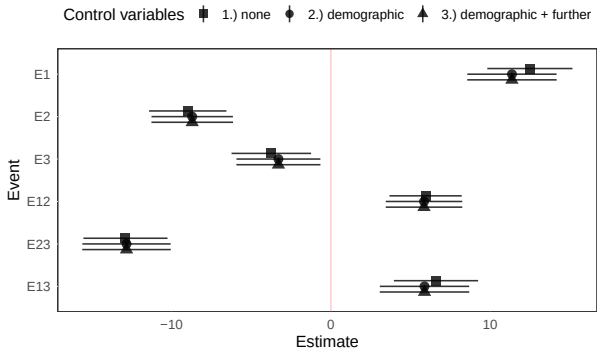


(b) Effect of information treatments (both, interval) relative to best guess, confirmation treatments

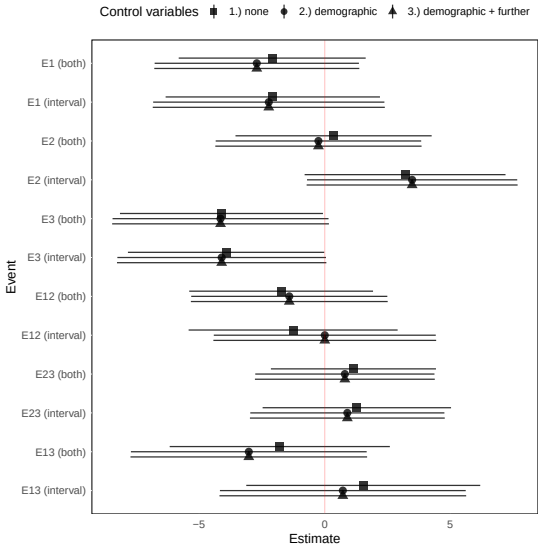


(c) Effect of information treatments (both, interval) relative to best guess, contradiction treatments

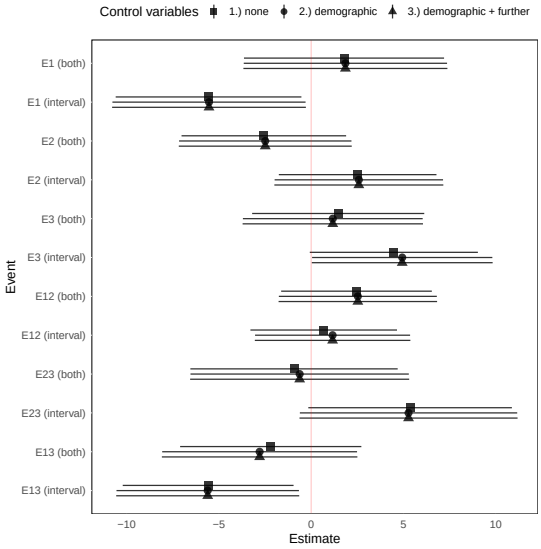
Figure OD.7 Treatment effects of regression equation (1) with dependent variables b and a (Subsample 4). Estimators with 95% confidence intervals. The underlying standard errors ("HC1") are clustered at the individual level and estimated with the R package sandwich (Zeileis, 2004; Zeileis et al., 2020).



(a) Effect of contradiction (relative to confirmation).



(b) Effect of information treatments (both, interval) relative to best guess, confirmation treatments



(c) Effect of information treatments (both, interval) relative to best guess, contradiction treatments

Figure OD.8 Treatment effects of regression equation (1) with matching probabilities for all events as dependent variables (Subsample 4). Estimators with 95% confidence intervals. The underlying standard errors ("HC1") are clustered at the individual level and estimated with the R package sandwich (Zeileis, 2004; Zeileis et al., 2020).

Online Appendix E

Experimental Instructions

The survey experiment was conducted in German. Below you will find a translation. Clarifications to participants' options are shown below in italics and square brackets.

Welcome!

Thank you for your interest in this experiment.

