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Social anchor effects in decision-making under ambiguity

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Abstract

I experimentally examine whether feedback about others' choices provides an anchor for decision-making under ambiguity. In a between-subjects design I vary whether subjects learn choices made individually by a "peer" in a first part when facing the same task a second time, and whether prospects are defined over gains or losses. My key findings are that the *relative* ambiguity attitude (compared to the peer's) significantly matters for shifts in individual attitudes, and that dynamics considerably differ between gain and loss domains. For gains, learning to be comparably ambiguity averse increases the likelihood for such shifts, relative to the individual condition; for losses, this likelihood decreases only if peers learn to exhibit exactly the same attitude. Further, I observe imitative shifts towards the peer's attitude in the gain domain, but only towards neutrality in the loss domain. Shifts towards neutrality for losses also appear significant without social anchor suggesting that ambiguity seeking might not be particularly robust. Moreover, cognitive ability positively correlates to shifts towards neutrality in the gain domain, but has no impact in the loss domain.

JEL codes: C91, D03, D81, D83.

Keywords: Decision-making under uncertainty, ambiguity, social comparison, learning, laboratory experiment.

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1 Introduction

Peer effects are documented in a variety of economic decisions, such as stock market participation (Hong et al., 2004), insurance purchases (Cai et al., forthcoming), or investment choices (Bursztyn et al., forthcoming). Many of these environments involve ambiguity rather than risk, i.e. are characterized by distributions over outcomes which are likely to be unknown (Keynes, 1921; Knight, 1921). "*We might say, for example, that we do not know, when we go on a railway journey, the probability of death in a railway accident, unless we are told the statistics of accidents in former years; or that we do not know our chances in a lottery, unless we are told the number of the tickets.*" (Keynes, 1921, p. 31). Similarly, we might argue that investors usually do not know expected returns in exact numbers, nor do insurance customers perfectly assess the probability for a loss. Likewise, when choosing pension plans contributors are not able to predict interest rates curves in fixed-income markets. Not surprisingly, people often appear to be averse against ambiguous compared to risky situations. Intuitively, individuals may not feel confident in assessing true probabilities, especially if outcomes might entail detrimental consequences. Such ambiguity aversion might inhibit individuals from taking up costless genetic tests (Hoy et al., 2014) and explain the stock market participation puzzle (Dow and Werlang, 1992; Easley and O'Hara, 2009), among other examples. At the same time, ambiguity aversion has been found to correlate with irrational appraisals of ambiguous situations, such as over-pessimistic beliefs about probabilities or a perceived lack of information (Keren and Gerritsen, 1999). These behavioral biases do not seem consistent with normative models of individual decision-making under uncertainty. Furthermore, in contrast to risk aversion which might, for example, protect individuals from irrecoverable economic shocks by buying insurance, ambiguity aversion might induce truly suboptimal decisions in terms of departures from subjective expected utility theory (Savage, 1954) and probabilistic sophistication (Machina and Schmeidler, 1992). The conjecture that learning whether others also fear (or even seek) ambiguous events might enforce such irrational behavior, appears straightforward. However, learning that others treat risk and ambiguity in a fairly indifferent manner, might also convey a doctrine of ambiguity neutrality. In this paper I study individual ambiguity attitudes and examine how these attitudes are affected by feedback about others' choices under ambiguity.

Models on rational learning under ambiguity predict that Bayesian decision makers, who update their beliefs about ambiguous probabilities, should asymptotically converge towards ambiguity neutral preferences (see, e.g., Epstein and Schneider, 2007). In addition to receiving signals about outcomes from ambiguous lotteries, learning about others' decisions might influence subjective probabilities of a probabilistically sophisticated decision maker, or impact his[1] confidence in the ambiguous environment.[2] Some experimental evidence indeed shows that social interaction might induce a

[1] I refer to a decision maker as "he" throughout this paper.

[2] Epstein and Schneider (2007) introduce learning in the maximin framework of Gilboa and Schmeidler (1989); in particular they allow a Bayesian decision maker to adjust his confidence as well as his beliefs. Learning under ambiguity is also addressed in models by Huber (1973), Walley (1991), and Marinacci (2002). Models that incorporate inter-

shift in attitudes towards ambiguity neutral preferences (Keck et al., 2011; Charness et al., 2013). In contrast, studies from social psychology suggest that choices of others generally provide an anchor to which decision makers wish to conform (e.g., Festinger, 1954; Cialdini and Trost, 1998; Cialdini and Goldstein, 2004). In the economic literature, models of distributional social preferences, such as the concept of inequity aversion by Fehr and Schmidt (1999)[3], have rather been used to explain peer effects in terms of imitative behavior (for example, in consumption choices or asset pricing, see Galí, 1994; Gebhardt, 2004, 2011, respectively). Either approach predicts changes towards the peer's ambiguity attitude, suggesting that prevailing attitudes might even be corroborated through feedback about others.

This paper provides additional evidence on shifts in ambiguity attitudes contingent on learning the choices of peers. Following the standard two-color Ellsberg setting (Ellsberg, 1961) I elicit matching probabilities in a laboratory experiment, which reflect indifferent preferences between a risky and an ambiguous prospect. Ambiguity attitudes are measured individually in a first part, and again in a second part, with respect to the same prospects and using the same task. In a between-subjects design, I exogenously vary whether lotteries are defined over gains or losses, and whether subjects are shown previous choices of another participant – additionally to their own – when making their choices a second time. I refer to this as providing subjects with a *social anchor* of a *peer*.[4] If a social anchor is available, subjects may have two incentives to take the peer's decisions into account: first, the rational information inherited in his decisions, providing an additional anchor for evaluating the choice situation; second, having social preferences with respect to the peer's outcome. By comparing treatments with and without social anchor, changes in ambiguity attitudes which may, e.g., be due to reconsideration or increased familiarity with the ambiguous task, can be distinguished from changes that result from learning others' attitudes.

Generally, the data suggests that ambiguity attitudes constitute a stable part of preferences: 90% of subjects exhibit the same attitude (ambiguity aversion or ambiguity seeking) in the first and in the second part, independent of having a social anchor available or not. However, the intensity of these attitudes does by far not appear to be as robust, and varies between Part 1 and Part 2 in 50% of all cases. In the analysis I, hence, particularly focus on the frequency with which subjects change their matching probabilities, and on the direction of shifts in ambiguity attitudes, conditional on such a change.

My key finding is that individual dynamics and peer effects in ambiguity attitudes considerably differ in the loss compared to the gain domain. In the domain of gains, the individual's ambiguity

temporal settings, such as Epstein and Wang (1994) and Epstein and Schneider (2003) who build on the maximin model, establish a basis for these contributions.

[3]For a survey on models of distributional preferences see Camerer (2003) and Fehr and Schmidt (2006).

[4]The term *anchor* is often used to describe "a stimulus or a message that is clearly designated as irrelevant and uninformative" (Kahneman, 1992, p. 308). I slightly deviate from this definition and use the term to describe additional information which should be irrelevant for a rational and selfish decision maker. In this setting, choices of others might, however, be relevant in individual decision-making if individuals exhibit distributional preferences or perceive others to be more competent with respect to the task.

attitude does not have any significant effects on the likelihood to change or on the direction of a change, neither in the absence nor in the presence of a social anchor. However, learning to be more ambiguity averse than a peer significantly increases the likelihood to change, relative to the individual condition. That is, the *relative* ambiguity attitude, i.e. the ambiguity attitude compared to the peer's, matters. Further, conditional on a change in matching probabilities, decision makers tend to imitate their peer's attitude, towards ambiguity aversion, seeking, or neutrality. Ultimately, the provision of a social anchor in the gain treatments predominantly induces subjects who perceive themselves to be comparably ambiguity averse to shift towards neutrality.

In the domain of losses, in contrast, individual attitudes significantly matter in the individual treatment, such that ambiguity seeking subjects are significantly more likely to change compared to ambiguity averse ones. However, this relationship fades out when a social anchor becomes available. In the social anchor treatments it is again the relative ambiguity attitude that matters, but in a different way compared to the gain domain: if peers learn to exhibit exactly the same attitudes, their likelihood to change is significantly reduced, relative to the individual condition, which I label a *reassurance effect*. Again in contrast to the gain domain, conditional on a change in matching probabilities, I observe significant shifts from ambiguity seeking towards neutrality, with and without social anchor. Overall, these findings suggest that ambiguity seeking might not be particularly robust in such settings (in line with experimental evidence as discussed below).

Moreover, I find that cognitive ability significantly and positively correlates to shifts towards neutrality in the gain domain, while any relationship is of negligible relevance in the loss domain. This suggests that ambiguity aversion in the standard Ellsberg setting might be driven by bounded rationality, while ambiguity seeking might rather be of instinctive nature.

Overall, my data suggests three main conclusions. The intensity of ambiguity attitudes is likely to fluctuate, even if no social anchor is available; nevertheless, peers seem to be important for decision-making under ambiguity; and being provided with a social anchor seems to affect individual attitudes differently in the domain of gains compared to losses.

In the economics literature social interaction in decision-making under ambiguity has been examined early on. In a seminal paper Curley et al. (1986) find evidence for the "Other-evaluation hypothesis". That is, if individuals anticipate negative evaluation by others, they tend to make choices which are perceived to be most justifiable to others; and often, the choice most easily justified seems to be the ambiguity averse.[5] Intuitively, a bad outcome might be indisputably deluded to bad luck if it results from a risky prospect, which would not be as easy if it results from an ambiguous prospect. That the fear of negative ex-post evaluation by others is likely to increase ambiguity aversion is also confirmed by Trautmann et al. (2008) and Muthukrishnan et al. (2009).

[5] For example, Heath and Tversky (1991), Fox and Tversky (1998), and Fox and Weber (2002) show that individuals become more ambiguity averse if they make choices in the presence of others who they perceive to be more competent than themselves. Following the terminology of Watson and Friend (1969) the Other-evaluation hypothesis is also referred to as the "fear of negative evaluation", and is also addressed in Knight (1921), Fellner (1961), Ellsberg (1963), Roberts (1963), Toda and Shuford (1965) and Gärdenfors (1979).

Basically, these studies already suggest how sensitive ambiguity attitudes might be with respect to changes in the social environment.

Two other studies are particularly related to this paper. Keck et al. (2011) and Charness et al. (2013) (in the following referred to by KDB and CKL, respectively) compare ambiguity attitudes in the domain of gains, elicited in isolation and elicited after face-to-face consultation with peers. Both studies find that social interaction causes a shift in ambiguity attitudes towards neutrality. In CKL, this shift predominantly stems from ambiguity seeking individuals and those who exhibit incoherent attitudes. KDB, on the other hand, report that the shift towards neutrality is caused by a reduction in both ambiguity aversion and ambiguity seeking.[6] My results are consistent with their findings as they show that subjects take information about their peer's attitude into account when making individual choices. I observe significant shifts in ambiguity attitudes, although not exclusively towards ambiguity neutrality, but predominantly so if losses are involved. At this point, it is important to note that having a social anchor available compared to interacting with others face-to-face might have very different effects. In particular, following the arguments of CKL and KDB, face-to-face interaction might be even more powerful in enforcing ambiguity neutrality as a persuasive argument (Burnstein and Vinokur, 1977).

This paper complements both studies in several respects. First of all, to cleanly isolate the effect of peers, I implement a baseline treatment which allows me to control for changes in ambiguity attitudes due to repeated decision-making. Thus, I control for the possibility that individuals might move towards ambiguity neutral preferences if they are only given the opportunity to reconsider their choices.[7] In this way, I am able to show that significant shifts from ambiguity seeking to ambiguity neutrality occur even if a social anchor is not available. I also abstain from allowing face-to-face interaction between participants since these are not under the control of the experimenter – although direct consultation might induce stronger peer effects.[8] Further, in my experiment subjects do not experience any outcomes between successive decisions (as in the experiment of CKL), as this may cause income effects or changes in ambiguity attitudes through the signal they received. Moreover, I particularly focus on the standard 50/50 Ellsberg setting which has been of most interest in the experimental literature and, hence, in which experimental achievements on individual ambiguity attitudes might be most reliable. Although empirical applications in finance or insurance might often relate to asymmetric distributions, I constitute a foundation of results in a well-studied setting that can be easily extended to, for example, low probability events or

[6] CKL also introduce incentives to persuade peers, which significantly increase peer effects but leaves the tendency towards neutrality at the expense of ambiguity seeking and incoherent attitudes unchanged. KDB additionally elicit decisions made in groups, and compare "shared consequences" to "individual consequences" in outcomes. Group decisions also show a tendency towards ambiguity neutrality, which is largely independent of payoff complementarities. In a different paper on group decision-making, Keller et al. (2007) find that groups exhibit risk and ambiguity aversion and are likely to exhibit a cautious shift when ambiguity is introduced.

[7] This has been neglected in both studies above. KDB implement a control treatment, but only to validate that group choices are closer to ambiguity neutrality compared to individual choices.

[8] Keck and co-authors even state that "subjects were particularly instructed to take into account the opinion and attitudes of group members when making their subsequent individual decisions" (Keck et al., 2011, p. 21).

ambiguity over mixed domains. Moreover, the elicitation method allows me to cleanly distinguish between ambiguity aversion and ambiguity seeking, and provides a measure for the intensity of these attitudes.[9] In this respect, eliciting matching probabilities has been shown to identify ambiguity aversion, neutrality, and seeking in various domains (see, e.g., Kocher et al., 2014). I restrict from using direct choice methods which might stimulate ambiguity aversion (Trautmann et al., 2011), and which would not permit to identify changes in attitudes due to indifference between ambiguity and risk. In the experiment I also minimize any suspicion of subjects that ambiguous lotteries might be stacked against their favors. I do so by letting participants choose their individual decision color which indirectly defines their ambiguous prospect.

