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Reacting to Ambiguous Messages: An Experimental Analysis

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Abstract
Ambiguous language is ubiquitous and often deliberate. Recent theoretical work (Beauchêne et al., 2019; Bose and Renou, 2014; Kellner and Le Quement, 2018) has shown how language ambiguation can improve outcomes by mitigating conflict of interest. Our experiment finds a significant effect of language ambiguation on subjects who are competent Bayesian updaters. For both ambiguity averse and neutral subjects within this population, one significant channel is behavioral in nature (anchoring). For ambiguity averse subjects, another channel of similar magnitude is hedging motivated by the desire to reduce ambiguity. This channel is absent in the case of ambiguity neutral subjects. (JEL: C91; D01; D81)

Keywords: Ambiguity aversion; Communication; Persuasion; Laboratory experiment.

1. Introduction

Ambiguity in language often appears deliberate as it could easily be eliminated. A classical example is the cryptic language used by governors of the US central bank. Blume and Board, 2014 cite a 1995 speech by A. Greenspan giving

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rise to very different headlines the next day, the New York Times writing "Doubts voiced by Greenspan on a rate cut" and the Washington Post writing instead "Greenspan hints Fed may cut interest rates".[1] Other examples include contracts or advertising messages as well as political speech (e.g. former UK labour leader Jeremy Corbyn's stance on Brexit).

The study of strategic communication goes back to the seminal contribution of Crawford and Sobel, 1982, which has since spurned a very vast literature; theoretical, applied and experimental (see Sobel, 2013 as well as Blume, Lai, et al., 2020 for reviews). Key applications include settings with multiple senders or receivers, repeated communication over time, boundedly rational players or image concerns. Equilibrium communication in the baseline Crawford and Sobel, 1982 model features vagueness rather than ambiguity. In partitional equilibria, intervals of sender types pool on the same messages and thus leave the receiver ex post uncertain.

We view the difference between vagueness and ambiguity as follows. A vague statement generates a commonly agreed imprecise meaning. An ambiguous statement instead conveys a multiplicity of relatively precise meanings and implicitly suggests that the correct (i.e. intended) meaning could be identified. When exposed to ambiguous statements, a frequent occurrence is that different people revert to different interpretations.

Kellner and Le Quement, 2018 as well as Beauchêne et al., 2019 have shown how ambiguity might emerge in addition to vagueness in Crawford and Sobel, 1982. The communication strategy now combines partitioning with ambiguous randomization and messages now leave the receiver with multiple posteriors.

1. See also the following excerpt from a 2001 Congressional hearing speech by A. Greenspan "The members of the Board of Governors and the Reserve Bank presidents foresee an implicit strengthening of activity after the current rebalancing is over, although the central tendency of their individual forecasts for real GDP still shows a substantial slowdown, on balance, for the year as a whole." (Federal Reserve Board's semiannual monetary policy report to the Congress Before the Committee on Banking, Housing, and Urban Affairs, U.S. Senate February 13, 2001)

A central insight is that rather than hindering communication, language ambiguation (i.e. making language ambiguous) can help improve communication by mitigating conflict of interest. The insight is relevant to important applications (see for example Evdokimov and Garfagnini, 2019 for an experiment on communication in organizations).

Our experiment aims at testing whether real subjects' response to language ambiguation echoes theory. Does ambiguation affect behavior in the expected direction and in a quantitatively significant way? If so, via which channels? Besides ambiguity averse (or loving) subjects' specific response to ambiguity, behavioral effects could potentially be significant.

Overall, we find that ambiguation shifts behavior in the expected direction and in a significant way. We restrict our analysis to subjects who demonstrate good Bayesian updating skills when faced with standard partitional messaging rules, and we call these Bayes-Competent. For Bayes-Competent subjects who are ambiguity averse, a significant part of the effect of language ambiguation operates through a specific hedging mechanism driven by subjects' desire to reduce ambiguity. This effect complements an anchoring effect of similar magnitude. Among Bayes-Competent subjects who are ambiguity neutral, the hedging effect is absent.

In the main treatment task, the subject (also called DM) must choose a number after observing a message issued by an automated process. The message provides information on an unobservable state drawn from $[0, 100]$. DM's payoff decreases linearly in the distance between number and state. We run variations of this task within and between subjects. Our main focus is on the ambiguous variant, which we now describe.

The state ω is drawn from a uniform distribution on $[0, 100]$. The latter interval is partitioned into three subintervals $[0, 50)$, $[50, c)$ and $[c, 100]$, for some known c. There are three messages $\{" \star "", "X", "\#"\}$.

If $\omega \in [0, 50)$, the message sent is "$\star$" whatever θ. If instead ω lies in $[50, c)$ or $[c, 100]$, the message conditions also on an unobservable draw from a so-called Ellsberg urn featuring blue and red balls in unknown proportions. If the draw is red, the message is "X" if the state lies in $[50, c)$ and "#" if lies in $[c, 100]$. If the draw is blue, the use of "X" and "#" is reversed.

After observing "$\star$", DM has a unique posterior, so we expect her to choose 25, the conditional expectation of ω. In contrast, "X" and "#" leave DM with multiple posteriors and her choice should thus depend on her ambiguity attitude and belief updating. If DM is ambiguity averse and uses prior by prior updating, her choice should strictly increase in c and equal 75 only if $c = 75$. Similar behavior could arise under a known urn composition if DM does not reduce compound lotteries. An ambiguity neutral DM considering both colors equally likely (at least on average) should choose 75 after "X" and "#".

We run a two by two treatment design. The first variable is subjects' knowledge of the composition of the urn (so-called risky vs ambiguous treatments). The second variable is whether subjects are given help in updating their beliefs.

After the main treatment task, subjects execute a set of control tasks checking their 1) ability to update beliefs, 2) anchoring tendency, 3) risk and ambiguity aversion and 4) cognitive ability.

Literature review. Starting from Ellsberg, 1961, a rich theoretical literature has developed on the subject of decision-making under ambiguity. [2] Decision-making under ambiguity has also been studied experimentally. [3]

A new experimental literature studies responses to ambiguous signals. Epstein and Halevy, 2019 study signals of ambiguous precision and distinguish between attitudes towards "prior-ambiguity" and "signal-ambiguity". They find non-indifference to signal-ambiguity and association between attitudes towards prior- and signal ambiguity. Shishkin and Ortoleva, 2019 and Kops and Pasichnichenko, 2020 study the value of ambiguous signals in the case where "all news is bad news".[4] In this case, an ambiguity averse decision maker using prior-by-prior updating assigns a lower valuation to a given bet after *every* signal realization. The key is that for such signals (call them dilation signals), the set of posteriors after any signal realization contains the original set of

2. Ellsberg, 1961 presents a thought-experiment displaying behavior incompatible with subjective expected utility maximization. He rationalizes behavior by introducing ambiguity aversion. The max-min Expected Utility model (Gilboa and Schmeidler, 1989) posits that an ambiguity averse DM facing multiple priors evaluates each action according to its worst case expected utility across priors and maximizes the thereby constructed lower envelope. The smooth model of ambiguity aversion (Klibanoff et al., 2005) incorporates second order beliefs (a prior over priors) and quantifies the degree of ambiguity aversion through a concavity parameter which is a counterpart of the standard risk parameter. The max-min model and the smooth model yield similar predictions in our setup. Given ambiguity averse preferences (defined over an unrestricted domain) and an updating rule, behavior must violate either dynamic consistency or consequentialism (see e.g. Hanany and Klibanoff, 2007, 2009; Siniscalchi, 2011).

3. Fox and Tversky, 1995 finds that the effect of ambiguity is greater if only a subset of options features ambiguity. Halevy, 2007 shows that ambiguity aversion strongly associates with the failure to reduce compound lotteries. Cubitt et al., 2019 find evidence that choices are more in line with the smooth ambiguity model than with max-min. Bleichrodt et al., 2018; Dominiak et al., 2012 find that subjects' updating procedure is harder to reconcile with dynamic consistency than with consequentialism.

4. For theoretical discussions of the value of information under ambiguity aversion see Li, 2019; Siniscalchi, 2011.

priors.[5] Shishkin and Ortoleva, 2019 compare the willingness to pay for a 50-50 bet with and without being exposed to a dilation signal. The authors find that empirically, decision makers do not assign negative value to dilation signals, in contrast to theoretical predictions. Kops and Pasichnichenko, 2020 instead offer a choice between two comparable options, both of which involve being exposed to a dilation signal. The signal provides payoff-relevant information only for the second of two options, and this second option yields slightly higher payoffs in all states. They find that decision makers prefer the first option, where the dilation option is not payoff-relevant, and, when given a further choice, prefer not to be exposed to the dilation signal.