Study Name Weather Forecasts

Study Duration Approximately 25 minutes: Reading the instructions takes about 10 minutes. Answering the questions takes another 15 minutes.

Payment 2 Euros as well as a bonus, the amount of which depends on your decisions.

Technical Requirements The study works on both laptops and PCs and in all modern browsers. For the smoothest possible process, we advise using a laptop or PC with a stable Internet connection and not to using a smartphone or tablet.

Privacy I agree to the anonymized analysis of my answers for the purpose of scientific evaluation according to the privacy policy.

[Submit Button]

[*The following instructions consisted of five sections (General - Comprehension Questions), where one could go back and forth on the individual sections.*]

General

Procedure

You can win a bonus payment of 10 € in this study. To qualify for that bonus, you will have to make 6 trade-offs twice. Subsequently, we will ask you some questions about yourself. Finally, we will show you how much money you earned in this study.

The whole study will take about 25 minutes of your time. Reading the instructions accounts for approximately 10 minutes while the participation in the study, that is, the trade-offs as well as the questionnaire take about 15 minutes. Each trade-off consists of two options: a bet on the weather as well as a lottery. To better assess the weather situation, you will receive information about previously measured temperatures. For the time being, you will not know anything about the location or the time the weather information refers to. After making the first 6 trade-offs, you will receive additional information. More precisely, you will be exposed to a weather forecast that you can then use to make the same 6 trade-offs once more.

Bet

We will ask you to bet on certain temperatures. You may bet that the temperature will be at least 17°C on a certain day at 14:00 (CET) [1]. If the temperature turns out to be 17°C or higher, you can earn 10 €. The bet corresponds to the same time and location in each of the trade-offs. The only difference between the trade-offs is the temperature interval you can bet on. As a consequence, one trade-off may consider a temperature of 17°C or more, while another trade-off involves a bet on the temperature being 8°C or less. For this reason, we advise you to carefully examine the bets' temperature intervals that can earn you the bonus.

Lottery

To better understand the lottery you can imagine an urn containing 100 colored balls. Some of the balls are colored green, the others are red. Drawing a ball randomly and blindly, you can earn 10 € if the ball turns out to be green and nothing if the ball is red.

Trade-off

You have to decide under which conditions you prefer the lottery over the bet. We'll therefore ask you how many of the above mentioned 100 balls have to be green such that you prefer the lottery.

[1] Mentioning the time zone (CET) does not necessarily imply that the location of the bet is referring to a location within the central European time zone.

Earnings

Basics

At the end of this study, one of your trade-offs is drawn randomly to determine whether you will win 10 € or not. For that reason, each of the trade-offs can turn out to be relevant for your payment. While you are reading these instructions, a computer program prepares a virtual lottery involving an urn with 100 red or green balls. The corresponding color composition is random: the urn may contain 5 green and 95 red balls, 72 green and 18 red balls or even 0 green and 100 red balls. Each composition that adds up to 100 balls is possible and equally likely.

Bet

If this particular urn contains less green balls than you require in the trade-off that is relevant for your earnings, the outcome of the bet will decide whether you will win the bonus payment. In this case, you will win 10 €, if the actual temperature falls into the interval you were betting on. If not, you will not win the bonus.

Lottery

In case the urn contains at least as many green balls as you require in the trade-off that is relevant for your earnings, the outcome of the lottery will decide whether you will win the bonus payment. In that case, you will win 10 €, if a green ball is drawn.

Weather

Basics

The weather this study is referring to lies in the past, which is why you will be exposed to historic weather data and forecasts. This allows us to calculate your earnings immediately in case it is determined by the bet. Note that all the displayed weather information is real. At the beginning of your participation, a computer program randomly chose a location, a time and the kind of information you will receive. This may be any location in the world at any time. You will learn to which time and location the weather data is referring to but not until finishing the trade-offs. This way, we can be certain, that you can only utilize the information we provided. If your earnings are determined by the bet eventually, we can immediately check whether your bet was correct and inform you about the outcome.