Notably, all of the studies mentioned above involve prospects in the gain domain only. But given that numerous experiments documented differences in ambiguity attitudes with respect to the outcome domain, it seems obvious to extend this literature by studying behavior in the gain and loss domain. While there is broad consensus about the persistence of ambiguity aversion in settings that involve prospects over gains of moderate likelihoods, evidence on preferences over ambiguous prospects which involve low likelihood events and/or losses are less clear-cut (see, e.g., Camerer and Weber, 1992). If outcomes refer to losses some studies report ambiguity seeking, while others document ambiguity neutrality as the predominant attitude.[10] I contribute to the literature by showing that individual and social dynamics as well as cognitive ability might shape ambiguity attitudes in very different ways, depending on the specific outcome frame.

Examining the role of peers in decision-making under ambiguity and understanding when and why consultation with others or receiving professional advice might be beneficial, has important implications, e.g., for decision-making in finance. In this respect, field studies highlight the role of observing other people's behavior. For example, Bursztyn et al. (forthcoming) report that investment rates substantially increase if private investors can learn from their peer's investment choice, and if relative payoff concerns might additionally play a role. Cai et al. (forthcoming) examine insurance demand in rural China and observe significant spillover effects of insurance knowledge and experience, ultimately affecting insurance demand. Yet, the particular sources of imitative behavior

[9] CKL use a three-color Ellsberg design and employ a choice list including direct choices between risk and ambiguity. They report a substantial fraction of ambiguity incoherent attitudes, which might be partially due to the fact that the likelihood of the known and ambiguous colors change both at the same time across decision items. KDB elicit certainty equivalents for risky and ambiguous gambles, using multiple choice lists for different likelihoods and degrees of ambiguity. This implies that subjects fill out a considerable number of choice lists with a considerable number of decision items. When receiving feedback about others subjects may learn about their peer's inconsistencies, and, moreover, disentangling effects over time (e.g., individual decisions might be biased towards the end of the task), order effects and peer effects, is statistically demanding.

[10] Ambiguity seeking was reported by Casey and Scholz (1991); Di Mauro and Maffioletti (1996); Ho et al. (2002); Abdellaoui et al. (2005); Chakravarty and Roy (2009); Baillon and Bleichrodt (2013); Kothiyal et al. (2014); ambiguity neutrality was found by Einhorn and Hogarth (1986); Cohen et al. (1987); Mangelsdorff and Weber (1994); Eisenberger and Weber (1995); Du and Budescu (2005); De Lara Resende and Wu (2010); Trautmann and Wakker (2012); Tymula et al. (2012). Some studies also report a fourfold pattern, documenting ambiguity aversion for prospects over gains of moderate likelihoods and losses of low likelihoods, but ambiguity seeking for prospects over gains of low likelihoods and losses of high likelihoods (Hogarth and Kunreuther, 1985; Kahn and Sarin, 1988; Hogarth and Kunreuther, 1989; Viscusi and Chesson, 1999; Di Mauro and Maffioletti, 2004; Vieider et al., 2012).

cannot be completely disclosed, e.g., it is not clear whether such peer effects are due to changes in ambiguity attitudes or due to other factors, such as changes in the willingness to take risk. While disentangling the role of peers is difficult empirically (Manski, 1993), laboratory experiments provide an important complement to field studies to identify the underlying sources of peer effects, by cleanly controlling exogenous variations in the decision-making and social environment. However, experimental studies on social interaction in *ambiguous* choice situations are still rare, in contrast to studies on peer effects in decision-making under *risk*, which have received great attention lately (for a recent survey see Trautmann and Vieider, 2011). This paper takes one step to bridge the gap between field studies on peer effects in decisions under ambiguity, and laboratory studies on peer effects in risk taking. Whether social anchors effects work differently depending on initial individual ambiguity attitudes is just one question which can be tested in the lab.

This paper proceeds as follows. Section 2 describes the experimental design, results are presented in section 3. Section 4 provides a discussion of findings and concludes.

2 Experimental design

I conduct a laboratory experiment and examine individual ambiguity attitudes in the absence and in the presence of feedback about others' choices under ambiguity. By eliciting individual choices twice, in Part 1 and Part 2 of the experiment, and comparing changes in choices across treatments, I control for the variability of ambiguity attitudes, e.g., for any effects which occur through familiarity of subjects with the particular elicitation task.

Part 1 and Part 2 are identical to a large extend: ambiguity attitudes are elicited with respect to the same ambiguous prospect, using the same task which is described in section 2.1. The experiment is then based on a 2×2 between-subjects design with respect to two dimensions, as outlined in detail in section 2.2: first, the outcome domain of lotteries varies between gains and losses. Second, in Part 2, subjects either only face their own choices made in Part 1, or they are additionally provided with a *social anchor*, that is, learn the choice profile of another participant.

After Part 2, subjects face an intelligence test which is independent of any treatment variation. It provides a measure for subjects' cognitive ability and allows to smooth income from Part 1 and 2 which might vary considerably between gain and loss treatments.[11]

Experimental procedure are summarized in section 2.3.

2.1 Elicitation task

Ambiguity attitudes are measured in terms of matching probabilities with respect to an ambiguous prospect which is described by an urn, labeled A in the following.

[11] In this task subjects had to solve ten questions on Raven's progressive matrices (Raven et al., 1998), each incentivized by a piece rate. Details can be received from the author.

Urn A contains in total 100 chips of two different colors (red and blue), reflecting the standard Ellsberg setting of moderate likelihoods with an ambiguity neutral probability $p = 0.5$. The distribution of red and blue chips is *unknown* to both subjects and the experimenter. To ensure credibility and avoid any suspicion that urn A might be biased against subjects, every participant is asked to select his individual decision color (red or blue) in the very beginning of the experiment, i.e., before the instructions for Part 1 are handed out. A subject's decision color indirectly defines the ambiguous prospect that he can choose to play in the experiment: if a chip is drawn from A that is of his individual decision color, he is paid an amount x, and zero otherwise.

In the experiment subjects face a choice list with 21 binary choices between the ambiguous prospect A and different risky lotteries, respectively. The risky lotteries are again represented by urns, each filled with a *known* distribution of 100 chips which are red or blue. In decision item i ($i = 1, \dots, 21$) the respective risky urn, R_i, contains exactly $q_i \cdot 100$ red chips and $(1 - q_i) \cdot 100$ blue chips. Choosing R_i is equivalent to choosing a prospect that pays an amount x if a red chip is drawn from R_i, and zero otherwise. Hence, the color "red" takes on the same role for any R_i as the decision color for the ambiguous prospect A. Within the choice list A and x remain constant, while q_i increases monotonically.

If a subject switches from A to R_j (or vice versa), i.e., in decision item j, his matching probability, denoted by mp, is defined by the midpoint between q_{j-1} and q_j. Thus, mp approximates the probability which makes him indifferent between risk and ambiguity.[12] Comparing mp and p then provides a measure for a subject's ambiguity attitude, taking into account the domain of outcome x (as explained in the following section). Using a choice list instead of eliciting direct choices between a risky (with ambiguity neutral distribution) and ambiguous urn has the particular advantage that it allows to gain a measure for the intensity of ambiguity aversion and ambiguity seeking, and to identify ambiguity neutrality. If subjects would only face a direct choice between a risky and an ambiguous prospect, then ambiguity neutral subjects might make opposite choices in Part 1 and Part 2 simply because they exhibit indifferent preferences.[13]

2.2 Treatment variation

Outcome domain. Expected Utility Theory still serves as the standard normative approach to model decision-making under uncertainty, as formalized by von Neumann and Morgenstern (1947). Yet, in order to explain choices under uncertainty and incorporate behavioral and cognitive biases, Prospect Theory was proposed as a descriptive approach by Kahneman and Tversky (1979). One

[12] More specifically, if a subject switches in decision item $j \in \{1, \dots, 21, \emptyset\}$, where $j = \emptyset$ denotes that he never switches at all, then his matching probability is defined as follows: if $j \neq \emptyset, 1$, mp is the midpoint between q_{j-1} and q_j; if $j = 1$, mp is extrapolated to $q_1 - \frac{1}{2}(q_2 - q_1)$; if $j = \emptyset$, mp is extrapolated to $q_{21} + \frac{1}{2}(q_{21} - q_{20})$. q_i ranges from 0.26 to 0.66, increasing in steps of 0.02; one item also captures the ambiguity neutral probability $p = 0.5$ which would make an ambiguity neutral subject indifferent between choosing the ambiguous and the risky prospect.

[13] I do not explicitly consider ambiguity neutrality. The choice lists are constructed such that matching probabilities are midpoints of the intervals $[0.26,\ 0.28], [0.28,\ 0.30], \dots, [0.64,\ 0.66]$, and hence should never take on value 0.5. Since I am interested in changes in ambiguity attitudes between Part 1 and Part 2, this does not constrain the analysis.

key feature of Prospect Theory is that it assumes changes of wealth relative to a reference point, instead of total wealth, to be carriers of utility, and, moreover, that losses loom larger than gains. Such a framing effect is also commonly observed with respect to risk attitudes and the shape of the utility function which is modeled as concave in the gain domain, reflecting risk aversion, and as concave in the loss domain, reflecting risk loving preferences (Tversky and Kahneman, 1991). As previously noted, similar preference reversals have also been documented in choices under ambiguity (see, e.g., Hogarth and Kunreuther, 1985; Vieider et al., 2012).

To account for differing ambiguity attitudes in the gain and loss domain experimental treatments either involve lotteries defined on the domain of gains or losses, with $x =$ €10 in the gain, and $x = -$€10 in the loss treatments.

In the gain domain, the chance of winning x by choosing R_i increases with each decision item i. In this case, subjects might choose the ambiguous urn A for low likelihoods p_i, but switch to a risky prospect at some j. Hence, if a subject's matching probability mp is smaller than the ambiguity neutral probability p, i.e., $mp < p$, he is classified as *ambiguity averse*, and as *ambiguity seeking* if $mp > p$. In the loss domain, in contrast, the chance of loosing x from choosing R_i increases with each decision item i. Hence, subjects might choose R_i for small probabilities p_i, but switch to the ambiguous urn A at some j. In this case, an individual is classified as *ambiguity seeking* if mp is smaller than p, $mp < p$, and as *ambiguity averse* if $mp > p$.

Social anchor. In Part 2, subjects are given the opportunity to reconsider their choices from Part 1. Therefore, they are shown their own choice profile completed in Part 1. In the individual treatments any information about others' choices is excluded. In the social anchor treatments, in contrast, subjects are randomly assigned to *groups* of two. That is, each subject is randomly matched to another participant in the beginning of Part 2, whom I might refer to as a *peers* in what follows. Additionally to viewing their own choice profiles, they learn the choice profile of their peer. Screenshots of the complete choice lists of the individual as well as the social anchor treatment in Part 2 are provided in Figures 6 and 7, in appendix A. Table 1 summarizes the between-subjects design.

Predictions. Motivated by empirical regularities with respect to imitative behavior commonly observed in the lab (such as in the seminal study of Asch, 1956) and in the field (as previously discussed, among others, in financial decisions; e.g., Bursztyn et al., forthcoming), one may easily come up with the following straightforward predictions. First, if ambiguity attitudes are a stable part of individual preferences, one should expect that choices in Part 1 and Part 2 reflect the same attitudes.

$P1$: In Part 2 subjects exhibit the same ambiguity attitude as in Part 1.

Second, if peer effects are present in decision-making under ambiguity, as identified in risky choices in the lab and in financial choices in the field, then one should expect that imitative behavior lets

Outcome domain	Information (about choice profiles in Part 1 provided in Part 2) Individual	Social anchor
Gain	$x = €10$ Own choices *GAIN-IND*	$x = €10$ Own choices + peer's choices *GAIN-PEER*
Loss	$x = -€10$ Own choices *LOSS-IND*	$x = -€10$ Own choices + peer's choices *LOSS-PEER*
	Two experimental sessions à 20 subjects per treatment	

Notes: x denotes the outcome of the binary prospect, which is different to zero; treatment labels printed in italics.

Table 1: Between-subjects design

peers converge to each others' attitudes.

$P2$: Being provided with a social anchor makes subjects shift in their ambiguity attitudes towards the peers' attitudes.

Third, if shifts occur towards a peer's attitude, then individuals should change their matching probabilities more frequently in the presence than in the absence of a social anchor.

$P3$: Being provided with a social anchor increases the frequency with which subjects change the intensity of their attitudes.

However, as becomes clear in section 3, the dynamics behind changes in ambiguity attitudes seem to be slightly more manifold and hard to capture by plain conjectures.

2.3 Experimental procedures

In the beginning of the experiment, when subjects have not seen any instructions about Part 1, participants receive an initial endowment of €10 and select their individual decision color. Participants also learn that choices from some parts might be shown to other participants in succeeding parts of the experiment. If individuals anticipate negative evaluation by others, as suggested by the "Other-evaluation hypothesis", choices might be biased towards ambiguity aversion in Part 1 and 2, in *all* treatments (as mentioned in the introduction, see Curley et al., 1986). However, subjects are also told that they remain completely anonymous throughout the entire experiment, that outcomes are private information, and that payments are made in private. Hence, I do not expect that this information significantly affects individual ambiguity attitudes.