In contrast to these two papers, in our experiment signals have positive ex ante value—a relevant case for many applications—as they always reveal whether ω lies above or below 50. Yet, between our ambiguous treatment and an alternative in which "X" or "#" would be merged, a DM would prefer the latter. Without commitment, the ambiguity contained in "X" or "#" has a negative value ex-ante. To reconcile Shishkin and Ortoleva, 2019 with our findings, one could posit that DMs ignore only signals that are not valuable from an ex-ante perspective.

A rich body of work studies behavioral biases in belief updating (see for example Kahneman and Tversky, 1974; Oechssler et al., 2009). Anchoring occurs when irrelevant information becomes a reference point distorting peoples' belief updating and action choice. For example, exposure to a random integer might affect guesses on the percentage of African countries in the UN. Cognitive sophistication has been shown to negatively correlate with such bias (see Bergman et al., 2010; Oechssler et al., 2009).

We build on the theory proposed in Kellner and Le Quement, 2018 and Beauchêne et al., 2019.[6] Evdokimov and Garfagnini, 2019 investigate experimentally communication within organisations à la Alonso et al., 2008

5. See Seidenfeld and Wasserman, 1993 for the first definition of dilations.

6. Both build on Bose and Renou, 2014, where a principal can use an Ellsbergian device to make the agents face ambiguity. Ambiguity in strategic settings has been studied in general

and conjecture that receivers' biased behavior might originate in ambiguous communication as in Kellner and Le Quement, 2018. A seminal paper on ambiguity and language is Blume, Board, and Kawamura, 2007, studying cheap talk with a noisy communication channel. [7]

2. Experimental design

Key features of our experimental design are as follows:

(i) We computerize the sender, making the problem under consideration a decision problem as opposed to a game between a strategic sender and a receiver. This leaves no scope for other-regarding or moral preferences (Gneezy, 2005; Wang et al., 2010). It also implies that the receiver has full clarity concerning the sender's communication strategy, and in particular the type of ambiguity contained in messages.

(ii) We elicit individual measures of ambiguity attitudes in a different context via price-list choices.

(iii) We devise tasks to control for non-expected utility behavior.

2.1. General aspects of the decision environment

Main treatments. In the main treatment task, the state of the world ω is given by a number between 0 and 100, which is drawn from a uniform distribution on $[0; 100]$.[8]

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in Azrieli and Teper, 2011, Bade, 2011 and Riedel and Sass, 2014. See also Lo, 1996 and Klibanoff, 2001 on equilibrium in ambiguous beliefs.

7. As in Kellner and Le Quement, 2018, noise helps the receiver act more cooperatively. The source of noise however differs (exogenous), it takes a different form (unambiguous) and influences receiver behavior via other motives. See also Blume and Board, 2014 and Lipman, 2009

8. Within the experiment all random draws are simulated using the random number generator of zTree (Fischbacher, 2007).

An automated process generates an informative signal (also called message) about the state. Upon observing the signal, a subject has to choose a point estimate of the true state and is rewarded in money according to the distance between the state and her estimate. If the chosen action is denoted by a, the payoff function is simply given by $-|\omega - a|$. Accordingly, given a unique probability distribution of ω, the subject's expected payoff maximizing action is the median value of the state.

We now describe the signal generating process in more detail. The state space $[0, 100]$ is partitioned into three adjacent intervals $[0, 50)$, $[50, c)$ and $[c, 100]$, which we call intervals 1, 2 and 3, respectively. Moreover, there is an urn containing 100 balls which can be either red or blue. Before a message is sent, a ball is drawn randomly from the urn whose color is not observed by the subject. Let θ be a random variable that takes either value r if the drawn ball is red or b if it is blue.

The message sent depends on ω and θ as follows: If $\omega \in [0, 50)$, the signal sent is "$\star$" no matter the value of θ. If on the other hand ω lies in any of the two remaining intervals (2 or 3), the emitted message depends on ω and on the value of θ. If $\theta = r$, then the sent message is "X" if the state is in interval $[50, c)$ while the message is "$\#$" if the state is in interval $[c, 100]$. If, on the other hand, $\theta = b$, then the messaging rule on these two intervals is reversed. I.e., the message is "$\#$" if the state is in interval $[50, c)$ and the message is "X" if the state is in interval $[c, 100]$.

We will refer to this decision environment as MAIN-TREATMENT. Participants make nine decisions in MAIN-TREATMENT. The value of c changes with each repetition and is drawn from the set $\{54, 64, 86, 96\}$. The values of c are assigned in random order, in a way that guarantees that each subject was assigned each value at least twice over the nine iterations.

Between subject variations. For the main treatment, we consider two independent dimensions of between subjects variation. These are described below.

First, we consider two different informational environments that differ w.r.t. how much the subject knows concerning the distribution of colors in the urn. In the so-called Risky environment, the subject knows that there are 50 red and 50 blue balls in the urn. In the so-called Ambiguous environment, the subject has no information regarding the proportion of red and blue balls in the urn.

The second dimension of between subjects variation is whether or not we provide subjects with help in forming beliefs. In the Risky environment, when providing help, we point out that given $\omega \in [50, c)$, the messages X and $\#$ each have a probability $\frac{1}{2}$ of being sent, and that the same holds true conditional on $\omega \in [c, 100]$. The exact text reads as follows: *Given the composition of the urn, (50 red and 50 blue balls), and given each possible interval of the state space (1, 2 or 3), we show you the probability of each of the messages ($\star$,X,$\#$).* Beneath, a table with results is presented. The key is that participants should understand that, say, message X appears with probability $1/2$ if and only if the state is 50 or above. The help in the Ambiguous environment comes in the following form: Subjects are asked to propose a potential composition of the urn. Given this composition, for each possible interval of the state space (1, 2 or 3) they are given the probability of the three messages $\star$, X and $\#$. Subjects are asked to repeat this procedure for several possible urn compositions (at least two, at most four).

2.2. Controls related to the main treatment

Pre-treatment control questions. Before the main task, subjects have to answer questions concerning the signaling rule and pay-off calculations which are aimed at verifying that they understood the instructions. In order to make guessing more tedious, subjects are told that whenever they make mistakes, they will be asked to answer the concerned questions again, without being told in which questions they made a mistake. This procedure aims at incentivizing subjects to think more carefully about the correct answers.

Choice after message $\star$. As the message "$\star$" does not depend on draws from the Ellsberg Urn, it allows us to evaluate to which extent the participants follow

Bayesian reasoning in the absence of ambiguity. The control variable *starchoice* records the difference between the choice after this message and the Bayesian choice 25.

MAIN-CONTROL *tasks.* Participants do three different control tasks that are directly related to the MAIN-TREATMENT. We refer to these tasks as MAIN-CONTROL. In each, we slightly modify a specific aspect of the core task to control for possible confounds. Each task is repeated three times.

The RED BALLS ONLY control task is the first explicit control task. Its purpose is to understand if people have difficulties in processing the signal even if they are facing a slightly simpler form of it. The decision is identical to the MAIN-TREATMENT task, with the difference that subjects are told that the urn contains only red balls. As before, a new independent random draw of the state is drawn in each repetition.

We now introduce the ANCHORING 1 and ANCHORING 2 control tasks. A concern in our setup is that the partitioning of the $[0, 100]$ interval potentially makes threshold c an anchor. Anchoring subjects might display a tendency to choose an action close to c. Control tasks ANCHORING 1 and ANCHORING 2 aim at testing for anchoring effects caused by varying the threshold c over the repetitions of the main task. Both provide simplified environments in comparison to the MAIN-TREATMENT task. The expectation is that subjects who anchor in the treatment also anchor in these simpler tasks. These control tasks thus aim at identifying subjects who probably anchored in the treatment. ANCHORING 1 and ANCHORING 2 share the following basic features. The task is iterated 3 times with an independent draw of the state in each repetition. The value of c changes across periods. Each subject observes three out of the four values in the set $\{54, 64, 86, 96\}$. Observed values and their order are randomly determined.

In the ANCHORING 1 control task, we reduce the signal space to $\{\star, X\}$ and subjects are informed that they will receive signal "$\star$" if the state is in interval 1 and "X" if it is either in interval 2 or in interval 3. The threshold between the intervals 2 and 3 has thus lost its significance, i.e. the threshold c should not affect the action taken by R in response to messages "X" and "#". Both of these messages contain only the information that $\omega \geq 50$, whatever the value of c.

In the ANCHORING 2 control task, the messaging rule conditions on the color of the ball drawn from the urn. For subjects participating in a risky treatment, the urn is known to contain 50% red balls. For subjects participating in ambiguous treatments, the composition of the urn is unknown. As usual the message is "$\star$" if the state is in interval 1. On the other hand, if the drawn ball is red and the state is either in interval 2 or 3, then the message is "X". If on the other hand the ball is blue and the state is either in interval 2 or 3, then the message "#". Again, note that the threshold c should not affect the action taken by R in response to messages "X" and "#". Both of these messages contain only the information that $\omega \geq 50$, whatever the value of c.