Description

The visualization illustrates the aforementioned weather data. You see temperatures of three consecutive days - each at 14:00 CET [1]. Your trade-off corresponds to a bet on the temperature 9 days later at the same daytime (the purple shaded area).

From the seventh round we will additionally show you the mentioned weather forecast. The forecast will be displayed in that purple shaded area. In addition, we will display a text explaining the forecast.

This is the place the weather forecast will be displayed from round seven on.

[*Figure OE.1 (a)*]

Proof of authenticity

All the information displayed is real and measured (or forecasted) by experts. We ceil the data such that you do not have to think about decimal places. At the end of the study, we will display the sources the information stem from.

Usability

Be aware that you can retrieve both these instructions as well as the visualization at any time. To recall the visualization, you just have to click on the [*thermometer*]-symbol in the top right. To recall the instruction, you have to click on the [*info*]-symbol next to it.

[1] Mentioning the time zone (CET) does not necessarily imply that the location of the bet is referring to a location within the central European time zone.

Demo

The trade-offs will look as follows. The left column displays the bet. The right column displays the lottery, which you can configure with the text field, where you enter the amount of green balls you need at least to prefer the lottery.

Consider the displayed trade-off carefully and feel free to enter different values. Notice how the visualizations change on input.

[*Demo screen here; similar to Figure OE.3*]

Comprehension Questions

Please review the exemplary trade off below and answer the questions. As soon as you answered them correctly, you can proceed with the study.

[*Another demo screen with 50 as a fixed input; similar to Figure OE.3 (b)*]

Question 1

Imagine that the screen shown above is decisive for your payment and that the lottery contains 40 green balls. The screen above shows that, given the 40 green balls, the bet is preferred.

This means that you would earn 10 Euro if the temperature ranges from 8 to 14 degrees Celsius.

Assume that you'll learn that the temperature was 15 degrees Celsius. How much would you earn in that situation?

- 10 Euros
- 7 Euros
- 3 Euros
- 0 Euros
- Don't know

Question 2

Imagine that the screen shown above is decisive for your payment and that the lottery contains 60 green balls. The screen above shows that, given the 60 green balls, the lottery is preferred.

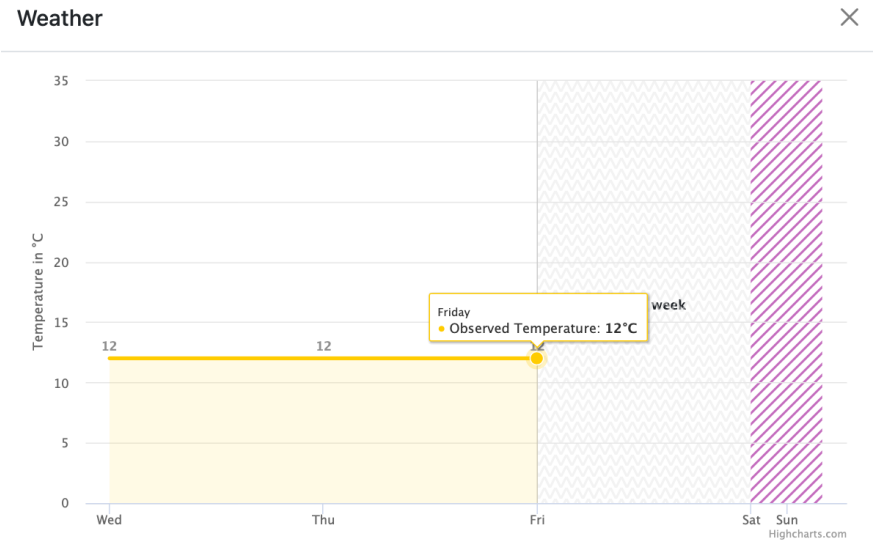
This means that you would earn 10 Euro a randomly drawn ball from that lottery was green.

Assume that a red ball was drawn. How much would you earn in that situation?