Risky and ambiguous lotteries are explained by using opaque bags which are filled with plastic chips of different colors. To improve participants' understanding of risky distributions, the composition of colored chips of each R_i ($i = 1, \ldots, 21$) is placed on a table in the middle of the lab room, visible to participants during the experiment (see Figure 5 in appendix A for a picture). For the ambiguous prospect one opaque bag has already been filled with 100 chips at the time when subjects enter the laboratory, and is also placed on that table. I emphasize in the instructions that the distribution of chips is unknown also to me as the experimenter, and I allow participants to inspect the bag when the experiment is finished.[14]

Only Part 1 or Part 2 is randomly chosen, and within each part, only one decision item is determined to be payoff relevant. In the individual treatments, the payoff relevant part and decision item are randomly selected on the subject level. In the social anchor treatments, however, within each group, one group member is paid for Part 1 while the other is paid for Part 2, which is randomly assigned (and common knowledge from the instructions). Then, the payoff relevant decision item is randomly selected on the group level. In this way, each Part is still equally likely for each participant. Further, an individual who exhibits relative payoff concerns with respect to the peer might have an additional incentive to imitate the peer's choices – since his choices in Part 2 can perfectly fit those of the peer from Part 1. This argument holds as long as the individual dislikes social losses more than they suffer from social gains, as already assumed in the classic inequity aversion model by Fehr and Schmidt (1999).[15]

To implement the design in the most transparent way two participants are randomly selected as assistants at the end of the experiment. One assistant fills all risky bags and draws one chip from each risky and from the ambiguous bag, respectively. The other assistant enters the colors on his screen, which determines final payoffs.[16] All instructions are handed out in printed version and read aloud to subjects. Instructions for any part are not handed out before the preceding part is finished. Instructions for the gain domain, for individual and social anchor treatments, are provided in appendix A.

Sessions were run at MELESSA, the Munich Experimental Laboratory for Economic and Social Sciences at the University of Munich, in February 2014. The experiment was computerized using zTree (Fischbacher, 2007). In total 160 subjects participated in 8 experimental sessions, with two sessions and 40 participants per treatment. 55% were female, the average age was 24 years, and 26% were students with an economics or business background.[17] Participants earned on average €15.60 (appr. $21.30 at the time of the experiment) and the experiment lasted roughly one hour.

[14] The composition was truly unknown to the experimenter: a student assistant blindly drew 100 chips out of an opaque bag filled with far more than 100 chips of both colors.

[15] The experimental design can be slightly extended to compare effects from learning the peer's choice profile and from exhibiting distributional preferences. For example, in the social anchor treatments payoff-relevant decision items and parts could be randomly selected on an individual level.

[16] In the interest of time, bags for R_i were only filled for decision problems 9 to 17 (symmetric around $p = 0.5$). For the remaining risky bags of decision problems 1 to 8 and 18 to 21 the computer randomly selected one color, according to the respective distribution of colored chips.

[17] Individual characteristics were balanced across treatments. Tow-sided Fisher exact tests yield p-values above conventional levels (> 0.1) with respect to compositions in gender or economic/non-economic students. Only age differed slightly between GAIN-IND and GAIN-PEER, with average age of 25.1 compared to 22.5 years, respectively; Wilcoxon rank-sum test yields p-value 0.001.

3 Results

In section 3.1 I first briefly comment on the dataset which is used for the empirical analysis. Results on individual ambiguity attitudes are reported in section 3.2. Changes in ambiguity attitudes are analyzed in section 3.3.

3.1 Data

The dataset consists of observations from 160 subjects. A subject's matching probability is derived from his choices in Part 1 and Part 2, denoted by mp_1 and mp_2, respectively.

As common in experiments on individual decision-making that use choice lists, some subjects indicate a conflicting pattern of choices.[18] In particular, a subject might switch from prospect A to R_i (or vice versa) multiple times, since I do not enforce a single switching point in the computer program. As long as his choice in the very first and very last decision item indicates different lotteries (ambiguous or risky), mp can be approximated by the midpoint of matching probabilities defined by the first and last switch.[19] However, if a subject switches an even number of times, in which case his choice in the very first and very last decision item would indicate the same type of prospect, defining a reliable approximation of mp is not possible. Also, as described earlier, a subject should switch from ambiguity to risk in the gain domain, and from risk to ambiguity in the loss domain. A reversed choice pattern does not seem rationalizable and might rather suggest that the participant did not follow the task carefully enough. For the analysis presented below I drop observations of those who exhibit an even number of switching points and who show a reversed pattern of choices in either Part 1 or Part 2 (or both). This leaves us with 35 subjects in GAIN-IND and LOSS-IND, 36 in GAIN-PEER, and 38 in LOSS-PEER.[20]

In the social anchor treatments subjects can be assigned to three categories: those who are more ambiguity averse compared to their peer, those who are less ambiguity averse compared to their peer, and those who exhibit exactly the same attitude as their peer. Technically, distinguishing between these categories is only necessary in the PEER-treatments: while all choices made in Part 1 are independent observations, choices in Part 2 are not statistically independent between group members since peers learn each others' Part 1 choices. Statistical tests, however, mostly require observations to be independent. I therefore assign observations to two groups, with statistically independent observations, each. Comparing matching probabilities in Part 1, I group those subjects who are more ambiguity averse than their peer (Group 1), and those who are less ambiguity averse

[18] Violations of monotonicity are a common phenomenon in experiments, see, e.g., Birnbaum (1992); Birnbaum et al. (1992); Birnbaum and Sutton (1992); Charness et al. (2007); Keck et al. (2011).

[19] Although, given the construction of the choice lists, mp should never take on value 0.5, one subject in Part 1 of LOSS-PEER switches multiple times, first between 0.38 and 0.40, and second between 0.60 and 0.62; taking the midpoint of both respective matching probabilities yields 0.5. Another subject in Part 2 of LOSS-IND also switches multiple times such that mp is estimated as 0.5. Both subjects are classified as ambiguity seeking/neutral.

[20] Results do not change if I generally drop those who switch multiple times. Details can be received from the author.

than their peer (Group 2); if group members exhibit the same attitude one subject is randomly assigned to one group and his peer to the other. Thus, these datasets of independent observations also differ with respect to subjects' *relative* ambiguity attitude. Where applicable I only report test results from two-sided tests, such as for t-tests or Fisher exact tests.

A measure for cognitive ability is given by the the number of correct answers in the intelligence test (Part 3), ranging from zero to 10, with an average of 6.4 scores, and 1.4 standard deviation. Besides age, gender and field of study, I also control for cognitive ability in the regression analyses. Across treatments, cognitive ability does not differ significantly (p-values of Kruskal Wallis tests >0.2 for each treatment comparison). Neither do matching probabilities differ significantly with respect to cognitive ability (rank-sum test; p-values 0.562, 0.681, for Part 1 and 2, respectively).[21]

3.2 Individual ambiguity attitudes

Table 2 summarizes the fraction of ambiguity averse subjects and the median matching probabilities in Part 1 and Part 2, by treatment and subgroup. (Mean values of mp_1 and mp_2 are discussed later in section 3.3.1, but can be found in Table 7 in appendix B, by treatment and subgroup.)

Within treatments, subjects predominantly exhibit ambiguity aversion in the gain domain, while the majority of subjects are classified as ambiguity seeking in the loss domain, in Part 1 and Part 2. Using t-tests and Wilcoxon sign-rank tests median matching probabilities indicate significant ambiguity aversion in the gain domain and significant ambiguity seeking in the loss domain in Part 1; p-values for all samples are provided in Table 6 in appendix B. The cumulative distribution functions of matching probabilities, presented in Figure 1, are in turn left skewed, with means and medians below $p = 0.5$. Comparing Figure 1(a) for Part 1 and Figure 1(b) for Part 2, does not reflect considerable changes, suggesting that the distribution of ambiguity attitudes remains largely unaffected within each treatment. In fact, as given in Table 2, patterns in ambiguity attitudes persists to be significant in Part 2, and on the aggregate level, i.e., pooling data from Group 1 and Group 2 in the social anchor treatments, median values of mp_1 and mp_2 even coincide.

However, distinguishing between those subjects who happened to be more ambiguity averse than their peer (Group 1) and those who were less ambiguity averse than their peer (Group 2), I find a slight shift towards ambiguity neutrality.[22] In contrast, for those who are relatively more ambiguity seeking the median matching probability increases, again by two percentage points.

Across treatments, ambiguity attitudes support the typical two-fold pattern with respect to gains and losses. On the aggregate level, the distributions of ambiguity aversion in Part 1 and Part 2 are significantly different between GAIN and LOSS treatments (χ^2-test and Fisher exact test;

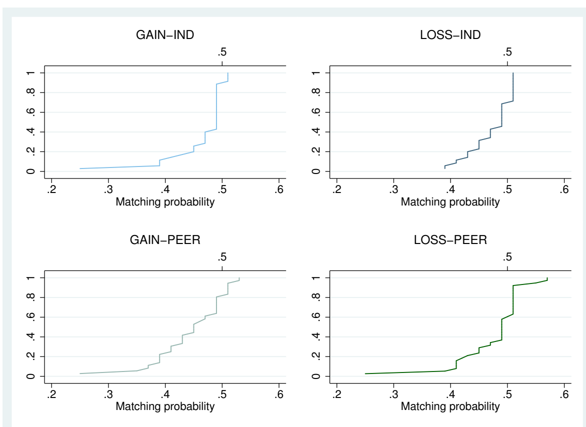
[21] Correlation coefficients between matching probabilities and the numbers of correct answers are -0.16 and 0.16 in the gain and loss domain in Part 1, respectively, and 0.07 and 0.01 in the gain and loss domain in Part 2, respectively.

[22] In GAIN-PEER the median matching probability increases by two percentage points for the relatively more ambiguity averse subjects, while it remains unchanged for the relatively less ambiguity averse. In contrast, in LOSS-PEER the median matching probability does not change for the more ambiguity averse subjects, who are actually not statistically distinguishable from ambiguity neutrality.

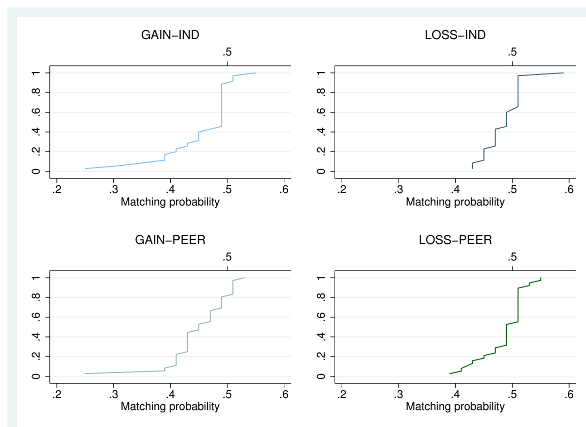
Treatment	N	Part 1 % AA	Part 1 mp_1 [a]	Part 2 % AA	Part 2 mp_2 [a]	% consistent between Part 1 and 2[b]
GAIN-IND	35	88.6%	0.49 AA***	88.6%	0.49 AA***	82.9
LOSS-IND	35	31.4%	0.49 AS***	37.1%	0.49 AS***	82.9
GAIN-PEER	36	80.6%	0.45 AA***	80.6%	0.45 AA***	94.4
Group 1	19	94.7%	0.41 AA***	94.7%	0.43 AA***	100.0
Group 2	17	64.7%	0.49 AA**	64.7%	0.49 AA**	88.2
LOSS-PEER	38	39.5%	0.49 AS**	47.4%	0.49 AS**	81.6
Group 1	19	52.6%	0.51 (AA)	57.9%	0.51 (AA)	73.7
Group 2	19	26.3%	0.47 AS***	36.8%	0.49 AS**	89.5

Notes: N denotes number of observations; AA=ambiguity averse; AS=ambiguity seeking; a: median; b: classified as AA (AS) in Part 1 and in Part 2; two-sided t-test against p=0.5; *** (**, *) denotes significance on level $p < 0.01$ ($p < 0.05$, $p < 0.1$).

Table 2: Distribution of ambiguity attitudes



(a) Part 1



(b) Part 2

Figure 1: Cumulative distribution functions

p-values for all subsamples are provided in Table 8 in appendix B).[23] Moreover, results are more pronounced in Part 1, where differences are significant on the aggregate as well as for each subgroup, compared to Part 2. This variation allows to examine changes in ambiguity attitudes anchored in an aversion against, or a preference for ambiguity.

Across treatments, with respect to the feedback dimension, the distribution of probability equivalents between IND and PEER treatments does not significantly differ in Part 1, as expected (based on rank-sum tests for the distributions of matching probabilities, and χ^2-test and Fisher exact tests for the distributions of ambiguity attitudes; p-values of all tests provided in Table 9, appendix B).[24]

[23] It is not possible to test for differences in ambiguity attitudes by comparing matching probabilities between GAIN and LOSS treatments. While $mp < 0.5$ implies ambiguity aversion in the gain domain, it corresponds to ambiguity seeking in the loss domain. Also, since choice lists are not symmetric around 0.5, recoding mp does not offer a clean approach to test for differences between outcome domains.

[24] Only in Group 1 the relatively more ambiguity averse subjects appear significantly more ambiguity averse in GAIN-PEER compared to GAIN-IND; but this holds for Part 1 as well as for Part 2 (rank-sum test, p-values 0.037

Lastly, Table 2 also reports on consistency: a subject is said to be consistent if he is classified as ambiguity averse (seeking) in Part 1 and in Part 2. On the aggregate level, consistency is high and lies between 81.6% in LOSS-PEER and 94.4% in GAIN-PEER. Moreover, I do not find any systematic relationship between treatment and consistency rates. In support of prediction $P1$, the distribution of attitudes does not differ between Part 1 and 2 for any subgroup (McNemar change test; all p-values>0.1).