Table 1 summarizes the control tasks MAIN-CONTROL and their relation to the MAIN-TREATMENT.

TABLE 1. Meaning of signals in MAIN-TREATMENT and MAIN-CONTROL

	Color	[0,50)	[50,c)	[c,100]	Urn composition
MAIN-TREATMENT	red ball	$\star$	X	#	risky or ambiguous
	blue ball	$\star$	#	X	
RED BALLS ONLY	red ball	$\star$	X	#	all balls are red
	blue ball	$\star$	#	X	
ANCHORING 1	red ball	$\star$	X	X	as in main task
	blue ball	$\star$	X	X	
ANCHORING 2	red ball	$\star$	X	X	as in main task
	blue ball	$\star$	#	#	

We conclude with a general comment on the control tasks. Given that the state belongs to interval 1 with probability one half, the probability that a subject receives three times the message "$\star$" is $.5^3$. In each of the control tasks, we thus expect to receive an informative answer for each of the subjects in $1-(.5)^3 = 87.5\%$ of the cases. We will therefore have a full set of controls for approximately 76% of the subjects. As this subset is randomly determined and not correlated with any decisions made by the subjects, we can separately analyze this subset without worrying about selection due to the availability of controls.

2.3. Cognition and attitude tasks

Belief elicitation task. In order to better identify mechanisms underlying the observed behavior in the MAIN-TREATMENT part of the experiment, we wish to separately check subjects' ability to update beliefs over the random number that constitutes the state. We do so by employing a specific belief elicitation task that explicitly elicits subjects' probabilistic beliefs over the actual interval within which the random number is contained. We will refer to this set of controls as BELIEFS.

Subjects face the same signal generating process as in the MAIN-TREATMENT task. However, the value for c is fixed at 80 *and* they now are informed about the distribution of colours in the urn, independent of the previously encountered treatment in which they were faced with either a risky or an ambiguous urn.

The nature of the decision after receiving a signal differs from that encountered in the MAIN-TREATMENT task. A specific task is repeated twice with minimal modification. In the first variant of the task, subjects can choose between a fixed option A and a list of versions of Option B, each being indexed by a value of $x \in (0, 1)$. Option A yields 100 ECU if the state is in interval 2 and 0 otherwise. Option (B, x) yields 100 ECU with probability x and otherwise nothing. The values of x considered are $\{.1, .2, .3, .35, .4, .45, .5, .55, .6, .65, .7, .75, .8, .9.\}$. We chose this grid to be sufficiently fine in the region of interest. The second variant of the task is identical, except that option A yields 100 ECU if the state is in interval 3 and 0 otherwise.

In the two above tasks, the value of x at which the subject switches from option A to option B indicates the probability that she attributes to the respective interval (2 in the first task, 3 in the second). For an expected utility decision maker, this should be 0 after message "$\star$" for both intervals, .6 for

X and # for interval 2 and .4 after X and # for interval 3. If the latter two probabilities elicited in this way do not add up to one, this could be a sign that, perhaps due to difficulties in updating, participants consider also the risky treatment in fact as ambiguous.

*Risk and ambiguity aversion test (*Ambiguity-Attitude*).* We elicit risk and ambiguity aversion within the same framework in order to construct a risk corrected measure of ambiguity aversion, our control variable of interest.

In the risk aversion elicitation task, subjects can choose between a fixed Option B and a list of versions of an Option A, each being indexed by a value of $x \in (0, 1)$. The payoff of Option B depends on a draw from an urn containing 50% white balls and 50% black balls. It yields 100 ECU if the drawn ball is white and otherwise 0. Option (A,x) yields x ECU for sure. We consider a grid of equally spaced values for x given by $0, 5, \ldots, 100$.

Our ambiguity aversion test is similar in structure to the one used for risk aversion and comes in two similar variants. The first variant is identical to the risk aversion test, with the difference that the composition of the urn determining the payoff of Option B is now unknown. The second variant is identical to the first variant, with the only difference that Option B now yields 100 ECU if the drawn ball is black and 0 otherwise. This allows us to partition the set of subjects into three categories, independent of their level of risk aversion: *Ambiguity averse*, *Ambiguity loving*, and *Ambiguity neutral*.

Cognitive ability test. We employ a test of cognitive ability that is highly correlated with general intelligence and the willingness and/or ability to deliberate over decisions: the cognitive reflection test (CRT Frederick, 2005). This measures subjects' proneness to give answers governed by impulses rather than deliberation. The task is numerical, which matches the nature of our experiment.

Table 2 gives an overview of the sequence of tasks performed by subjects together with elicited variables.

TABLE 2. Summary of experiment

MAIN-TREATMENT	Treatments: $c \in \{54, 64, 86, 96\}$ Variations: (RISKY / AMBIGUOUS $\times$ HELP /NO HELP) 9 repetitions
MAIN-CONTROL	*Three repetitions for each control task*
Further controls	
BELIEFS	Belief elicitation
AMBIGUITY-ATTITUDE	Ambiguity and risk aversion test
CRT	Cognitive reflection test
RAVEN	Raven's matrices 9 items assessment

2.4. Implementation and procedures

The experiment was conducted at the experimental laboratories at Mannheim and Düsseldorf in May 2016 and April 2017, respectively, with a standard student subject pool recruited with ORSEE (Greiner, 2004). We ran in total 12 sessions where each session lasted around 45 minutes. The experiment was programmed in Fischbacher, 2007. The average payoff was 9.56 euro.

3. Theoretical predictions for the main task

Expected utility behavior. In the risky environment, the messages "#" and "X" provide no more information than the fact that $\omega \geq 50$. Indeed, the probability of any of these being sent given $\omega \in [50, c)$ is $\frac{1}{2}$ and the same holds true conditional on $\omega \in [c, 100]$. It follows that R's best response to these messages is $E[\omega | \omega \in [50, 100]] = 75$. This carries over to the ambiguous environment if, at least on average, R considers both colors equally represented.

Ambiguity averse behavior. We focus first on the ambiguous environment. Given that she does not know the distribution of colors in the urn, a subject faces ambiguity when deciding after observing "#" and "X". If she is ambiguity averse and follows max-min decision-making with prior by prior updating, she will choose the action with the highest worst case expected payoff across priors. The max-min best-response a^* can be shown to be given as follows.

$$a^* = \begin{cases} 100 - 5\sqrt{100 - c} & \text{if } c \le 75 \\ 50 + 5\sqrt{c - 50}, & \text{if } c > 75 \end{cases} \tag{1}$$

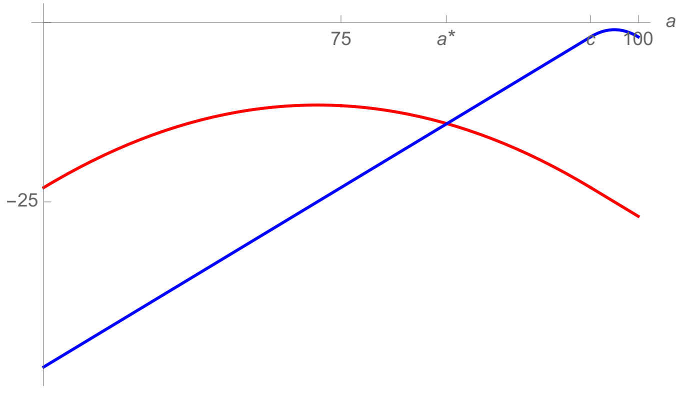


Figure 1. Expected utilities given extreme urn compositions

To understand this, simply note that we only need to look at the intersection between two different expected payoff functions. The first function indicates, for all possible actions, the expected payoff of R under the assumption that all balls in the urn (and hence the drawn ball) are red. The second function is the counterpart for the other possible color, blue. Figure 1 shows these two functions. When the message is “X”, the red line depicts the first function, and the blue line the second function. When the message is “#”, the labels are reversed. These constitute the two most extreme expected utility curves, each arising under a scenario where all balls have the same color. Counterparts for other urn compositions are located between these curves. For a max-min decision maker, guided by the worst case scenario, the objective function is the lower envelope of the two curves, and it is maximized at the point where the two curves intersect.[9]

9. For an ambiguity loving “max-max” decision maker, the objective function is the upper envelope of the two curves. As illustrated in the graph, the optimal action for a cutoff above 75 is to state a number above 75. It can be shown that for any value of the threshold c, the max-max action is on the same side of 75 as the max-min action, but further away from 75.