- 10 Euros
- 7 Euros

- 3 Euros
- 0 Euros
- Don't know

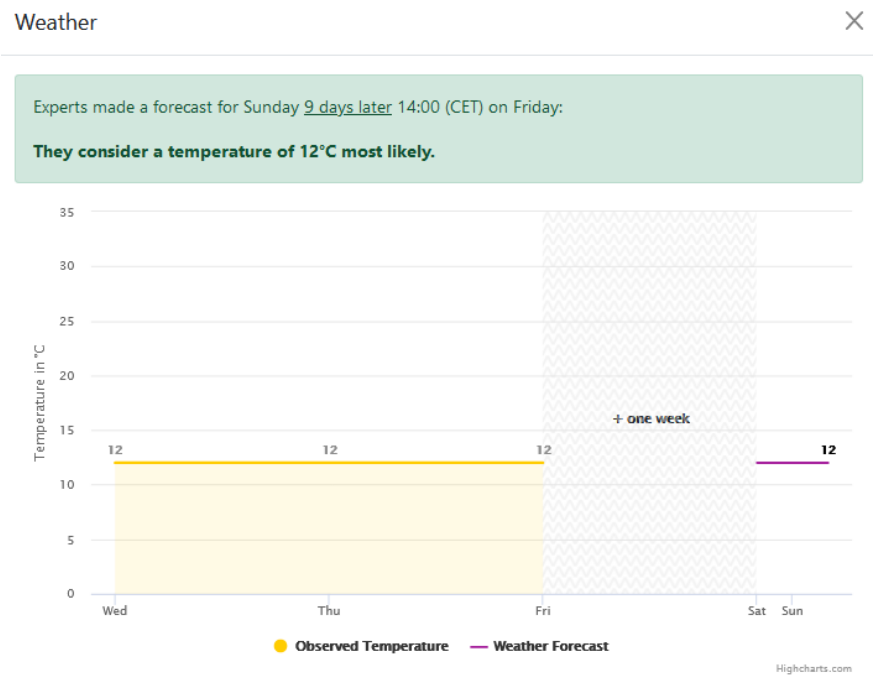
[*If both questions were answered correctly, the experiment could begin. Before the first elicitation of the matching probabilities, the weather of the last three days was presented (see Figure OE.1 (a)). Before the second elicitation, a randomized treatment was also presented (see Figure OE.1 (b)). The six events per ambiguity elicitation were asked in a randomized order.*]



Temperatures were 12°C (at 14:00) between Wednesday and Friday.

Without knowing what location and time the weather shown above refers to, the following tasks require you to estimate what temperature ranges you think are likely to occur on Sunday 9 days later at the same location and time of day.