3.3 Changes in ambiguity attitudes

So far the data does not suggest substantial changes in ambiguity attitudes itself. However, changes in the intensity of ambiguity attitudes seem to be more frequent. In the following, I say that a *change* in a subject's ambiguity attitude occurs if mp_1 differs from mp_2. I define a *shift* in matching probabilities as the difference $mp_2 - mp_1$. This variable embodies the direction and extent of changes in attitudes.

There might be heterogeneity in the likelihood to change across treatments, which in turn might bias location parameters of shifts in ambiguity attitudes. For example, providing a social anchor might per se influence frequencies of change. I therefore examine shifts in ambiguity attitudes conditional on a change in a first step. In a second step, I examine the likelihood that subjects actually change their matching probability between Part 1 and Part 2.

3.3.1 Shifts in ambiguity attitudes

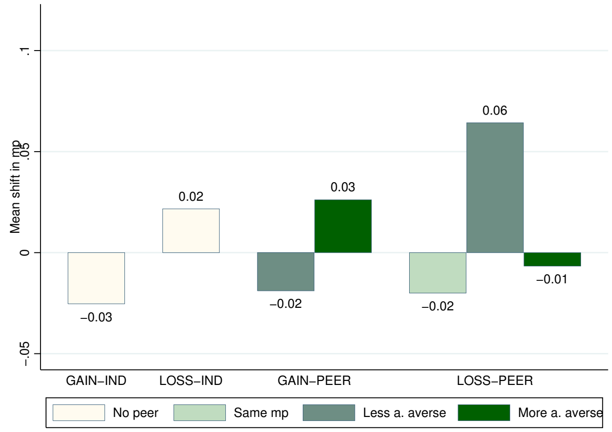
Consider only those who actually change, i.e. $mp_1 \neq mp_2$, who represent 50% of the whole sample (as explicitly discussed later in this section).[25] Then, Figure 2 pictures the average shift in matching probabilities, distinguishing by treatment, and by relative ambiguity attitudes in the PEER treatments. In the individual treatments matching probabilities decrease on average by three percentage points in the gain domain – corresponding to a shift in 1.5 choice items in the choice list – and increase by two percentage points in the loss domain. This shift towards ambiguity neutrality is only significant in the loss domain (Wilcoxon sign-rank test; p-values 0.047).[26]

If a social anchor is available, average matching probabilities do not change on the aggregate in the gain domain (see Table 7, appendix B). Essentially, subjects move towards their peer's attitude: those who are less ambiguity averse than their peer become more ambiguity averse, and vice versa. I observe a similar movement in the loss domain: those who were more ambiguity seeking become more ambiguity neutral. The convergence to peers' attitudes is significant when comparing the

and 0.056 for Part 1 and Part 2, respectively). In order to test Group 1 and Group 2 samples of PEER treatments against comparable subsamples in the IND treatment, subjects are randomly assigned to another participant and classified accordingly. In Part 2, the distribution of ambiguity attitudes still does not differ significantly on the aggregate level.

[25] In total, $mp_1 \neq mp_2$ holds for 15 out of 35 subjects in GAIN-IND, for 18 out of 35 subjects in LOSS-IND, for 22 out of 36 subjects in GAIN-PEER, and for 17 out of 38 subjects in LOSS-PEER.

[26] I provide average values of mp_1 and mp_2, by treatment and subgroup, for those who change and those who do not change in Table 7 in appendix B, where I also report the number of observations in each cluster.



Notes: Bars are based on the following total numbers of observations. IND: GAIN-IND: 15; LOSS-IND: 18. PEER: N=(Same mp_1, less AA, more AA). GAIN-PEER: (-, 9, 13); LOSS-PEER: (1, 7, 9).

Figure 2: Average shift between mp_1 and mp_2 (given change)

absolute difference between matching probabilities of the decision maker and his peer, between Part 1 and Part 2 (Wilcoxon sign-rank test; p-values 0.015, 0.036 for the more and less ambiguity averse in GAIN-PEER, and 0.017 for the less ambiguity averse in LOSS-PEER). Those who were more ambiguity averse (or closer to ambiguity neutrality) in LOSS-PEER move only slightly towards ambiguity seeking, which is not significant (p-value 0.629).[27] Still, the results strongly support prediction $P2$ in the gain domain, namely that subjects tend to shift towards their peers' attitudes.

Overall, if attitudes are volatile and therefore change, then attitudes seem to move towards neutrality in individual conditions. Especially ambiguity seeking in the loss domain appears to be less robust than ambiguity aversion or neutrality, since it significantly attenuates both in the individual and social anchor condition. Moreover, imitative shifts in the gain domain suggest that a social anchor affects individual attitudes differently in the domain of gains compared to losses. This can be summarized as follows.

Result 1 (Shifts in attitudes conditional on changes in mp)**.**

1. *Without social anchor, subjects move towards ambiguity neutrality in the loss domain. A shift towards ambiguity aversion in the gain domain is not significant.*
2. *With social anchor, subjects move towards the peer's ambiguity attitude ($P2$)*
   - *(i) towards both directions in the gain domain, but*
   - *(ii) only towards ambiguity neutrality in the loss domain.*

[27] Similarly, shifts are significantly different from zero for the relatively more ambiguity averse in GAIN-PEER, Wilcoxon sign-rank test, p-value 0.010; for the relatively less ambiguity averse in GAIN-PEER and LOSS-PEER, p-values 0.036 and 0.024; but not for the relatively more ambiguity averse in LOSS-PEER, p-value 0.465.

In a next step, I test whether these dynamics might suppress (or enforce) prevailing attitudes. Therefore, I estimate probit models which regress the likelihood that subjects become more ambiguity neutral. Interdependencies between peers are controlled for by clustering robust standard errors on the group level. Results are reported in Table 3.

In the gain domain, being provided with a social anchor significantly increases the likelihood for a shift towards ambiguity neutrality, relative to the individual treatment as a baseline. This suggests that the slight shift towards aversion in GAIN-IND is counterbalanced in GAIN-PEER, where subjects tend to move towards the peer's attitude, in both directions. It also appears that the ambiguity averse are significantly more likely to move towards neutrality, which is likely due to the scope for becoming even more ambiguity averse being limited. However, this effect is significantly stronger in the IND compared to the PEER condition suggesting that individual attitudes play a more prominent role if a social anchor is not available (model (3); Wald test between coefficients of AA-IND and AA-PEER, p-value < 0.01).

	(1)	(2)	(3)	(4)	(5)	(6)
shift → AN	GAIN	GAIN	GAIN	LOSS	LOSS	LOSS
PEER	0.378**	0.373**	1.354***	-0.057	0.078	0.162
	[0.131]	[0.131]	[0.285]	[0.148]	[0.146]	[0.162]
AA		0.266			-0.454***	
		[0.172]			[0.110]	
AA-IND			1.225***			-0.221
			[0.244]			[0.231]
AA-PEER			0.218			-0.575***
			[0.214]			[0.137]
Cogn. ability	0.146***	0.109***	0.108**	-0.016	-0.011	-0.014
	[0.037]	[0.041]	[0.042]	[0.056]	[0.040]	[0.039]
Observations	37	37	37	35	35	35
Log.-lik.	-18.38	-17.62	-17.50	-20.79	-16.27	-15.65

Notes: Marginal effects of a probit regression on the likelihood to become more ambiguity neutral; independent variables include a dummy variable for PEER treatments, where IND treatments are the baseline category, a dummy variable for AA(-IND, -PEER)=ambiguity aversion (in IND, PEER treatment), and the measure for cognitive ability. I control for gender, age and economic/business studies. Robust standard errors, clustered on group level; *** (**, *) denotes significance on level $p < 0.01$ ($p < 0.05$, $p < 0.1$).

Table 3: Probit model for shifts towards ambiguity neutrality

In the loss domain, in contrast, there is no significant difference in the likelihood to move towards ambiguity neutrality between PEER and IND treatments. This is consistent with the significant shifts towards neutrality in both treatments. Mirroring the previous finding from the gain domain, ambiguity aversion makes a shift towards ambiguity neutrality significantly less likely compared to ambiguity seeking. In this case, being classified as ambiguity averse corresponds an average matching probability of 0.53, with median 0.51, i.e. these subjects are relatively close to neutrality already. Moreover, the effect appears to be driven by the PEER treatment (model (6)). Yet, this might be confounded by a paradigm that is shown in the next section: the majority of subjects who actually change in LOSS-IND is ambiguity seeking already (in contrast to LOSS-PEER), hence, providing more scope for shifts towards neutrality.

Apparently, being of high cognitive ability significantly increases the likelihood for a shift towards neutrality in the gain domain suggesting a cognitive component within ambiguity attitudes, whereas marginal effects are of negligible and insignificant size in the loss domain. Hence, while ambiguity seeking migh instinctively decline, biases towards ambiguity aversion might be overcome by rational reasoning.

Overall, complementing the previous findings, the provision of a social anchor results in different dynamics in the domain of gains compared to losses.

Result 1 (Shifts in attitudes conditional on changes in mp (cont'd.))**.**

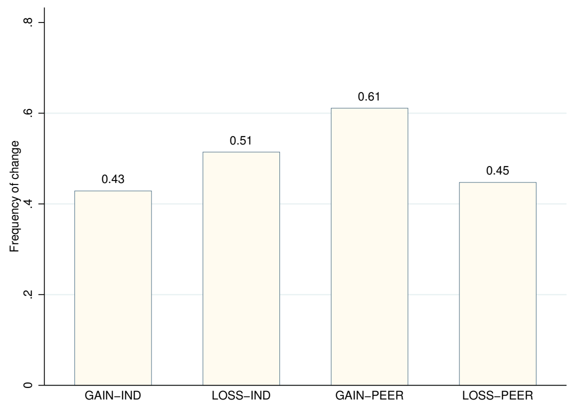
3. *In combination, a social anchor significantly increases the likelihood for a shift towards ambiguity neutrality in the gain, but not in the loss domain.*
4. *Cognitive ability significantly and positively correlates to shifts from ambiguity aversion towards neutrality in the gain domain, while it is not of relevance in the loss domain.*

3.3.2 Frequencies of change

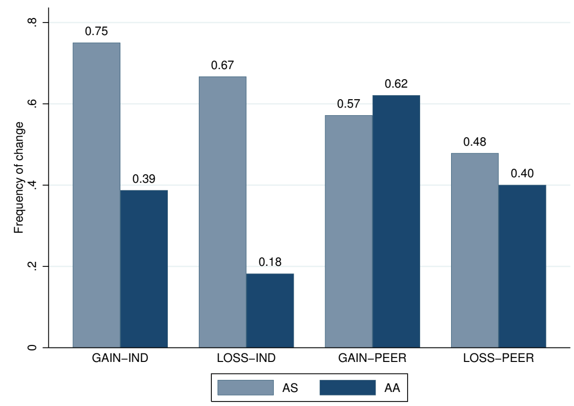
So far, I examined effects conditional on changes in matching probabilities. But how frequent are changes actually? And how do frequencies of change relate to treatment variations? At a first glance, I observe an average frequency of change of 50% over the whole sample. Thus, the intensity of ambiguity attitudes is likely to fluctuate, also if no social anchor is available.

Figure 3 reports the average frequency of change, distinguishing by treatment in subfigure (a), and by treatment and ambiguity aversion in subfigure (b). Figure 3(a) again suggests that social anchor effects differ in their nature between gain and loss domains. Changes are more frequent in the gain domain if a social anchor is available compared to the individual condition. This finding exactly reverses in the loss domain, where changes are in fact less frequent if a social anchor is available compared to the individual condition. Hence, there is no general support for prediction $P3$, namely that the presence of a social anchor makes changes more likely.

However, turning to Figure 3(b), frequencies of change seem to be systematically correlated with individual ambiguity aversion in the individual treatments, independently of the outcome domain. While 75% and 67% of the ambiguity seeking subjects change in the gain and loss domain, respectively, this frequency drops to 39% for the ambiguity averse subjects in the gain domain, and to only 18% for the ambiguity averse subjects in the loss domain. The difference is significant for LOSS-IND (χ^2-test and Fisher exact test; p-values 0.008 and 0.012; p-values for all subsamples considered in Figure 3 provided in Table 10, appendix B), and remains significant on the aggregate



(a) By treatment



(b) By treatment and ambiguity attitude

Notes: Bars are based on the following total numbers of observations. (a) GAIN-PEER: 35; LOSS-IND: 35; GAIN-PEER: 36; LOSS-PEER: 38. (b) N=(AS, AA). GAIN-PEER: (4, 31); LOSS-IND: (24, 11); GAIN-PEER: (7, 29); LOSS-PEER: (23, 15).

Figure 3: Average frequency of change

level, pooling GAIN-IND and LOSS-IND (p-values 0.005, 0.007).[28] In contrast, Figure 3(b) also shows that frequencies of change are not systematical and less affected by ambiguity aversion if a social anchor is available.