Table 3. Max-min action a^*

c	$c - 75$	a^*	$a^* - 75$
54	-21	66.1	-8.9
64	-11	70	-5
86	11	80	5
96	21	83.90	8.9

To gain some intuition, observe that one could think about the problem as finding the right compromise between the two actions which are optimal given each of the two possible sub-intervals $[50, c]$ and $[c, 100]$, each of these actions being located on different sides of 75. The smaller sub-interval warrants a larger deviation from 75 then the larger sub-interval. An expected utility decision maker takes into account that the smaller sub-interval is less likely to be the relevant one, so that 75 is her optimal compromise action. Instead, an ambiguity averse decision maker is not concerned with the probability of the smaller interval but guided by the worst-case scenario. Hence, she behaves as if over-weighting the smaller sub-interval, leading to a deviation from 75. Note that from an ex-ante point of view, the decision maker prefers to play 75 after both “X” and “#”, but her preferences change after receiving these messages. We refer to Kellner and Le Quement, 2018 for further explanations.

Note that the formula obtained for the optimal receiver action is derived under the assumption that participants have max-min preferences using all possible compositions of the urn. If they perceive the urn as less ambiguous or e.g. display smooth ambiguity aversion, the effect of changing c would go in the same direction but would be smaller in magnitude. For the values of c used in the experiment, Table 3 summarizes the corresponding max-min actions and how much they deviate from 75.

In that sense, the predicted effect of our form of language ambiguation on the decisions of ambiguity loving subjects is of a similar nature as the predicted effect on ambiguity averse subjects, but simply more extreme.

Finally, observe that these predictions may carry over to the risky urn, if decision makers fail to reduce compound lotteries, as demonstrated e.g. in Halevy (2007). A higher aversion towards second-order risk generates similar predictions as the ambiguity aversion model.

We summarize these results by stating the following key prediction:

PREDICTION 1. *In the ambiguous environment:*

(i) *The level of threshold c will affect, on average, the number chosen by participants after messages "X" and "#".*

(ii) *The effect is present for ambiguity averse participants, but not for ambiguity neutral participants.*

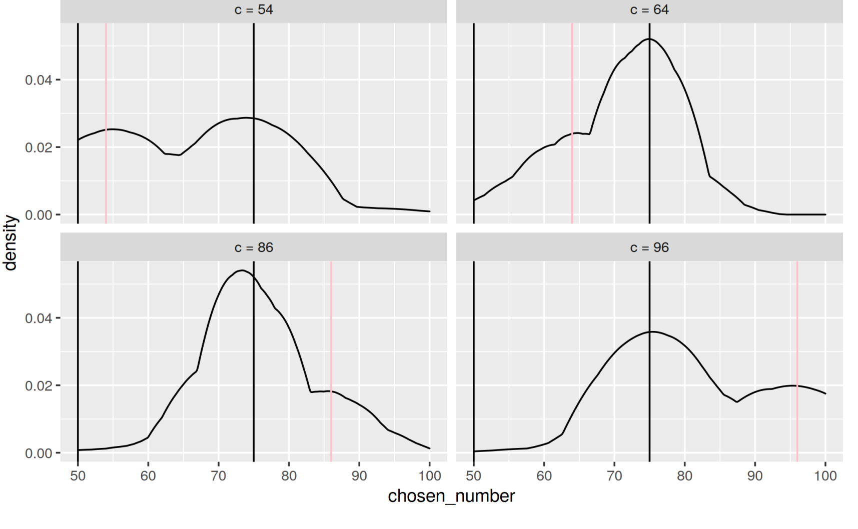
These predictions apply to ambiguity averse or neutral decision makers who are quantitatively sophisticated enough to understand the messaging rules and who are free from anchoring biases. We expect anchoring bias to influence choices in the same direction as ambiguity aversion. In contrast, the implications of low sophistication are difficult to predict. In consequence, in our main analysis we restrict ourselves to studying quantitatively sophisticated participants. The regressions we run on this selected population to identify a possible hedging effect explicitly control for subjects' anchoring tendency as estimated from the anchoring tasks.

Finally, note that a property of our setup is that whatever the value of threshold c, the DM attaches strictly positive ex ante value to the ambiguous signal if she evaluates the signal in terms of his consistent planning ex ante utility. The latter corresponds to her expected utility, anticipating her future (dynamically inconsistent) behavior. Though ambiguity leads DM to take an ex ante suboptimal action whenever the state is above 50, this is more than compensated by the fact that the signal always reveals whether the state is below or above 50. Recall that after observing the ambiguous messages "#" and "X", the DM chooses an action such that her expected utility is the same no matter the urn composition. The DM's consistent planning ex ante utility thus also corresponds to her expected interim max-min utility.

4. Results

We first present subjects' behavior pooled across all variants of the MAIN-TREATMENT (risky and ambiguous, help and no help), after these received either "X" or "#". Figure 2 shows the estimated density of choices using an Epanechnikov kernel pooled over ambiguous and risky urn. Visual inspection reveals that choices are skewed in the direction of c. Using Wilcoxon-rank-sum tests making pairwise comparisons of distributions of choices across different levels of c, we find significant differences between all pairs of c (p-value$<.01$) except for the comparison pairs ($c \in 86, 96$ and $c \in 54, 64$, p-values 0.820 and 0.827, respectively). Our evidence thus supports Prediction 1 (i). One aspect of the estimated densities is that these visually resemble a mixture of two densities, one centered around c and another centered around 75, though this description is not exhaustive.

FIGURE 2. Density of choices in MAIN-TREATMENT



Note: The figure shows the smoothed density of choices for the four different values of the threshold $c \in 54, 64, 86, 96$ using an Epanechnikov kernel in MAIN-TREATMENT when receiving an ambiguous message. There are significant differences between all pairs of c (p-value$<.01$) except for the comparisons ($c \in 86, 96$ and $c \in 54, 64$, p-values 0.820 and 0.827, respectively)

Given the complexity of the main treatment task, we would expect that behavior differs not only between ambiguity averse and ambiguity neutral participants, but also between subjects displaying different levels quantitative sophistication (basic conceptual understanding of signaling rules, ability to do Bayesian updating). As a measure for this quantitative sophistication, we classify participants as "Bayes-Competent" based on their decisions in the two instances where only one layer of uncertainty is involved in the message. One instance is if they see the "$\star$" message in the main treatment. Another instance is when they perform the Red Balls Only control task. The total number of decisions, across these two instances, is at least 6. Across these instances, a decision is marked as correct if and only if the DM chooses the exact expected value of the state conditional on the observed message. To allow for occasional errors, we require a subject to be correct in these tasks 80 percent of the time in order to be classified as "Bayes-competent". This results in 47.90 percent of subjects in our sample being classified as Bayes-competent.[10]

In the main analysis presented in what follows, we focus exclusively on such participants. Within this population, we study separately ambiguity averse and neutral subjects. Ambiguity averse subjects constitute 53.78 percent of the full population of subjects and 56.14 percent of the population of of subjects classified as Bayes-Competent. The corresponding frequencies of ambiguity neutral subjects are respectively 27.73 percent and 24.56 percent. The corresponding frequencies of ambiguity loving subjects are respectively 18.49 percent and 19.30 percent.

In the following analysis, we relax the assumption of independence of observations. We analyze choices using a panel regression framework accounting for the panel structure of our data and differentiating out the decisions in Main-Treatment. The independent—exogenous—variable is c, the dependent variable is the chosen action a. We estimate the following linear panel model:

10. As a robustness check, we have also tried close variations of our classification rule, where a decision is classified as correct if it is located within a small region around the optimal choice. This yields essentially the same classification of subjects into Bayes-Competent and non Bayes-Competent.

TABLE 4. Effect of c by urn type and ambiguity attitude and more than 80% of Bayes control correct

Panel A: Ambiguity averse	Pooled	Ambiguous	Risky
c	0.116**	0.126**	0.096
	(0.049)	(0.061)	(0.078)
Anchoring control	-6.145	-0.940	-12.095
	(4.674)	(5.906)	(7.385)
c x Anchoring control	0.086	0.035	0.146
	(0.060)	(0.076)	(0.094)
Num.Obs.	272	144	128
R2	0.151	0.137	0.188
R2 Adj.	0.030	0.013	0.053
Panel B: Ambiguity neutral	Pooled	Ambiguous	Risky
c	0.024	0.015	-0.161
	(0.073)	(0.248)	(0.172)
Anchoring control	-16.503**	-26.525	0.583
	(6.691)	(19.010)	(18.766)
c x Anchoring control	0.193**	0.289	0.257
	(0.092)	(0.281)	(0.253)
Num.Obs.	112	30	109
R2	0.182	0.251	0.225
R2 Adj.	0.044	0.055	0.128

Note: This table reports the effects of c on the choice of *Bayes-Competent* subjects using fixed effect panel regressions. Column (1) reports the effects when pooling all urn types, column (3) and (4) report the effects for the ambiguous and the risky urn types, respectively. In Panel A we present the results for subjects classified as Ambiguity averse by our control task, while Panel B reports the effects of for the Ambiguity neutral subjects. Significance is reported at the following levels: *** $< .001$, ** $< .01$, * $< .05$.

$$a_{it} = \alpha + \beta_1 \mathbf{c_{it}} + \beta_2 Anchor_{it} + \beta_3 \mathbf{c_{it}} \times Anchor_{it} \tag{2}$$

In the above regression, the second and the third variable control for subjects' individual tendency to anchor their decision on the threshold c, and thus allow us to differentiate out the behavior in our ANCHORING 1 and ANCHORING 2 anchoring control tasks. Coefficient β_3 captures the part of the effect of c which is due to anchoring. Instead, coefficient β_1 captures the part of the effect of c that is not due to anchoring. This lies at the core of our analysis as it should be expected to capture the hedging effect of c when ambiguity averse decision makers face an ambiguous urn.