(a) Pop-up after the comprehension questions

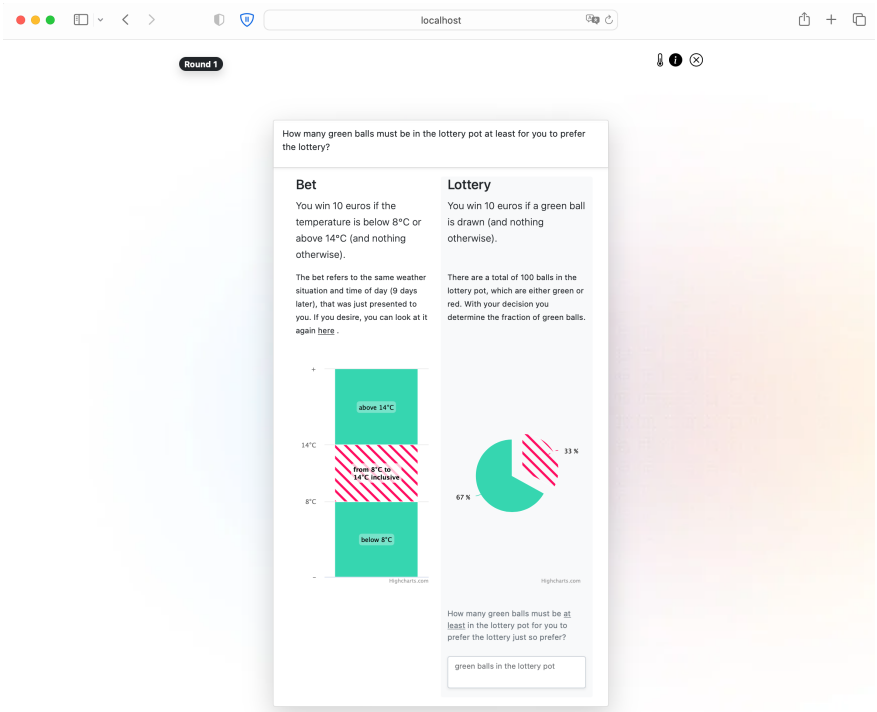


Temperatures were 12°C (at 14:00) between Wednesday and Friday.

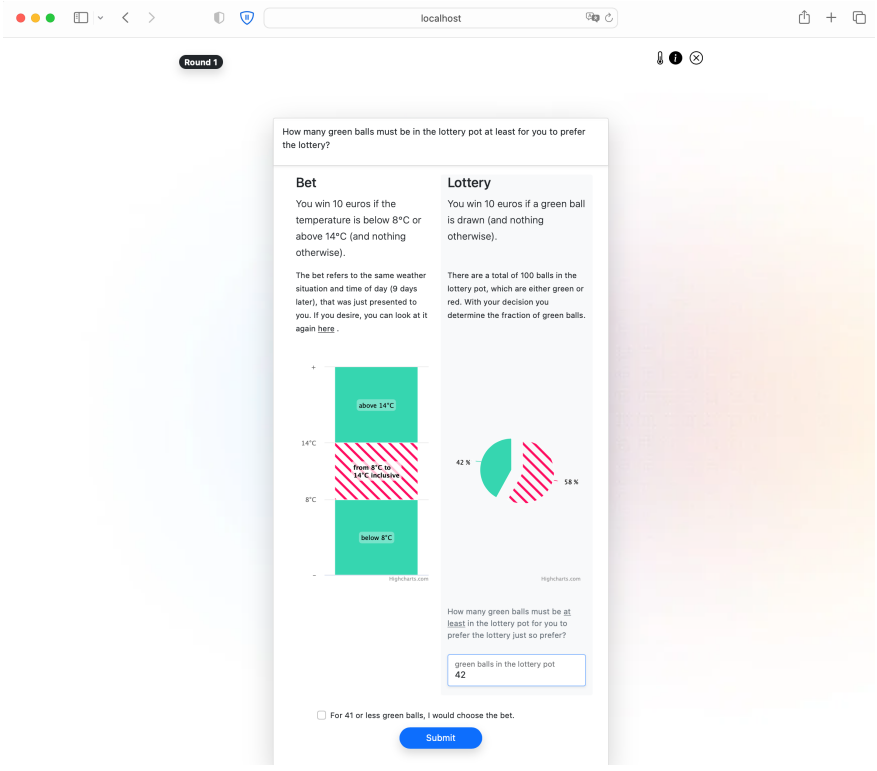
Without knowing what location and time the weather shown above refers to, the following tasks require you to estimate what temperature ranges you think are likely to occur on Sunday 9 days later (i.e., in the purple shaded area) at the same location and time of day.

(b) Pop-up including one treatment after the first completion of the six matching probabilities. Please note that we consider the treatment texts in section 2.2 as more accurate.