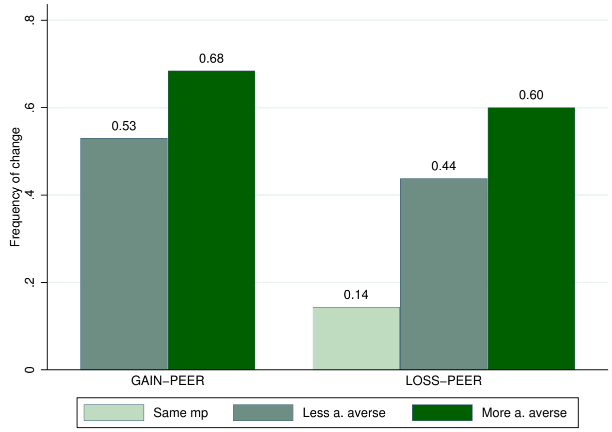
Why does the relationship between an individual's ambiguity aversion and the likelihood to change vanish in the presence of a social anchor? Figure 4 pictures the frequencies of change in both PEER treatments, distinguishing by *relative* ambiguity aversion, i.e. between those who are more ambiguity averse, and those who are less ambiguity averse than their peer (who might also be framed as more ambiguity seeking in the loss domain). In LOSS-PEER, there are also four pairs of peers who indicated the same matching probabilities, which does not occur in GAIN-PEER.[29]

I observe a monotonous relationship between relative ambiguity aversion and the likelihood to change. The finding that subjects who are more ambiguity averse than their peer change more frequently than subjects who are less ambiguity averse, parallels the previous result that ambiguity aversion generally tends to decrease frequencies of change in the individual treatments.

Do these patterns with respect to individual and relative ambiguity aversion possibly interact? To answer this question I estimate probit models which regress the likelihood to change on the presence of a social anchor using the individual condition as the baseline category (model (1));

[28] The difference is not significant in GAIN-IND (p-values 0.167, 0.292). This might be partially due to the fact that the distribution of ambiguity averse and ambiguity seeking subjects is skewed: in GAIN-IND only 11.4% are ambiguity seeking, while the vast majority of 88.6% are ambiguity averse (see Table 2). In contrast, in the distribution in LOSS-IND is more symmetric, with 68.6% being ambiguity seeking and 31.4% being ambiguity averse. If there is a generally negative relationship between ambiguity aversion and the variability of ambiguity attitudes (in the absence of a social anchor), this might (partly) explain why changes are on average less frequent in the gain compared to the loss domain.

[29] In one of these groups, one subject was dropped due to violation of a consistency criterium; thus Figure 4 only covers seven subjects in this group.



Notes: Bars are based on the following total numbers of observations, with N=(same a. attitude, less a. averse, more a. averse). GAIN-PEER: (0, 17, 19); LOSS-PEER: (7, 16, 15).

Figure 4: Average frequency of change by relative ambiguity attitude

controlling for ambiguity aversion of the decision maker (2); and allowing for the possibility that ambiguity aversion has a different impact in the IND compared to the PEER condition (3). Then, I estimate the impact of learning to be less or more ambiguity averse compared to the peer, relative to the baseline of having no social anchor at all (models (4) - (6)).[30]

There are sizable effects in the gain domain; results are reported in Table 4.

The provision of a social anchor increases (though only close to marginal significance) the likelihood to change, consistent with Figure 3(a). Further, being more ambiguity averse than the peer has a positive marginal effect on the likelihood to change relative to the individual condition, significant at the 10% level. Consistent with Figure 4, this does not apply for learning to be less ambiguity averse.[31] This is also consistent with Result 1 *3.*, namely that a social anchor increases shifts towards ambiguity neutrality. While individual ambiguity aversion does not significantly matter, high cognitive ability again has a significant and negative marginal effect on the likelihood to change. This is particularly striking given that initial matching probabilities and cognitive ability are not significantly correlated. Hence, it rather suggests that the confidence in the "correctness" of one own's choices in the standard Ellsberg (gain) setting might correlate with ability in other cognitive tasks.

Turning to the loss domain, results are presented in Table 5. In line with Figure 3(b), ambiguity aversion decreases the likelihood to change, but significantly so only in the individual condition. Again, being provided with a social anchor generally has no significant impact (models (1)-(3)). This suggests that ambiguity seeking goes along with a higher variability of attitudes; but this

[30] Coefficients of interaction terms in non-linear models might be biased in sign (see Ai and Norton, 2003). Thus, I only compare ambiguity aversion in the IND and PEER treatments to ambiguity seeking in all treatments. Additionally, I estimated OLS regressions which yield qualitatively similar results.

[31] Coefficients are, however, not significantly different between PEER×less AA and PEER×more AA; linear hypotheses tests, p-values>0.2.

Likelihood to change	GAIN domain (1)	(2)	(3)	(4)	(5)	(6)
PEER	0.152	0.153	-0.184			
	[0.106]	[0.105]	[0.267]			
PEER				0.051	0.044	-0.204
× less AA				[0.137]	[0.142]	[0.220]
PEER				0.242*	0.244*	-0.048
× more AA				[0.132]	[0.134]	[0.307]
AA		0.017			-0.036	
		[0.142]			[0.161]	
AA-IND			-0.217			-0.221
			[0.254]			[0.252]
AA-PEER			0.173			0.099
			[0.139]			[0.189]
Cogn. ability	-0.110**	-0.111**	-0.111**	-0.118**	-0.115**	-0.114**
	[0.039]	[0.042]	[0.041]	[0.038]	[0.041]	[0.040]
Observations	71	71	71	71	71	71
Log.-lik.	-44.15	-44.15	-43.41	-43.44	-43.42	-42.94

Notes: Marginal effects of a probit regression on the likelihood to change; independent variables are given as in Table 3; dummies PEER×less (more) AA indicate whether the individual is less (more) ambiguity averse than his peer; controls for gender, age and economic/business studies are included. Robust standard errors, clustered on group level; *** (**, *) denote significance on levels $p < 0.01$ ($p < 0.05$, $p < 0.1$).

Table 4: Probit regression for the GAIN domain

relation fades out as soon as a social anchor becomes available.[32] Further, I observe a *reassurance effect*: compared to the baseline of having no social anchor available, those peers who exhibit exactly the same ambiguity attitude are less likely to change. Instead, those who are less or more ambiguity averse than their peer are not significantly different in terms of their likelihood to change, compared to IND. Hence, realizing that attitudes towards ambiguity are similar might serve as a confirmation device. Reflecting Figure 4, marginal effects are significantly different comparing those who are more ambiguity averse to those who have the same attitude as their peer.[33]

Since the impact of individual ambiguity aversion only significantly matters in IND, the reassurance effect vanishes if I only control for a subject's ambiguity aversion (model (5)) but not allow for differences between a subject's ambiguity aversion in IND and PEER (as in model 6). However, I also need to note that those peers who have the same ambiguity attitudes were predominantly ambiguity averse (6 subjects), compared to ambiguity seeking (only 1 subject), which might also drive the overall effect of ambiguity aversion in model (5). As a robustness check, I exclude observations of peers with identical ambiguity attitudes (models (7)-(8)), and the previous result remains

[32]Coefficients of AA-IND and AA-PEER are significantly different based on linear hypothesis test; p-values 0.094, 0.041, 0.063 for models (3), (6), and (8), respectively. I observe the same relationship in the gain domain (Table 4), although effects are not significant in that case.

[33]Linear hypothesis test; p-values=0.056, 0.035 in models (4) and (6).

Likelihood to change	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				LOSS domain				
PEER	-0.050	-0.036	-0.161					
	[0.121]	[0.117]	[0.134]					
PEER				-0.059	-0.253	-0.206	-0.114	-0.194
× less AA				[0.163]	[0.198]	[0.160]	[0.163]	[0.162]
PEER				0.075	-0.114	-0.077	0.112	-0.060
× more AA				[0.154]	[0.159]	[0.175]	[0.154]	[0.176]
PEER				-0.352*	0.107	-0.476**		
× same AA				[0.160]	[0.156]	[0.156]		
AA		-0.225**			-0.222*		-0.252*	
		[0.102]			[0.111]		[0.120]	
AA-IND			-0.445**			-0.432**		-0.442**
			[0.169]			[0.160]		[0.166]
AA-PEER			-0.066			0.024		-0.004
			[0.129]			[0.143]		[0.157]
Cogn. ability	-0.015	-0.004	0.000	-0.011	0.003	0.003	0.003	0.003
	[0.033]	[0.033]	[0.032]	[0.035]	[0.035]	[0.034]	[0.040]	[0.040]
Observations	73	73	73	73	73	73	66	66
Log.-lik.	-48.63	-46.88	-45.62	-46.73	-45.34	-43.69	-42.10	-40.76

Notes: Marginal effects of a probit regression on the likelihood to change; independent variables are given as in Table 4, PEER×same A-attitude is a dummy for whether the subjects has exactly the same ambiguity attitude as his peer; controls for gender, age and economic/business studies are included. Robust standard errors, clustered on group level; *** (**, *) denote significance on levels $p < 0.01$ ($p < 0.05$, $p < 0.1$).

Table 5: Probit regression LOSS domain

unchanged: ambiguity aversion significantly decreases frequencies of change in the absence, but does not play a significant role in the presence of a social anchor.

Result 2 (Frequencies of change)**.**

1. *In the absence of a social anchor individual attitudes matter for the likelihood of change: ambiguity averse subjects change less frequently compared to ambiguity seeking subjects; this is significant in the loss domain.*
2. *The presence of a social anchor affects the likelihood of change in particular circumstances:*
   - *(i) being more ambiguity averse than the peer increase the likelihood to change in the gain domain;*
   - *(ii) having exactly the same ambiguity attitude as the peer significantly decreases the likelihood to change in the loss domain.*

To evaluate the predictive power of the reported regressions I contrast predicted and true values for models (1)-(6) (reported in Table 11, appendix B). Model (6) indeed performs best. While (4) and (5) overestimate the likelihood to change in IND for the ambiguity averse, and underestimate the likelihood to change for the ambiguity seeking subjects, the predictions for the likelihood to change conditional on the relative ambiguity aversion in the PEER treatments remain the same across models (4)-(6).

Given that ambiguity seeking subjects in the loss domain are significantly more likely to change in the individual condition, this attitude might not be particularly robust. Moreover, individual attitudes might even predict the likelihood to change, however, only if a social anchor is not available. For gains and in the presence of a social anchor, those who learn to be more ambiguity averse than their peers switch more often. Based on Result 1 which states that decision makers tend to shift towards their peers' attitudes, this is likely to induce a shift towards neutrality on the aggregate level. Nevertheless, as noted earlier in section 3.2, actual attitudes are indeed quite stable, especially given that the distributions of ambiguity averse and ambiguity seeking subjects do not differ considerably between Part 1 and Part 2.

4 Discussion

In this paper I provide new experimental evidence on the effect of being provided with a social anchor on attitudes towards ambiguity. Hereby, I focus on the standard Ellsberg setting (Ellsberg, 1961), with an ambiguity neutral probability of 50%, for gains and losses. In the experiment matching probabilities are elicited twice, in two consecutive rounds, individually in Part 1, and again in Part 2. In the social anchor treatments, subjects are provided with the choice profile of another participant from the first part when making their choices a second time. To distinguish between the impact of a social anchor and a general anchoring effect, everyone is shown his own complete choice profile from the first part, in the individual and social anchor treatments.

My results generally support the common two-fold pattern of individual ambiguity attitudes, indicating significant ambiguity aversion in the gain domain, and significant ambiguity seeking in the loss domain. These preferences appear stable in the sense that if individuals exhibit ambiguity aversion (seeking) in the first part, roughly 90% also do so in the second part, independent of any treatment variation. In contrast, the intensity of these attitudes does not prove to be as robust; in 50% of all cases subjects' matching probabilities do not coincide between Part 1 and Part 2.

In some respects, the availability of a social anchor seems to have rather weak effects. For example, receiving a social anchor does not significantly alter the likelihood with which subjects change their matching probabilities. In other respects, peers seem to be important. For example, conditional on a change, I mostly observe shifts towards ambiguity neutrality in the individual treatments, while subjects are very likely to converge towards their peer's attitude in the social anchor treatments. However, the analysis suggests that individual dynamics as well as peer effects differ considerably between gains and losses.

In the domain of gains, the individual's ambiguity attitude does not significantly influence the likelihood to change nor the likelihood to shift towards neutrality, neither in the individual nor in the social anchor treatment. However, learning to be more ambiguity averse than a peer significantly increases the likelihood to change, relative to having no social anchor available. That is, the *relative* ambiguity attitude, i.e., the ambiguity attitude compared to the peer's, matters. Further, conditional on a change in matching probabilities, decision makers tend to follow their peer's attitude, towards ambiguity aversion, seeking, or neutrality. Ultimately, receiving a social anchor in the gain treatments predominantly induces comparably ambiguity averse subjects to shift towards ambiguity neutrality.

In the domain of losses, in contrast, individual attitudes matter in the individual treatment, such that ambiguity seeking subjects are significantly more likely to change compared to ambiguity averse subjects. But this relationship breaks down when a social anchor becomes available, where it is again the relative ambiguity attitude that matters, but in a way that learning to have the same attitude as the peer significantly reduces the likelihood to change. I label this a *reassurance effect*. Generally, again in contrast to the gain domain, conditional on a change in matching probabilities, I observe significant shifts only from ambiguity seeking towards neutrality in the loss domain, with and without social anchor, suggesting that ambiguity seeking might not be very robust over time in such settings. This is in line with mixed evidence on ambiguity attitudes in the domain of losses, where some experiments report neutrality while others report a preference for ambiguity.

The persistent finding that cognitive ability significantly and positively correlates to shifts towards neutrality in the standard Ellsberg setting over gains further suggests that the common finding of ambiguity aversion might be driven by bounded rationality of subjects. The fact that no correlation between cognitive ability and ambiguity seeking over losses is found corroborates the conjecture that this attitude might rather be of instinctive and flighty nature.