Panel A of Table 4 reports regression results for ambiguity averse Bayes-Competent subjects, pooling Help and No Help treatments. Column (1) shows coefficients when pooling both urn types, while columns (2) and (3) show the results when considering separately the *Ambiguous* and the *Risky* urn treatments. The coefficient on c is positive and significant in the pooled regression and in the ambiguous urn regression. The coefficient on c in the risky urn regression is slightly smaller and not significantly different from zero. This in line with our Prediction 1(ii). We summarize the results of Panel A of Table 4 in what follows:

RESULT 1. *Among Bayes-Competent and ambiguity averse subjects facing an ambiguous urn, the threshold c has a significantly positive influence on the chosen number, after controlling for their susceptibility to anchoring.*

Notice that our point estimate of .12 for β_1 in Panel A of Table 4 is below the upper bound suggested by the theoretical predictions in equation 1, which imply a slope between .354 (for c=86 or 64) and .417 (for c=96 or 54). This can be explained by risk aversion and by the fact that subjects may perceive less ambiguity or be less ambiguity averse than assumed in the theoretical framework. Alternatively, some—but not all—of the ambiguity averse decision makers may resort to a dynamically consistent updating procedure (as in Hanany and Klibanoff, 2007, 2009.)

In the light of Halevy, 2007, who finds that subjects treat purely risk compound lotteries as if they were ambiguous, it is worth noting that we obtain more clear results for the ambiguous urns. Abdellaoui et al., 2015 find that the correlation between ambiguity attitudes and non-reduction of compound lotteries is weaker for quantitatively sophisticated decision makers. This provides indication that our binary Bayes-competence classification captures variation across subjects in a way that echoes the quantitative sophistication measure used in Abdellaoui et al., 2015.

Panel B of Table 4 reports regression results for ambiguity neutral Bayes-Competent subjects, pooling Help and No Help treatments. Results reveal that such subjects' decisions are not significantly affected by c when controlling for the anchoring effect of c. This is true when considering only the ambiguous urn or only the risky urn, or both together. We summarize the results of Panel B of Table 4 in what follows:

Result 2. *Among Bayes-Competent and ambiguity neutral subjects facing an ambiguous urn, the threshold c does not have a significantly positive influence on the chosen number, after controlling for their susceptibility to anchoring.*

Taken together, Results 1 and 2 thus provide support for Prediction 1(ii) for the population of quantitatively sophisticated subjects. In Appendix E, we provide a counterpart of the above two regression tables for Bayes-Competent ambiguity loving subjects. Point estimates are in line with what we would expect from max-max decision-making.

We present results for subjects who are not Bayes-Competent in Appendix B. Such subjects react to the threshold c even when controlling for anchoring, but the effect appears to be overall orthogonal to their ambiguity attitude. There are not enough observations for ambiguity loving subjects to meaningfully interpret their results. As a robustness check, we also conducted a median split by the performance in the Cognitive Reflection Test instead of using Bayes-competence as a measure of sophistication. We find qualitatively and quantitatively similar results to those obtained in our main analysis. These are presented in Table D.1 in the Appendix. Finally, we find no significant qualitative or quantitative differences between Help and No Help treatments, as reported in Table C.1 in the Appendix.

5. Conclusion

In our experiment, language ambiguation affected the decisions of quantitatively sophisticated and ambiguity averse subjects by triggering hedging behaviour, in line with the predictions of models of ambiguity aversion. This effect operates in an environment where receivers ex ante benefit from the information contained in messages, though they would benefit if they could selectively ignore the ex post ambiguity created by messages.

As noted in existing contributions, the use of ambiguous communication strategies in sender-receiver games would in principle allow for the emergence of equilibria featuring more informative communication than the standard equilibria predicted by expected-utility theory. Future experimental work should study games where both the sender and the receiver are real subjects, and study equilibrium behavior when the sender is known to observe some privately observed, payoff-irrelevant, and ambiguously distributed variable. Would the sender make use of the opportunity to condition his messages on such a variable? Would the receiver anticipate this? Would the overall effect be beneficial to both parties?

References

Abdellaoui, Mohammed, Peter Klibanoff, and Lætitia Placido (2015). "Experiments on Compound Risk in Relation to Simple Risk and to Ambiguity". *Management Science* 61.6, pp. 1306–1322.

Alonso, Ricardo, Wouter Dessein, and Niko Matouschek (Mar. 2008). "When Does Coordination Require Centralization?" *American Economic Review* 98.1, pp. 145–79. DOI: 10.1257/aer.98.1.145. URL: http://www.aeaweb.org/articles?id=10.1257/aer.98.1.145.

Azrieli, Yaron and Roee Teper (2011). "Uncertainty Aversion and Equilibrium Existence in Games with Incomplete Information". *Games and Economic Behavior* 73.2, pp. 310–317. ISSN: 0899-8256. DOI: 10.1016/j.geb.2011.03.005.

Bade, Sophie (2011). "Ambiguous Act Equilibria". *Games and Economic Behavior* 71.2, pp. 246–260. ISSN: 0899-8256. DOI: 10.1016/j.geb.2010.04.006.

Beauchêne, Dorian, Jian Li, and Ming Li (Jan. 1, 2019). "Ambiguous Persuasion". *Journal of Economic Theory* 179, pp. 312–365. ISSN: 0022-0531. DOI: 10.1016/j.jet.2018.10.008.

Bergman, O., T. Ellingsen, M. Johannesson, and C. Svensson (2010). "Anchoring and Cognitive Ability". *Economics Letters* 107.1, pp. 66–68. DOI: 10.1016/j.econlet.2009.12.028.

Bleichrodt, Han, Jurgen Eichberger, Simon Grant, David Kelsey, and Chen Li (2018). *A Test of Dynamic Consistency and Consequentialism in the Presence of Ambiguity*. Discussion Papers 1803. University of Exeter, Department of Economics. URL: https://ideas.repec.org/p/exe/wpaper/1803.html.

Blume, Andreas and Oliver J. Board (2014). "Intentional vagueness". *Erkenntnis* 79.4, pp. 855–899.

Blume, Andreas, Oliver J. Board, and Kohei Kawamura (2007). "Noisy Talk". *Theoretical Economics*, pp. 395–440.

Blume, Andreas, Ernest K Lai, and Wooyoung Lim (2020). "Strategic information transmission: A survey of experiments and theoretical foundations". *Handbook of Experimental Game Theory*. Edward Elgar Publishing.

Bose, Subir and Ludovic Renou (2014). "Mechanism Design With Ambiguous Communication Devices". *Econometrica* 82.5, pp. 1853–1872. ISSN: 1468-0262. DOI: 10.3982/ecta10285.

Crawford, Vincent P and Joel Sobel (Nov. 1982). "Strategic Information Transmission". *Econometrica* 50.6, pp. 1431–1451. ISSN: 0012-9682. DOI: 10.2307/1913390.

Cubitt, Robin, Gijs van de Kuilen, and Sujoy Mukerji (2019). "Discriminating Between Models of Ambiguity Attitude: A Qualitative Test". *Journal of the European Economic Association*. DOI: 10.1093/jeea/jvz005.

Dominiak, Adam, Peter Duersch, and Jean-Philippe Lefort (July 2012). "A Dynamic Ellsberg Urn Experiment". *Games and Economic Behavior* 75.2, pp. 625–638. ISSN: 08998256. DOI: 10.1016/j.geb.2012.01.002.

Ellsberg, Daniel (1961). "Risk, Ambiguity, and the Savage Axioms". *The Quarterly Journal of Economics* 75.4, pp. 643–669. DOI: 10.2307/1884324.

Epstein, Larry G. and Yoram Halevy (July 2019). *Hard-to-Interpret Signals*.

Evdokimov, Piotr and Umberto Garfagnini (May 2019). "Communication and behavior in organizations: An experiment". *Quantitative Economics* 10.2. [Online; accessed 8. Nov. 2019], pp. 775–801. ISSN: 1759-7323. DOI: 10.3982/TE673.