Figure OE.1 Pop-ups

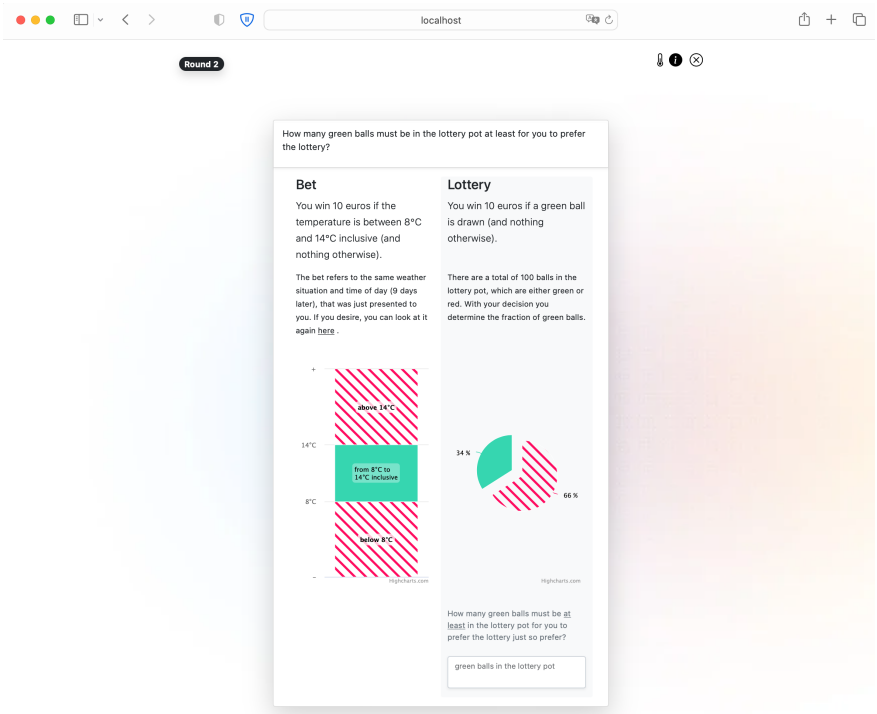


(a) Experiment screen for a composite event; default without having entered anything

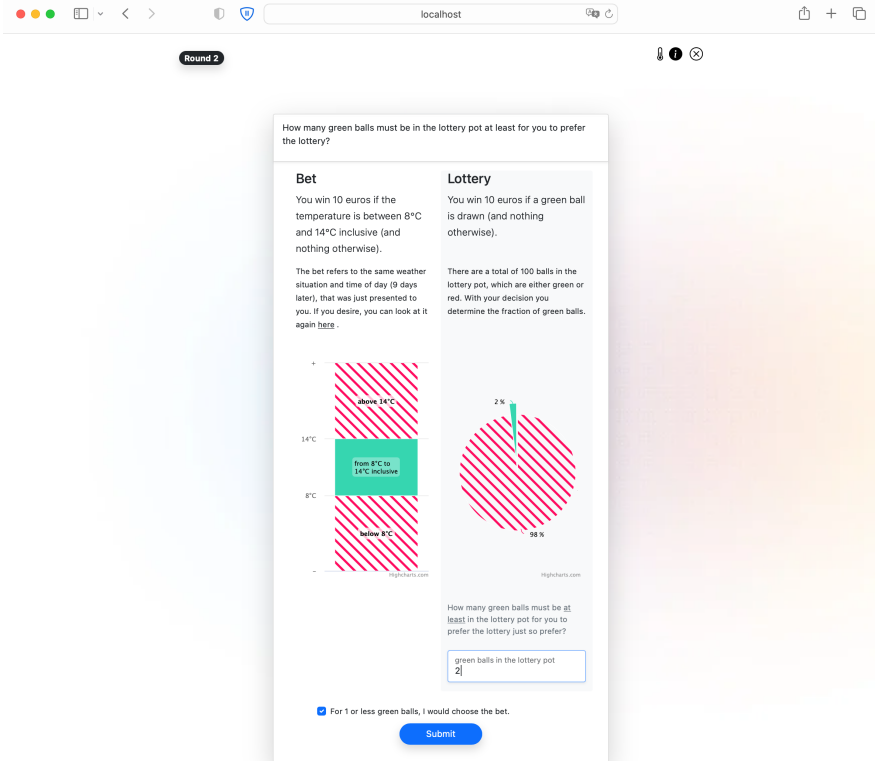


(b) Experiment screen for a composite event; Having entered 42; Note that below the input box, the following information appears; "For 41 or less green balls, I would choose the bet."