In summary, I derive three main conclusions. The intensity of ambiguity attitudes is likely to fluctuate, even if no social anchor is available; nevertheless, peers seem to be important for decision-making under ambiguity; and being provided with a social anchor seems to affect individual attitudes differently in the domain of gains compared to losses.

In the introduction I noted that this paper is closely related to the studies by Keck et al. (2011) and Charness et al. (2013), who examine changes in individual ambiguity attitudes after consultation with others. Both studies agree in their result that ambiguity attitudes shift towards neutrality as a result of social interaction. Concordantly, the authors of both studies agree in their hypothesis that ambiguity neutrality might be perceived as a persuasive argument (Burnstein and Vinokur, 1977). The present study replicates this shift towards ambiguity neutrality in the presence of others, but reports two additional findings. First, although the relative ambiguity attitude matters for the likelihood to change, ambiguity aversion over gains might also be corroborated since individuals seem to converge to the peer's attitude in either direction, conditional on a change. Second, in the domain of losses, the shift towards ambiguity neutrality might be present whether or not a social anchor is available.

A crucial difference between this and the other two studies lies in the way in which feedback about others is introduced. The present experiment only provides subjects with information about others choices, while the cited papers allow for face-to-face interaction between peers. Thus, although feedback about others' choices might already cause peer effects in terms of shifts towards the peers' attitudes, establishing ambiguity neutrality as a persuasive argument in individual choices might be not as evident if the social anchor purely refers to hard-coded information instead of discussion or consultation.

The present study is restricted to ambiguity attitudes with respect to symmetric and moderate probabilities. Future research is needed to uncover dynamics behind peer effects in situations in which events occur with small likelihoods, where hopes or fears might drive individual choices (following the terminology of Viscusi and Chesson, 1999). Moreover, in this study I do not disentangle any effects which occur through distributional preferences with respect to the peer, from effects that stem from learning the peer's choices. The fact that I do observe relatively weak social anchor effects might suggest that either channel does not have a substantial impact on individual choices. However, studies on peer effects in risk taking actually suggest that distributional and informational channels might be orthogonal (see, e.g., Cooper and Rege, 2011; Bursztyn et al., forthcoming), i.e., induce different shifts in attitudes independently of each other. Thus, disentangling distributional and informational channels in social anchor effects might be worthwhile to understand how ambiguity attitudes can be shaped by information about others.

This study has important implications with respect to economic behavior where discriminating ambiguity from risk may have detrimental effects. Ambiguity aversion, in particular, has been proposed among economic theorists to explain suboptimal choices in decisions under uncertainty, such as with respect to the stock market participation puzzle (Easley and O'Hara, 2009) or the reluctance to take up (costless) genetic tests (Hoy et al., 2014). In this respect, my study suggests that social interaction – and even individual dynamics over time – might establish neutral preferences towards ambiguity, which might ultimately inhibit adverse effects in decision-making under uncertainty. Finally, my findings suggest that individual dynamics as well as peer effects in ambiguity attitudes might work differently in different outcome domains, and, similarly, that cognitive ability is likely to affect the evaluation of ambiguous events only in some specific settings. Obviously, further research is needed to fully understand in which settings consultation with others or providing professional advice might be particularly beneficial.

References

Abdellaoui, M., F. Vossmann, and M. Weber (2005). Choice-based elicitation and decomposition of decision weights for gains and losses under uncertainty. *Management Science 51*(9), 1384–1399.

Ai, C. and E. C. Norton (2003). Interaction terms in logit and probit models. *Economics Letters 80*(1), 123–129.

Asch, S. E. (1956). Studies of independence and conformity: I. a minority of one against a unanimous majority. *Psychological Monographs: General and Applied 70*(9), 1–70.

Baillon, A. and H. Bleichrodt (2013). Testing ambiguity models through the measurement of probabilities for gains and losses. Working Paper.

Birnbaum, M. H. (1992). Violations of monotonicity and contextual effects in choice-based certainty equivalents. *Psychological Science 3*(5), 310–314.

Birnbaum, M. H., G. Coffey, B. A. Mellers, and R. Weiss (1992). Utility measurement: Configural-weight theory and the judge's point of view. *Journal of Experimental Psychology: Human Perception and Performance 18*(2), 331–346.

Birnbaum, M. H. and S. E. Sutton (1992). Scale convergence and utility measurement. *Organizational Behavior and Human Decision Processes 52*(2), 183–215.

Burnstein, E. and A. Vinokur (1977). Persuasive argumentation and social comparison as determinants of attitude polarization. *Journal of Experimental Social Psychology 13*(4), 315–332.

Bursztyn, L., F. Ederer, B. Ferman, and N. Yuchtman (forthcoming). Understanding mechanisms underlying peer effects: Evidence from a field experiment on financial decisions. *Econometrica*.

Cai, J., A. De Janvry, and E. Sadoulet (forthcoming). Social networks and the decision to insure. *American Economic Journal: Applied Economics*.

Camerer, C. F. (2003). *Behavioral game theory: Experiments in strategic interaction.* Princeton: Princeton University Press.

Camerer, C. F. and M. Weber (1992). Recent developments in modeling preferences: Uncertainty and ambiguity. *Journal of Risk and Uncertainty 5*(4), 325–370.

Casey, J. T. and J. T. Scholz (1991). Boundary effects of vague risk information on taxpayer decisions. *Organizational Behavior and Human Decision Processes 50*(2), 360–394.

Chakravarty, S. and J. Roy (2009). Recursive expected utility and the separation of attitudes towards risk and ambiguity: An experimental study. *Theory and Decision 66*(3), 199–228.

Charness, G., E. Karni, and D. Levin (2007). Individual and group decision making under risk: An experimental study of bayesian updating and violations of first-order stochastic dominance. *Journal of Risk and Uncertainty 35*(2), 129–148.

Charness, G., E. Karni, and D. Levin (2013). Ambiguity attitudes and social interactions: An experimental investigation. *Journal of Risk and Uncertainty 46*(1), 1–25.

Cialdini, R. B. and N. J. Goldstein (2004). Social influence: Compliance and conformity. *Annual Review of Psychology 55*(1), 591–621.

Cialdini, R. B. and M. R. Trost (1998). Social influence: Social norms, conformity and compliance. *The Handbook of Social Psychology 55*(2), 151–192.

Cohen, M., J.-Y. Jaffray, and T. Said (1987). Experimental comparison of individual behavior under risk and under uncertainty for gains and for losses. *Organizational Behavior and Human Decision Processes 39*(1), 1–22.

Curley, S. P., J. F. Yates, and R. A. Abrams (1986). Psychological sources of ambiguity avoidance. *Organizational Behavior and Human Decision Processes 38*(2), 230–256.

De Lara Resende, J. G. and G. Wu (2010). Competence effects for choices involving gains and losses. *Journal of Risk and Uncertainty 40*(2), 109–132.

Di Mauro, C. and A. Maffioletti (1996). An experimental investigation of the impact of ambiguity on the valuationof self-insurance and self-protection. *Journal of Risk and Uncertainty 13*(1), 53–71.

Di Mauro, C. and A. Maffioletti (2004). Attitudes to risk and attitudes to uncertainty: Experimental evidence. *Applied Economics 36*(4), 357–372.

Dow, J. and S. R. d. C. Werlang (1992). Uncertainty aversion, risk aversion, and the optimal choice of portfolio. *Econometrica 60*(1), 197–204.

Du, N. and D. V. Budescu (2005). The effects of imprecise probabilities and outcomes in evaluating investment options. *Management Science 51*(12), 1791–1803.

Easley, D. and M. O'Hara (2009). Ambiguity and nonparticipation: The role of regulation. *Review of Financial Studies 22*(5), 1817–1843.

Einhorn, H. J. and R. M. Hogarth (1986). Judging probable cause. *Psychological Bulletin 99*(1), 3–19.

Eisenberger, R. and M. Weber (1995). Willingness-to-pay and willingness-to-accept for risky and ambiguous lotteries. *Journal of Risk and Uncertainty 10*(3), 223–233.

Ellsberg, D. (1961). Risk, ambiguity, and the savage axioms. *The Quarterly Journal of Economics 75*(4), 643–669.

Ellsberg, D. (1963). [Risk, ambiguity, and the savage axioms]: Reply. *The Quarterly Journal of Economics 77*(2), 336–342.

Epstein, L. G. and M. Schneider (2003). Recursive multiple-priors. *Journal of Economic Theory 113*(1), 1–31.

Epstein, L. G. and M. Schneider (2007). Learning under ambiguity. *The Review of Economic Studies 74*(4), 1275–1303.

Epstein, L. G. and T. Wang (1994). Intertemporal asset pricing under knightian uncertainty. *Econometrica 62*(2), 283–322.

Fehr, E. and K. M. Schmidt (1999). A theory of fairness, competition, and cooperation. *The Quarterly Journal of Economics 114*(3), 817–868.

Fehr, E. and K. M. Schmidt (2006). Chapter 8: The economics of fairness, reciprocity and altruism – experimental evidence and new theories. In S.-C. Kolm and J. M. Ythier (Eds.), *Foundations*, Volume 1 of *Handbook of the Economics of Giving, Altruism and Reciprocity*. Elsevier.

Fellner, W. (1961). Two propositions in the theory of induced innovations. *The Economic Journal 71*(282), 305–308.

Festinger, L. (1954). A theory of social comparison processes. *Human Relations 7*(2), 117–140.

Fischbacher, U. (2007). z-tree: Zurich toolbox for ready-made economic experiments. *Experimental Economics 20*(2), 171–178.

Fox, C. R. and A. Tversky (1998). A belief-based account of decision under uncertainty. *Management Science 44*(7), 879–895.

Fox, C. R. and M. Weber (2002). Ambiguity aversion, comparative ignorance, and decision context. *Organizational Behavior and Human Decision Processes 88*(1), 476–498.

Galí, J. (1994). Keeping up with the Joneses: Consumption externalities, portfolio choice, and asset prices. *Journal of Money, Credit and Banking 26*(1), 1–8.

Gärdenfors, P. (1979). Forecasts, decisions and uncertain probabilities. *Erkenntnis 14*(2), 159–181.

Gebhardt, G. (2004). Inequity aversion, financial markets, and output fluctuations. *Journal of the European Economic Association 2*(2-3), 229–239.

Gebhardt, G. (2011). Investment decisions with loss aversion over relative consumption. *Journal of Economic Behavior and Organization 80*(1), 68–73.

Gilboa, I. and D. Schmeidler (1989). Maxmin expected utility with non-unique prior. *Journal of Mathematical Economics 18*(2), 141 – 153.

Heath, C. and A. Tversky (1991). Preference and belief: Ambiguity and competence in choice under uncertainty. *Journal of Risk and Uncertainty 4*(1), 5–28.

Ho, J. L., L. R. Keller, and P. Keltyka (2002). Effects of outcome and probabilistic ambiguity on managerial choices. *Journal of Risk and Uncertainty 24*(1), 47–74.

Hogarth, R. M. and H. Kunreuther (1985). Ambiguity and insurance decisions. *The American Economic Review 75*(2), 386–390.

Hogarth, R. M. and H. Kunreuther (1989). Risk, ambiguity, and insurance. *Journal of Risk and Uncertainty 2*(1), 5–35.

Hong, H., J. D. Kubik, and J. C. Stein (2004). Social interaction and stock-market participation. *The Journal of Finance 59*(1), 137–163.

Hoy, M., R. Peter, and A. Richter (2014). Take-up for genetic tests and ambiguity. *Journal of Risk and Uncertainty 48*(2), 111–133.

Huber, P. J. (1973). The use of choquet capacities in statistics. *Bulletin of the International Statistical Institute 45*, 181–188.

Kahn, B. E. and R. K. Sarin (1988). Modeling ambiguity in decisions under uncertainty. *Journal of Consumer Research 15*(2), 265–272.

Kahneman, D. (1992). Reference points, anchors, norms, and mixed feelings. *Organizational behavior and human decision processes 51*(2), 296–312.

Kahneman, D. and A. Tversky (1979). Prospect theory: An analysis of decision under risk. *Econometrica 47*(2), 263–292.

Keck, S., E. Diecidue, and D. Budescu (2011). Group decision making under ambiguity. Working Paper.

Keller, L. R., R. K. Sarin, and J. Sounderpandian (2007). An examination of ambiguity aversion: Are two heads better than one? *Judgment and Decision Making 2*(6), 390–397.

Keren, G. and L. E. Gerritsen (1999). On the robustness and possible accounts of ambiguity aversion. *Acta Psychologica 103*(1), 149–172.

Keynes, J. M. (1921). *A treatise on probability.* London: Macmillan & Co.

Knight, F. H. (1921). *Risk, uncertainty and profit.* New York: Hart, Schaffner and Marx.

Kocher, M. G., A. M. Lahno, and S. T. Trautmann (2014). An anatomy of ambiguity attitudes. Working Paper.

Kothiyal, A., V. Spinu, and P. Wakker (2014). An experimental test of prospect theory for predicting choice under ambiguity. *Journal of Risk and Uncertainty 48*(1), 1–17.

Machina, M. J. and D. Schmeidler (1992). A more robust definition of subjective probability. *Econometrica 60*(4), 745–780.

Mangelsdorff, L. and M. Weber (1994). Testing choquet expected utility. *Journal of Economic Behavior & Organization 25*(3), 437 – 457.