Fischbacher, Urs (June 2007). "Z-Tree: Zurich Toolbox for Ready-Made Economic Experiments". *Experimental Economics* 10.2, pp. 171–178. DOI: 10.1007/s10683-006-9159-4.

Fox, C.R. and A. Tversky (1995). "Ambiguity Aversion and Comparative Ignorance". *The Quarterly Journal of Economics*, pp. 585–603. DOI: 10.2307/2946693.

Frederick, Shane (2005). "Cognitive Reflection and Decision Making". *Journal of Economic Perspectives* 19.4, pp. 25–42. DOI: 10 . 1257 / 089533005775196732.

Gilboa, Itzhak and David Schmeidler (1989). "Maxmin Expected Utility with Non-Unique Prior". *Journal of Mathematical Economics* 18.2, pp. 141–153. DOI: 10.1016/0304-4068(89)90018-9.

Gneezy, Uri (Mar. 2005). "Deception: The Role of Consequences". *American Economic Review* 95.1, pp. 384–394. DOI: 10.1257/0002828053828662.

Greiner, B. (2004). "An Online Recruitment System for Economic Experiments". *GWDG Bericht* 63. Ed. by Kurt KremerVolker Macho, pp. 79–93.

Halevy, Yoram (2007). "Ellsberg Revisited: An Experimental Study". 75.2, pp. 503–536.

Hanany, Eran and Peter Klibanoff (2007). "Updating Preferences with Multiple Priors". *Theoretical Economics* 2.3, pp. 261–298. URL: https://econtheory.org/ojs/index.php/te/article/view/20070261/0.

— (2009). "Updating Ambiguity Averse Preferences". *The B.E. Journal of Theoretical Economics* 9.1, pp. 1–53. URL: https://EconPapers.repec.org/RePEc:bpj:bejtec:v:9:y:2009:i:1:n:37.

Kahneman, D. and A. Tversky (1974). "Judgement under Uncertainty: Heuristics and Biases". *Science* 185, pp. 1124–1131. DOI: 10.1126/science.185.4157.1124.

Kellner, Christian and Mark T. Le Quement (Jan. 1, 2018). "Endogenous Ambiguity in Cheap Talk". *Journal of Economic Theory* 173, pp. 1–17. ISSN: 0022-0531. DOI: 10.1016/j.jet.2017.10.007.

Klibanoff, Peter (2001). "Characterizing Uncertainty Aversion through Preference for Mixtures". *Social Choice and Welfare* 18.2, pp. 289–301. DOI: 10.1007/s003550100104. JSTOR: 41106414.

Klibanoff, Peter, Massimo Marinacci, and Sujoy Mukerji (2005). "A Smooth Model of Decision Making under Ambiguity". *Econometrica* 73.6, pp. 1849–1892. DOI: 10.1111/j.1468-0262.2005.00640.x.

Kops, Christopher and Illia Pasichnichenko (2020). *A Test of Information Aversion.*

Li, Jian (2019). "Preferences for partial information and ambiguity". *Theoretical Economics, forthcoming.*

Lipman, Barton L. (Oct. 2009). "Why is Language Vague?"

Lo, Kin Chung (Nov. 1, 1996). "Equilibrium in Beliefs under Uncertainty". *Journal of Economic Theory* 71.2, pp. 443–484. ISSN: 0022-0531. DOI: 10.1006/jeth.1996.0129.

Oechssler, Jörg, Andreas Roider, and Patrick W Schmitz (2009). "Cognitive Abilities and Behavioral Biases". *Journal of Economic Behavior & Organization* 72.1, pp. 147–152. DOI: 10.1016/j.jebo.2009.04.018.

Riedel, Frank and Linda Sass (Apr. 1, 2014). "Ellsberg Games". *Theory and Decision* 76.4, pp. 469–509. ISSN: 1573-7187. DOI: 10.1007/s11238-013-9381-4.

Seidenfeld, Teddy and Larry Wasserman (Sept. 1993). "Dilation for Sets of Probabilities". *Annals of Statistics* 21.3, pp. 1139–1154. ISSN: 0090-5364. DOI: 10.2307/2242191.

Shishkin, Denis and Pietro Ortoleva (Nov. 2019). *Ambiguous Information and Dilation: An Experiment.*

Siniscalchi, Marciano (2011). "Dynamic Choice under Ambiguity". *Theoretical Economics* 6.3, pp. 379–421. ISSN: 1555-7561. DOI: 10.3982/te571.

Sobel, Joel (2013). "Giving and receiving advice". *Advances in economics and econometrics* 1, pp. 305–341.

Wang, Joseph Tao-yi, Michael Spezio, and Colin F. Camerer (June 2010). "Pinocchio's Pupil: Using Eyetracking and Pupil Dilation to Understand Truth Telling and Deception in Sender-Receiver Games". *American Economic Review* 100.3, pp. 984–1007. ISSN: 0002-8282. DOI: 10.1257/aer.100.3.984.

Appendix A: Ex-ante value of the signal

We here prove the following result.

Result A.1. *For any $c \in [50, 100]$ and not belonging to $\{50, 75, 100\}$, the DM's consistent planning ex ante utility from observing the message is strictly higher than his ex ante utility from not observing it.*

Proof. Assume that $c > 75$. Then the decision maker's consistent planning ex ante utility from observing the message is given by:

$$\begin{aligned} & \left(-\frac{1}{100}\right)\left(\begin{array}{c} \int_0^{25}(25-\omega)d\omega + \int_{25}^{50}(\omega-25)d\omega \\ +\int_{50}^{50+5\sqrt{c-50}}(50+5\sqrt{c-50}-\omega)d\omega \\ +\int_{50+5\sqrt{c-50}}^{100}(\omega-(50+5\sqrt{c-50}))d\omega \end{array}\right) \\ = \; & \frac{5}{2}\sqrt{c-50} - \frac{1}{4}c - \frac{25}{4} \end{aligned}$$

Assume that the decision maker does not observe the message. Then his ex ante expected utility is simply as follows:

$$\begin{aligned} & \left(-\frac{1}{100}\right)\left(\int_0^{50}(50-\omega)d\omega + \int_{50}^{100}(\omega-50)d\omega \right) \\ = \; & -25 \end{aligned}$$

It can be easily shown that $\frac{5}{2}\sqrt{c-50} - \frac{1}{4}c - \frac{25}{4} > -25$ for any $c \in (75, 100]$. The same argument can be made for $c \in (50, 75)$.

□

Appendix B: Non-Bayes-Competent

Table B.1 reports the result for Non-Bayes-Competent subjects. We show results for ambiguity neutral (Columns 1–3) and averse (columns 4–6) subjects.

Table B.1. Effect of c by urn type for Non-Bayes-Competent subjects

	Ambiguity neutral			Ambiguity averse		
	Pooled	Ambiguous	Risky	Pooled	Ambiguous	Risky
c	0.250***	0.231**	0.252**	0.170***	0.249***	0.087
	(0.078)	(0.105)	(0.121)	(0.061)	(0.084)	(0.087)
Anchoring control	-18.718**	-17.727*	-19.968*	-19.957***	-11.474	-28.714***
	(7.841)	(10.599)	(11.766)	(5.739)	(8.051)	(8.179)
c x Anch. ctrl.	0.263**	0.232	0.296*	0.273***	0.145	0.407***
	(0.104)	(0.140)	(0.157)	(0.076)	(0.106)	(0.110)
Num.Obs.	148	77	71	347	175	172
R2	0.362	0.335	0.391	0.260	0.241	0.294
R2 Adj.	0.255	0.197	0.289	0.150	0.120	0.185

Note: This table reports the effects of c on choices of Non-Bayes-Competent subjects. We employ a fixed effects panel model. Columns (1) to (3) report the effects for ambiguity neutral subjects, column (4) to (6) for ambiguity averse subjects. Significance is reported at the following levels: *** $<$ .001, ** $<$ .01, * $<$ .05.

Appendix C: Help and No Help treatments

Table C.1 reports the results by help and no-help treatments for subjects who are Bayes-Competent.

Table C.1. Effect of c by help treatments for Bayes-Competent subjects pooled over urn types

	Ambiguity averse		Ambiguity neutral	
	Help	No help	Help	No help
c	0.178*	0.327***	-0.230	-0.053
	(0.093)	(0.122)	(0.233)	(0.174)
Anchoring control	19.546*	30.229**	-11.428	5.868
	(10.146)	(13.488)	(26.907)	(18.304)
c × Anch. ctrl.	0.081	-0.113	0.492	0.210
	(0.133)	(0.180)	(0.364)	(0.246)
Num.Obs.	326	170	53	103
R2	0.314	0.286	0.286	0.260
R2 Adj.	0.307	0.273	0.242	0.238

Note: This table reports the effects of c on choice who are Bayes Competent. We employ a fixed effects panel model. Columns (1) to (3) report the effects for ambiguity neutral subjects, column (4) to (6) for ambiguity averse subjects. Significance is reported at the following levels: *** $<$ .001, ** $<$ .01, * $<$ .05.