Figure OE.2 Experiment screen for a composite event.



(a) Experiment screen for a single event; default without having entered anything



(b) Experiment screen for a single event; Having entered 2; Note that below the input box, the following information appears; "For 1 or less green balls, I would choose the bet."

Figure OE.3 Experiment screen for a single event.

Final questions

How do you see yourself?

Are you generally a risk-taker or do you try to avoid taking risks? Please tick one box on the scale, with a value of 0 meaning "not at all willing to take risks" and a value of 10 meaning "very willing to take risks". You can use the values in between to grade your assessment.

	not at all willing to take risk										very willing to take risk
	0	1	2	3	4	5	6	7	8	9	10
In general, are you a person who is fully willing to take risks or do you try to avoid risks?	○	○	○	○	○	○	○	○	○	○	○
Bad weather is announced in the weather forecast. In general, are you a person who is fully prepared to take risks (for example, leaving the house without an umbrella) despite announced bad weather, or do you try to avoid the risks?	○	○	○	○	○	○	○	○	○	○	○

[Submit button]

Final questions

Please rate the statement:

Please check one box on the scale, with a value of 0 indicating that the statement does not apply at all and 4 indicating that it applies completely. You can use the values in between to grade your rating.

Experts made a forecast on Friday for Sunday 9 days later:

[*Corresponding treatment text, for example:* They consider a temperature of 12°C as most probable]

	Does not apply at all				Applies completeley
	0	1	2	3	4
I believe the statement is accurate.	◯	◯	◯	◯	◯
I believe the statement is credible.	◯	◯	◯	◯	◯

[Submit button]

Final questions

Did you understand the tasks well?

◯ No

◯ Rather not

◯ Rather yes

◯ Yes

How often do you use weather forecasts on average?

◯ Several times a day

◯ Daily

◯ Several times a week

◯ Weekly

◯ Less frequent

◯ Never

How much °C is the outside temperature in your environment right now?

[Submit button]

Final questions

How old are you?

[ ]

Gender:

◯ Male

◯ Female

◯ Diverse

◯ no indication

What is your family status?

◯ Married, living with spouse

◯ Registered same-sex union living together

◯ Married, living permanently separated

◯ Registered same-sex union living separately

◯ Single, never been married

◯ Divorced / registered same-sex union dissolved

◯ Widowed / partner from registered same-sex union deceased

Do you have children?

◯Yes

◯No

Please select the highest level of education you have achieved to date.

◯ Finished school without degreee

◯ Still a student

◯Lowest high school [Volks-, Hauptschulabschluss, Quali]

◯Average high school or equivalent qualification [Mittlere Reife, Realschul- oder gleichwertiger

Abschluss]

◯ Completed apprenticeship

◯technical high school diploma, entrance qualification for a college

◯ high-school diploma, university entrance qualification

◯ college/ university degree

◯ Other diploma

What is your monthly budget? Please indicate your own monthly net income.

◯0-500 €

◯501-1000 €

◯1001-2000 €

◯2001-3000 €

◯3001-4000 €

◯more than 4000 €

◯ no indication

Where are you completing the survey from? Please enter your postal code.

[ ]

We are interested in the current vaccination situation in Germany and ask you to indicate your current vaccination status (against Covid-19):

◯I have already been vaccinated.

◯I still plan to be vaccinated.

◯I do not want to be vaccinated.

◯No indication.

[Submit button]

Final questions

When answering the following questions, please be careful not to provide any information that will allow us to identify you.

What do you see as the biggest challenge in terms of a changing climate?

[open field]

How do you deal with it?

[open field]

[Submit button]

[*This was followed by the resolution of the experiment (payoff, location, weather) at the end of the survey.*]