Manski, C. F. (1993). Identification of endogenous social effects: The reflection problem. *The Review of Economic Studies 60*(3), 531–542.

Marinacci, M. (2002). Learning from ambiguous urns. *Statistical Papers 43*(1), 143–151.

Muthukrishnan, A. V., L. Wathieu, and A. J. Xu (2009). Ambiguity aversion and the preference for established brands. *Management Science 55*(12), 1933–1941.

Raven, J., J. C. Raven, and J. H. Court (1998). *Manual for Raven's progressive matrices and vocabulary scales.* Oxford Psychologists Press.

Roberts, H. V. (1963). Risk, ambiguity, and the savage axioms: Comment. *The Quarterly Journal of Economics 77*(2), 327–336.

Savage, Leonard, J. (1954). *The foundations of statistics.* New York: Wiley.

Toda, M. and E. H. Shuford (1965). Utility, induced utilities, and small worlds. *Behavioral Science 10*(3), 238–254.

Trautmann, S. T. and F. M. Vieider (2011). Social influences on risk attitudes: Applications in economics. In S. Roeser (Ed.), *Handbook of Risk Theory.* Springer.

Trautmann, S. T., F. M. Vieider, and P. P. Wakker (2008). Causes of ambiguity aversion: Known versus unknown preferences. *Journal of Risk and Uncertainty 36*(3), 225–243.

Trautmann, S. T., F. M. Vieider, and P. P. Wakker (2011). Preference reversals for ambiguity aversion. *Management Science 57*(7), 1320–1333.

Trautmann, S. T. and P. P. Wakker (2012). Making the Anscombe-Aumann approach to ambiguity suited for descriptive applications. Working Paper, Erasmus University.

Tversky, A. and D. Kahneman (1991). Loss aversion in riskless choice: A reference-dependent model. *The Quarterly Journal of Economics 106*(4), 1039–1061.

Tymula, A., P. W. Glimcher, I. Levy, and L. A. Rosenberg Belmaker (2012). Separating risk and ambiguity preferences across the life span: Novel findings and implications for policy. Working Paper, New York University.

Vieider, F., P. Martinsson, and M. Haileselassie (2012). Stake effects on ambiguity attitudes for gains and losses. Working Paper, WZB Berlin.

Viscusi, W. and H. Chesson (1999). Hopes and fears: the conflicting effects of risk ambiguity. *Theory and Decision 47*(2), 157–184.

von Neumann, J. and O. Morgenstern (1947). *The theory of games and economic behavior*. Princeton: Princeton University Press.

Walley, P. (1991). *Statistical reasoning with imprecise probabilities*. London: Chapman and Hall.

Watson, D. and R. Friend (1969). Measurement of social-evaluative anxiety. *Journal of Consulting and Clinical Psychology 33*(4), 448–457.

A Instructions for the GAIN-IND and GAIN-PEER treatments

The instruction for Part I and with respect to general information about the experiment are identical in IND and PEER treatments. Instructions of IND and PEER treatments only differ in a few sentences in Part II. Sentences or words which are included in the PEER but not in the IND treatments are written in blue text color; sentences/words which are included in the IND but not in the PEER treatments are written in green text color.

Welcome to the experiment and thank you for your participation!
Please do not talk to other participants of the experiment from now on.

General information on the procedure

This experiment is conducted to investigate economic decision-making. You can earn money during the experiment. It will be paid to you privately and in cash after the experiment. The entire experiment lasts about 1 hour and consists of 3 parts. At the beginning of each part you will receive detailed instructions. If you have questions after the instructions or during the experiment please raise your hand. One of the experimenters will then answer your question privately. During the experiment you will be asked to make decisions. In the course of the experiment it is possible that other participants will get to know your decisions from a previous part of the experiment. In this case, this will happen anonymously: it is neither possible to allocate your decisions to your seat number or your person, nor to draw conclusions on your payment. Only your own decisions determine your payment, which is a result of the following rules.

Payment

In each part of the experiment your income is directly stated in Euros. Of Part I and Part II only one part will be paid out. Which of both parts will be relevant for payments will be chosen randomly and with equal probability by the computer at the end of the experiment (after Part III). Since you do not know which of the parts (Part I or Part II) will be selected, it is optimal for you to behave as if each part was to be paid out. Part III is definitely relevant for your payment.

In the beginning of the experiment you will also receive an endowment of 10 Euro. Your total income is then given by the sum of your credit, the income of Part III, and the part (I or II) which was selected for payment.

Anonymity

I evaluate all the data of the experiment only in aggregate form and never connect personal information to the data of the experiment. At the end of the experiment you have to sign a receipt for the payment. This only serves for our internal accounting.

Devices

At your place you will find a pen. Please leave it on the table after the experiment.

Start

In the beginning of the experiment I ask you to choose a color, which will be your personal decision color during the experiment. You will learn for what this color is important in the following instructions.

On the first screen a list of colors will be displayed. Please mark exactly one of those colors and confirm your choice by clicking the OK-button in the lower part of the screen. All participants choose from the same list of colors. As soon as every participant has chosen his personal decision color the instructions for the first part of the experiment will be distributed.

Part I

Task

In this part you receive 21 decision problems. These will be displayed simultaneously on your screen. In each of the decision problem you choose between two lotteries. I describe these lotteries with two opaque bags, bag A and bag B. In the end of the experiment one chip will be drawn randomly from each of these bags. This chip will determine your payment, as described further below. Thus, you choose whether your chip should be drawn from bag A or from bag B.

Bag A: Bag A was already filled with exactly 100 colored chips before the experiment. Those chips are either red or blue. The distribution of those colors is unknown to you: a student assistant has randomly drawn 100 chips from a bigger bag that contained far more than 100 chips - only red and blue ones. Thus, you do not know how many of the 100 chips are red or blue.

If you choose bag A, you receive 10 Euro if the color of the chip that will be drawn from bag A is of your personal decision color, and 0 Euro if the chip is of a different color.

Bag B: Bag B also contains in total 100 chips which are either red or blue. How many of the chips are red and blue will be displayed on your screen. If you choose bag B, you receive 10 Euro if the color of the chip that will be drawn from bag B is red, and 0 Euro if the chip is not red.

An example of one decision problem is illustrated in the following table:

Bag A	Bag B	Your decision
Bag A contains exactly 100 chips. You do not know how many of those are red or blue. If a chip is drawn that is of your personal decision color you receive 10 Euro. If a different chip is drawn you receive 0 Euro.	Bag B contains exactly 100 chips of which exactly 16 are red. If a red chip is drawn, you receive 10 Euro. If a different chip is drawn, you receive 0 Euro.	Bag A or Bag B

Example for choice between A and B

Your decision is not valid before you have made a choice for all decision problems and then clicked on the OK-button in the lower part of the screen. Take enough time for your decisions, as each decision can determine your payment from this part.

Payment

After the completion of Part III the computer will randomly choose whether Part I or Part II is relevant for your payment. Both parts will be selected with the same probability. If Part I is relevant for your payment, the computer will randomly and with equal probability select one of the 21 decision problems. Your decision in this problem determines your payment.

In addition, the computer will randomly choose two participants as assistants. For bags B of decision problems 9 to 17 an opaque bag will be filled with the corresponding number of red and blue chips. Assistant no. 1 will then draw one chip from each of those bags, and one chip from bag A, which will determine your payment. Assistant no. 2 will enter the colors of the drawn chips on his screen. In the interest of time, for the remaining bags B of decision problems 1 to 8 and 18 to 21 the computer will randomly draw a chip, corresponding to the respective distribution of red and blue chips.

If, for example, the above decision problem is chosen for you and you have chosen bag B, then you receive 10 Euro if the chip from this bag is red and 0 Euro otherwise. If you have chosen bag A in this decision problem, then you receive 10 Euro if the chip is of your personal decision color that you have chosen in the beginning of the experiment yourself. Since you do not know which of the 21 decision problems will be selected for your payment, it is optimal for you to make your choices as if each decision problem was relevant for payment.

Part II

Task

[PEER] In the beginning of Part II you are randomly assigned to another participant of the experiment, with who you will form a group. Your group number will be displayed on your screen in the beginning. In this part you have the opportunity to reconsider your decision from Part I. Therefore, the 21 decision problems will again be displayed simultaneously on your screen. Simultaneously, you see the decisions that you have made in Part I [PEER] and the decisions that your group member has made in Part I. Part II ends again after you have made all decisions. In this part you should also take enough time for your decisions, as every decision can determine your payment for this part of the experiment.

Payment

In the end of the experiment, the computer will randomly choose for each participant whether Part I or Part II is relevant for payment. [PEER] For each group holds that both members are paid for different parts: if for you part I is paid, then for your group member part II is Paid. If Part II is payoff relevant for you, then your group member is paid for Part I. Part I and Part II are selected with equal probability for every participant. Then, the computer will randomly and with equal probability choose one of the 21 decision problems for each [IND] participant [PEER] group. Your decision in this problem of your respective part determines your payment.

For bags B of decision problems 9 to 17 an opaque bag will be filled with the corresponding number of red and blue chips. Assistant no. 1 will then draw one chip from each of those bags, and one chip from bag A, which will determine your payment. Assistant no. 2 will enter the colors of the drawn chips on his screen. In the interest of time, for the remaining bags B of decision problems 1 to 8 and 18 to 21 the computer will randomly draw a chip, corresponding to the respective distribution of red and blue chips.

Since you do not know which of the 21 decision problems will be selected for payment, it is optimal for you to behave as if each decision problem was relevant for payment.

Figure 5: Picture of lab room

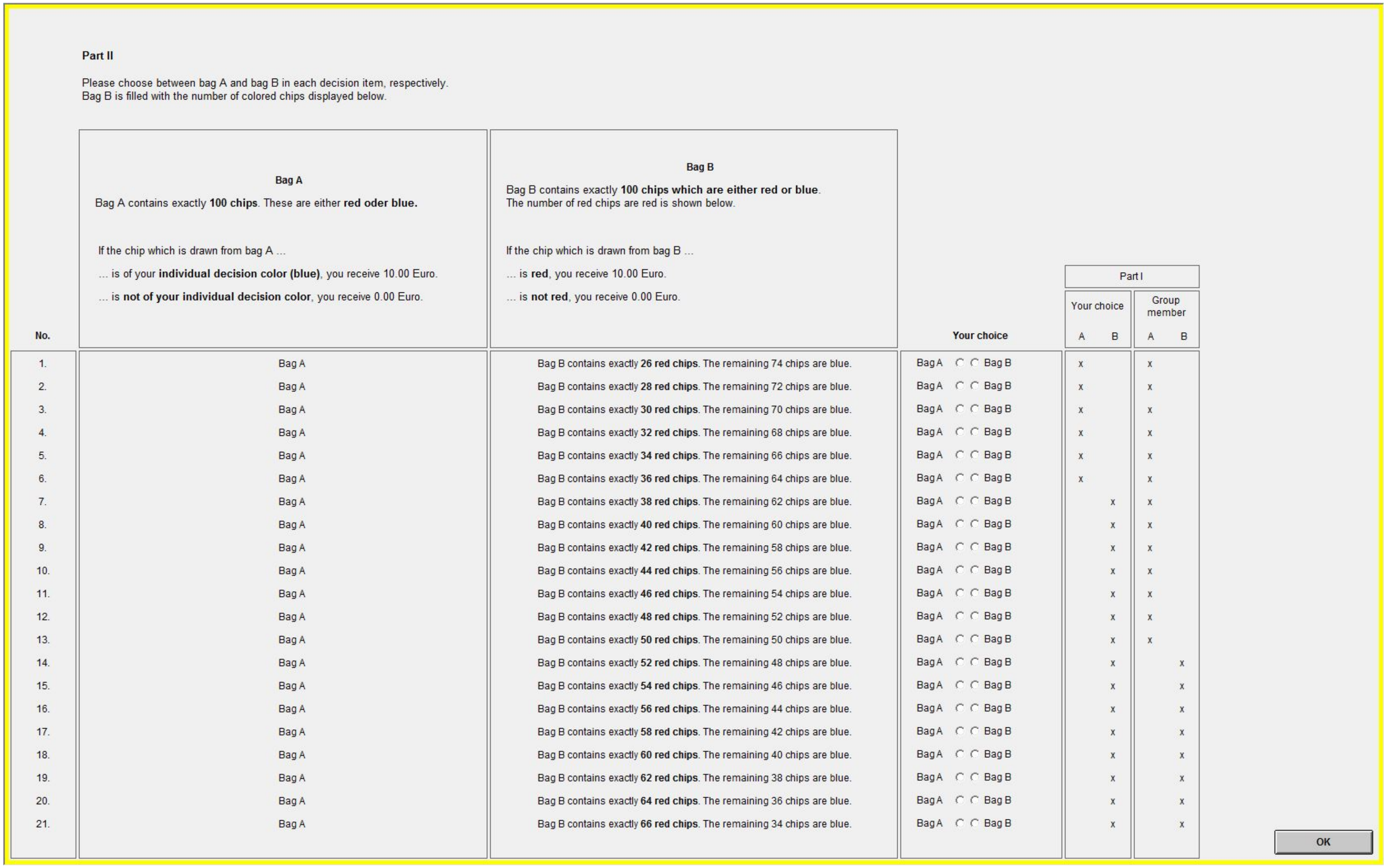
Part II

Please choose between bag A and bag B in each decision item, respectively.
Bag B is filled with the number of colored chips displayed below.