Appendix D: CRT Median split

As an alternative to measure subjects ability in logical and mathematical tasks, we split the sample by performance in the CRT test. Table D.1 reports the results and finds similar effects for subjects who performed better or equal to the median in the CRT compared to subjects who we classified as Bayes-Competent.

TABLE D.1. Effect of c by performance in the CRT task pooled over urn types

	CRT $\geq$ median			CRT $<$ median		
	Pooled	Non neutral	Neutral	Pooled	Non neutral	Neutral
c	0.160***	0.196***	0.090	0.169***	0.170**	0.267***
	(0.034)	(0.049)	(0.057)	(0.051)	(0.066)	(0.094)
Anchoring control	-6.868**	-6.301	-7.291	-22.414***	-15.324**	-32.288***
	(3.244)	(4.678)	(5.314)	(4.900)	(6.337)	(9.330)
c $\times$ Anch. ctrl.	0.091**	0.084	0.103	0.303***	0.212***	0.421***
	(0.043)	(0.061)	(0.070)	(0.065)	(0.082)	(0.127)
Num.Obs.	551	308	156	412	223	104
R2	0.181	0.212	0.167	0.283	0.234	0.503
R2 Adj.	0.176	0.204	0.150	0.278	0.223	0.488

Note: This table reports the effects of c by performance on the cognitive reflection test (CRT Frederick, 2005). We employ a fixed effects panel model. Columns (1) to (3) report the effects for subjects with equal or above median performance on the CRT, column (4) to (6) with less than median performance. Significance is reported at the following levels: *** $<$ .001, ** $<$ .01, * $<$ .05.

Appendix E: Ambiguity loving

Table E.1 reports the results for *Ambiguity Loving* subjects who are Bayes-Competent.

TABLE E.1. Effect of c for ambiguity loving subjects

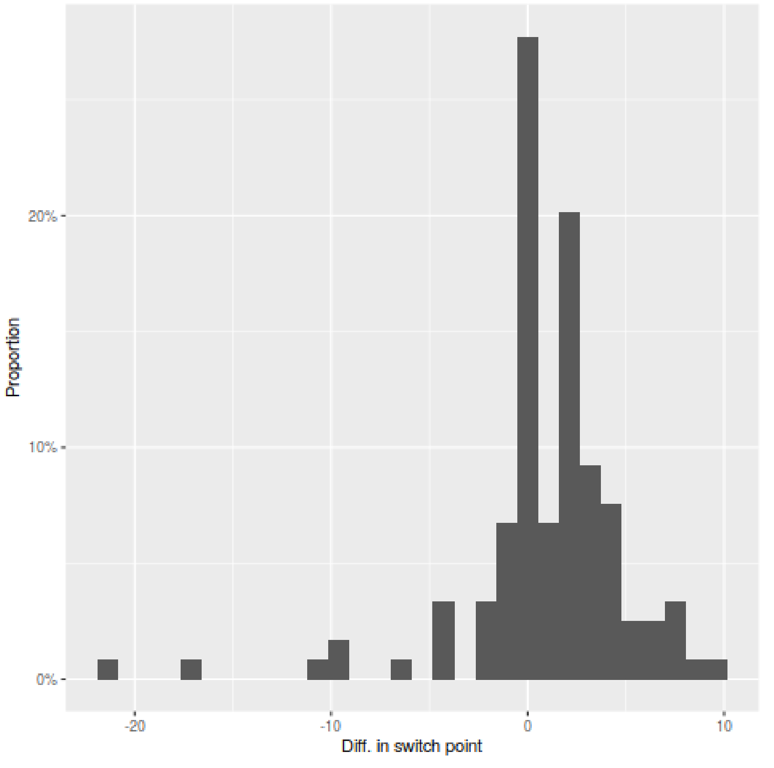
	Bayes-Competent		
	Pooled	Ambiguous	Risky
c	0.101	0.045	-0.612***
	(0.103)	(0.065)	(0.203)
Anchoring control	-15.630*	-1.190	-60.526***
	(9.274)	(6.626)	(22.202)
c x Anchoring control	0.205	0.000	1.220***
	(0.127)	(0.085)	(0.296)
Num.Obs.	84	45	55
R2	0.203	0.042	0.532
R2 Adj.	0.055	-0.171	0.463

Note: This table reports the effects of c on ambiguity loving subjects. We employ a fixed effects panel model. Columns (1) to (3) report the effects for subjects with equal or above median performance on the CRT, column (4) to (6) with less than median performance. Significance is reported at the following levels: *** $<$ .001, ** $<$ .01, * $<$ .05.

Appendix F: Ambiguity aversion and behavior in control tasks

Figure F.1 reports the distribution of ambiguity aversion corrected for risk aversion as elicited in the control tasks. Most of the subjects show ambiguity aversion and around 28 percent of the subjects are ambiguity neutral.

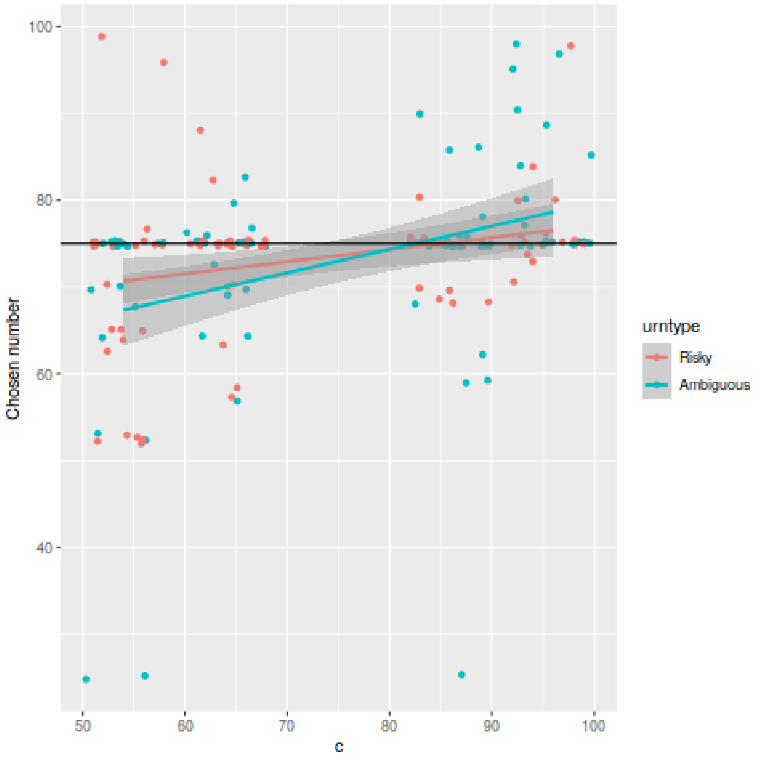
FIGURE F.1. Ambiguity aversion corrected for risk aversion



Note: This graph reports the choices in the ambiguity aversion task, corrected for the switching points in the risk aversion task. We define a subject as *Ambiguity Averse* if she scores strictly above zero on this measure, *Ambiguity Neutral* of she scores exactly zero, and *Ambiguity Loving* of she scores strictly below zero.

The graphs F.2 and F.3 report the reaction to c in control tasks ANCHORING 1 and ANCHORING 2.

FIGURE F.2. Reaction of subjects in control task ANCHORING 1

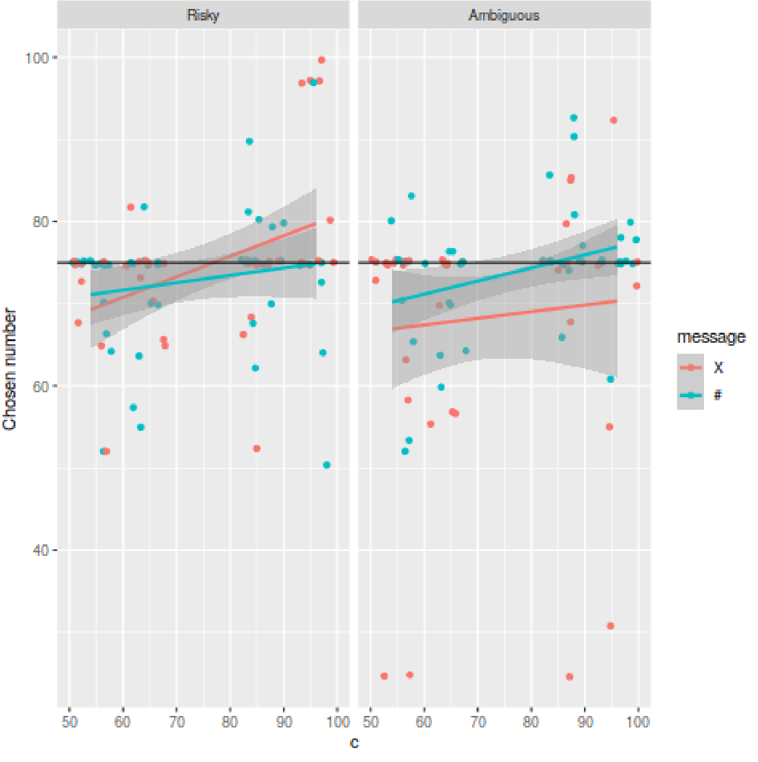


Note: This graph reports the reaction of subjects in ANCHORING 1 when the true state is between 50 and 100.