No.	**Bag A** Bag A contains exactly **100 chips**. These are either **red oder blue.** If the chip which is drawn from bag A ... ... is of your **individual decision color (blue)**, you receive 10.00 Euro. ... is **not of your individual decision color**, you receive 0.00 Euro.	**Bag B** Bag B contains exactly **100 chips which are either red or blue**. The number of red chips are red is shown below. If the chip which is drawn from bag B ... ... is **red**, you receive 10.00 Euro. ... is **not red**, you receive 0.00 Euro.	**Your choice**	Part I Your choice A	 B
1.	Bag A	Bag B contains exactly **26 red chips**. The remaining 74 chips are blue.	Bag A ○ ○ Bag B	x	
2.	Bag A	Bag B contains exactly **28 red chips**. The remaining 72 chips are blue.	Bag A ○ ○ Bag B	x	
3.	Bag A	Bag B contains exactly **30 red chips**. The remaining 70 chips are blue.	Bag A ○ ○ Bag B	x	
4.	Bag A	Bag B contains exactly **32 red chips**. The remaining 68 chips are blue.	Bag A ○ ○ Bag B	x	
5.	Bag A	Bag B contains exactly **34 red chips**. The remaining 66 chips are blue.	Bag A ○ ○ Bag B	x	
6.	Bag A	Bag B contains exactly **36 red chips**. The remaining 64 chips are blue.	Bag A ○ ○ Bag B	x	
7.	Bag A	Bag B contains exactly **38 red chips**. The remaining 62 chips are blue.	Bag A ○ ○ Bag B		x
8.	Bag A	Bag B contains exactly **40 red chips**. The remaining 60 chips are blue.	Bag A ○ ○ Bag B		x
9.	Bag A	Bag B contains exactly **42 red chips**. The remaining 58 chips are blue.	Bag A ○ ○ Bag B		x
10.	Bag A	Bag B contains exactly **44 red chips**. The remaining 56 chips are blue.	Bag A ○ ○ Bag B		x
11.	Bag A	Bag B contains exactly **46 red chips**. The remaining 54 chips are blue.	Bag A ○ ○ Bag B		x
12.	Bag A	Bag B contains exactly **48 red chips**. The remaining 52 chips are blue.	Bag A ○ ○ Bag B		x
13.	Bag A	Bag B contains exactly **50 red chips**. The remaining 50 chips are blue.	Bag A ○ ○ Bag B		x
14.	Bag A	Bag B contains exactly **52 red chips**. The remaining 48 chips are blue.	Bag A ○ ○ Bag B		x
15.	Bag A	Bag B contains exactly **54 red chips**. The remaining 46 chips are blue.	Bag A ○ ○ Bag B		x
16.	Bag A	Bag B contains exactly **56 red chips**. The remaining 44 chips are blue.	Bag A ○ ○ Bag B		x
17.	Bag A	Bag B contains exactly **58 red chips**. The remaining 42 chips are blue.	Bag A ○ ○ Bag B		x
18.	Bag A	Bag B contains exactly **60 red chips**. The remaining 40 chips are blue.	Bag A ○ ○ Bag B		x
19.	Bag A	Bag B contains exactly **62 red chips**. The remaining 38 chips are blue.	Bag A ○ ○ Bag B		x
20.	Bag A	Bag B contains exactly **64 red chips**. The remaining 36 chips are blue.	Bag A ○ ○ Bag B		x
21.	Bag A	Bag B contains exactly **66 red chips**. The remaining 34 chips are blue.	Bag A ○ ○ Bag B		x

OK

Figure 6: Screenshot: Part 2 – individual condition (IND)



Part II

Please choose between bag A and bag B in each decision item, respectively.
Bag B is filled with the number of colored chips displayed below.

No.	**Bag A** Bag A contains exactly **100 chips**. These are either **red oder blue.** If the chip which is drawn from bag A ... ... is of your **individual decision color (blue)**, you receive 10.00 Euro. ... is **not of your individual decision color**, you receive 0.00 Euro.	**Bag B** Bag B contains exactly **100 chips which are either red or blue**. The number of red chips are red is shown below. If the chip which is drawn from bag B ... ... is **red**, you receive 10.00 Euro. ... is **not red**, you receive 0.00 Euro.	**Your choice**	Part I: Your choice A	Part I: Your choice B	Part I: Group member A	Part I: Group member B
1.	Bag A	Bag B contains exactly **26 red chips**. The remaining 74 chips are blue.	Bag A ○ ○ Bag B	x		x	
2.	Bag A	Bag B contains exactly **28 red chips**. The remaining 72 chips are blue.	Bag A ○ ○ Bag B	x		x	
3.	Bag A	Bag B contains exactly **30 red chips**. The remaining 70 chips are blue.	Bag A ○ ○ Bag B	x		x	
4.	Bag A	Bag B contains exactly **32 red chips**. The remaining 68 chips are blue.	Bag A ○ ○ Bag B	x		x	
5.	Bag A	Bag B contains exactly **34 red chips**. The remaining 66 chips are blue.	Bag A ○ ○ Bag B	x		x	
6.	Bag A	Bag B contains exactly **36 red chips**. The remaining 64 chips are blue.	Bag A ○ ○ Bag B	x		x	
7.	Bag A	Bag B contains exactly **38 red chips**. The remaining 62 chips are blue.	Bag A ○ ○ Bag B		x	x	
8.	Bag A	Bag B contains exactly **40 red chips**. The remaining 60 chips are blue.	Bag A ○ ○ Bag B		x	x	
9.	Bag A	Bag B contains exactly **42 red chips**. The remaining 58 chips are blue.	Bag A ○ ○ Bag B		x	x	
10.	Bag A	Bag B contains exactly **44 red chips**. The remaining 56 chips are blue.	Bag A ○ ○ Bag B		x	x	
11.	Bag A	Bag B contains exactly **46 red chips**. The remaining 54 chips are blue.	Bag A ○ ○ Bag B		x	x	
12.	Bag A	Bag B contains exactly **48 red chips**. The remaining 52 chips are blue.	Bag A ○ ○ Bag B		x	x	
13.	Bag A	Bag B contains exactly **50 red chips**. The remaining 50 chips are blue.	Bag A ○ ○ Bag B		x	x	
14.	Bag A	Bag B contains exactly **52 red chips**. The remaining 48 chips are blue.	Bag A ○ ○ Bag B		x		x
15.	Bag A	Bag B contains exactly **54 red chips**. The remaining 46 chips are blue.	Bag A ○ ○ Bag B		x		x
16.	Bag A	Bag B contains exactly **56 red chips**. The remaining 44 chips are blue.	Bag A ○ ○ Bag B		x		x
17.	Bag A	Bag B contains exactly **58 red chips**. The remaining 42 chips are blue.	Bag A ○ ○ Bag B		x		x
18.	Bag A	Bag B contains exactly **60 red chips**. The remaining 40 chips are blue.	Bag A ○ ○ Bag B		x		x
19.	Bag A	Bag B contains exactly **62 red chips**. The remaining 38 chips are blue.	Bag A ○ ○ Bag B		x		x
20.	Bag A	Bag B contains exactly **64 red chips**. The remaining 36 chips are blue.	Bag A ○ ○ Bag B		x		x
21.	Bag A	Bag B contains exactly **66 red chips**. The remaining 34 chips are blue.	Bag A ○ ○ Bag B		x		x

OK

Figure 7: Screenshot: Part 2 – social feedback (PEER)

B Supplementary tables and figures

	Part 1		Part 2	
Treatment	t-test	signrank test	t-test	signrank test
GAIN-IND	0.000	0.000	0.000	0.000
LOSS-IND	0.000	0.001	0.010	0.011
GAIN-PEER	0.000	0.000	0.000	0.000
Group 1	0.000	0.000	0.000	0.000
Group 2	0.081	0.087	0.020	0.031
LOSS-PEER	0.020	0.039	0.046	0.168
Group 1	0.701	0.735	1.000	0.569
Group 2	0.004	0.005	0.019	0.036

Notes: two-sided t-test and Wilcoxon sign rank test; both test null hypothesis that matching probability is equal to 0.5 (ambiguity neutrality). Median matching probabilities are given in Table 2 in section 3.2.

Table 6: P-values for ambiguity attitudes

	No change		Change			Whole sample		
	Part 1 / 2	N	Part 1	Part 2	N	Part 1	Part 2	N
GAIN-IND	0.46	20	0.48	0.45	15	0.47	0.46	35
LOSS-IND	0.50	17	0.45	0.47	18	0.47	0.49	35
GAIN-PEER	0.46	14	0.44	0.44	22	0.45	0.45	36
Group 1	0.44	6	0.40	0.43	13	0.41	0.43	19
Group 2	0.48	8	0.49	0.47	9	0.49	0.48	17
LOSS-PEER	0.48	21	0.48	0.50	17	0.48	0.49	38
Group 1	0.49	10	0.51	0.51	9	0.50	0.50	19
Group 2	0.46	11	0.44	0.49	8	0.45	0.47	19

Table 7: Average mp_1 and mp_2 by changes in matching probabilities

Part 1		GAIN vs. LOSS	GAIN-IND vs. LOSS-IND	GAIN-PEER vs. LOSS-PEER
χ^2-test	Aggregate	0.000	0.000	0.000
	Group 1	0.000	–	0.003
	Group 2	0.000	–	0.021
Fisher exact test	Aggregate	0.000	0.000	0.000
	Group 1	0.000	–	0.008
	Group 2	0.000	–	0.042
Part 2		GAIN vs. LOSS	GAIN-IND vs. LOSS-IND	GAIN-PEER vs. LOSS-PEER
χ^2-test	Aggregate	0.000	0.000	0.003
	Group 1	0.009	–	0.008
	Group 2	0.000	–	0.095
Fisher exact test	Aggregate	0.000	0.000	0.004
	Group 1	0.017	–	0.019
	Group 2	0.000	–	0.181

Notes: χ^2-test and two-sided Fisher exact test to test for differences between the composition of ambiguity averse, neutral and seeking subjects between GAIN and LOSS treatments.

Table 8: P-values for differences in ambiguity attitudes in GAIN vs. LOSS

Part 1		IND vs. PEER	GAIN-IND vs. GAIN-PEER	LOSS-IND vs. LOSS-PEER
rank-sum test	Aggregate	0.748	0.137	0.435
	Group 1	0.346	0.037	0.672
	Group 2	0.513	1.000	0.472
χ^2-test	Aggregate	0.947	0.351	0.473
	Group 1	0.897	0.969	0.858
	Group 2	0.978	0.244	0.101
Fisher exact test	Aggregate	1.000	0.514	0.625
	Group 1	1.000	1.000	1.000
	Group 2	1.000	0.438	0.182
Part 2		IND vs. PEER	GAIN-IND vs. GAIN-PEER	LOSS-IND vs. LOSS-PEER
rank-sum test	Aggregate	0.979	0.476	0.403
	Group 1	0.249	0.056	0.673
	Group 2	0.160	0.194	0.531
χ^2-test	Aggregate	0.935	0.351	0.377
	Group 1	0.506	0.132	0.842
	Group 2	0.622	0.007	0.083
Fisher exact test	Aggregate	1.000	0.514	0.478
	Group 1	0.604	0.180	1.000
	Group 2	0.641	0.018	0.128

Notes: Wilcoxon rank-sum test to test for differences in the distribution of *mp* between IND and PEER treatments; χ^2-test and two-sided Fisher exact test to test for differences between the composition of ambiguity averse and seeking subjects between IND and PEER treatments.

Table 9: P-values for differences in ambiguity attitudes in IND vs. PEER

Treatment	χ^2-test	Fisher exact test
All	0.089	0.126
GAIN	0.405	0.518
LOSS	0.029	0.049
IND	0.005	0.007
PEER	0.701	0.814
GAIN-IND	0.167	0.292
LOSS-IND	0.008	0.012
GAIN-PEER	0.810	1.000
Group 1	0.130	0.316
Group 2	0.402	0.620
LOSS-PEER	0.635	0.744
Group 1	0.809	1.000
Group 2	0.243	0.338

Notes: χ^2-test and two-sided Fisher exact test to test for differences in the likelihood to change between Part 1 and Part 2 between ambiguity averse and ambiguity seeking subjects.

Table 10: P-values for differences in frequencies of change across ambiguity attitudes

	GAIN-IND		LOSS-IND		GAIN-PEER		LOSS-PEER		
Predictions model (1)	0.43		0.51		0.62		0.45		
True values	*0.43*		*0.51*		*0.61*		*0.45*		
	AA	AS	AA	AS	AA	AS	AA	AS	
Predictions model (2)	0.42	0.55	0.31	0.61	0.60	0.70	0.30	0.54	
Predictions model (3)	0.39	0.76	0.18	0.67	0.62	0.58	0.40	0.48	
True values	*0.39*	*0.75*	*0.18*	*0.67*	*0.59*	*0.69*	*0.40*	*0.48*	
					less AA	more AA	same AA	less AA	more AA
Predictions model (4)	0.43		0.51		0.53	0.68	0.15	0.44	0.60
	0.42	0.56	0.46	0.54					
Predictions model (5)	0.43		0.51		0.53	0.68	0.15	0.43	0.60
	0.41	0.59	0.32	0.60					
Predictions model (6)	0.43		0.51		0.53	0.68	0.14	0.44	0.60
	0.39	0.76	0.18	0.67					
True values	*0.43*		*0.51*		*0.53*	*0.68*	*0.14*	*0.44*	*0.60*
	0.39	*0.75*	*0.18*	*0.67*					

Notes: Predicted values for the likelihood to change based on models (1)-(4) from Tables **??** and 5.

Table 11: Model predictions for likelihood to change