Appendix G: Types of Belief Updaters

Moreover, we had a control task where we elicited directly subjects' beliefs over the section of the ball. Only twenty percent of the choices are according to Bayes rule. The vast majority of choices deviates from that, most probably due to task complexity, as it was substantially more demanding than the task in our main experiment. Figure G.1 shows the distribution of types of belief updaters.

FIGURE F.3. Reaction of subjects in control task ANCHORING 2



Note: This graph reports the reaction of subjects in ANCHORING 1 when the true state is between 50 and 100.

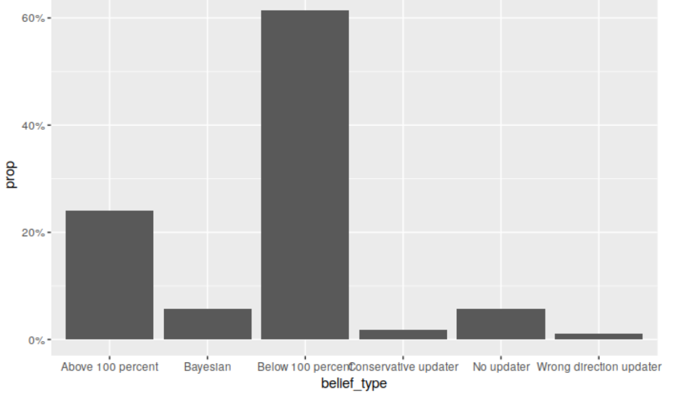


FIGURE G.1. Types of belief updaters

Appendix H: Instructions and screenshots

H.1. Paper instructions

These instructions have been translated from German.

Instructions

Welcome to the experiment, please read the instructions carefully.

Currency

In this experiment, we speak of ECU (Experimental Currency Units). ECU 100 is equivalent to EUR 8. Before the payment ECUs are converted into euros according to this exchange rate.

The Experiment

A random number generator chooses a number from zero (0) to hundred (100). The number determined in this way is denoted by *drawn number*. You do not know this number. Your task in the main part of the experiment is to state a number from zero to a hundred. Your choice will be with your *named number*. Your payout is the greater the closer the *named number* is to the *drawn number*. In addition, you receive certain information about the *drawn number*.

Payment

You will receive a maximum of 100 ECU if your *named number* corresponds exactly to the *drawn number*. Otherwise, the difference between the two figures is deducted in ECU. Your payoff can therefore be described by the following formula:

Your payout = 100 - *distance between drawn number and named number.*

After the experiment, a short questionnaire will be started. After the questionnaire you will be called for payment.

Repetitions

The experiment is repeated 20 times. The last decision situations differ from the first and are explained on the screen. Each time a **new** number is drawn. Besides, it can the information you have about the number you draw to change. At the end *one* of the tasks is drawn for payout.

please turn over

Message

Before you decide on a *number*, get A message that depends on the *number drawn*. The number space from 0 to 100 is divided into three sections:

section 1: From 0 to (including) a boundary at 50

section 2: Between the limit 50 and a c (the Borders themselves are not included here)

section 3: From (including) the limit c to 100

The value of c may differ between repetitions, however the relevant value will always be known to you (and displayed on the screen).

You will receive a message showing one of the three symbols $*$, $\times$, $\#$.

Which symbol the message shows depends on the drawn number and from the draw from an urn. This urn contains a total of 100 balls that can be either red or blue. This urn is simulated by a computer. You will get more information about the urn in the instructions on the screen. The message is also determined as follows:

- If the number is in section 1, which is less than 50 (or equal), then you get the message $*$, independently the color of the drawn ball.
- If the number is in section 2 or section 3, the Message of the color of the drawn ball:
  - If the ball is red then the message is $\times$ in section 2 and „ $\#$ “ in section 3.
  - If the ball is blue then the message is $\#$ in section 2 and $\times$ in section 3.

The following table summarizes the rule under which the message is sent to you. You can consult this table throughout the experiment.

	Section 1 (smaller/equal 50)	Section 2 (between 50 and c)	Section 3 (larger/equal c)
Red Ball	*	×	#
Blue Ball	*	#	×

H.2. Control questions (computerized)

Subjects could start the experiment only after answering all questions correctly. All questions were the same for all treatments, the correct answer options however could differ.

- Mark all correct statements:
- It is possible that ...
  - 50 balls are red and 50 balls are blue.
  - 100 balls are red and 0 balls are blue.
  - 0 balls are red and 100 balls are blue.
  - 60 balls are red and 60 balls are blue.
  - 75 balls are red and 25 balls are blue.
  - 25 balls are red and 75 balls are blue.
- What is your payout (in ECU) if the number drawn is 50 and the number you specify is 60?
- What is your payout (in ECU) if the number drawn is 50 and the number you specify is 45?
- What is the value of the border between Section 1 and Section 2?
- Assume that c=70, and the drawn number is 65. Wich statements are correct?
  - I receive signal *.
  - I receive signal #.
  - I receive signal x.
  - I receive signal x if the drawn ball is red, # if it is blue.
  - I receive signal # if the drawn ball is red, x if it is blue.

– I receive signal * if the drawn ball is red, x if it is blue.
– I receive signal x if the drawn ball is red, * if it is blue.
– I will never receive signal *.

Appendix I: Screenshots

Screen for risky urn

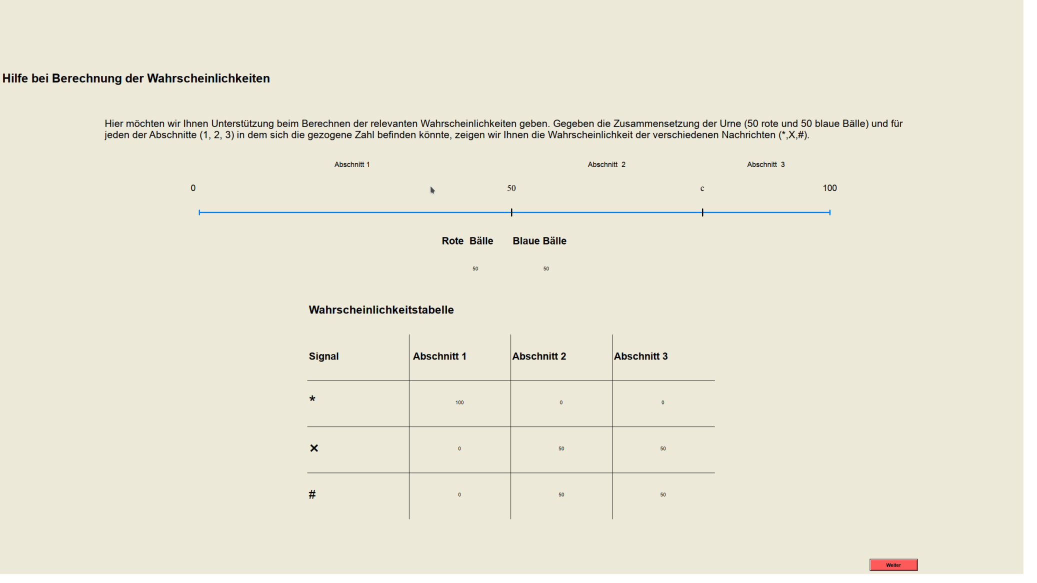
FIGURE I.1. Screen main decisions for risky urn

Translation.

- Task 4
- There are 50 red and 50 blue balls in the urn.
- Your message over drawn number: *
- Your choice of the number:
- If you do not know the key, you can have a look at your printed instructions.

Screen for risky urn in the help treatment

FIGURE I.2. Screen help with probability calculations



Translation.

- Help with the calculation of the probabilities
- here we would like to support you calculating the relevant probabilitie. Given the urn composition (50 red and 50 blue balls) and for the sections (1, 2, 3) in which the drawn number coud be, we show you the probability for the messages (*,X,#)
- Red Balls / Blue Balls
- Probability table
- Signal / Section 1 / Section 2 / Section 3

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