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Social learning under ambiguity - an experimental study

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Abstract

The social media age has meant that many behaviours spread through contact with others. The extent to which people adopt/imitate behaviour they observe, can critically affect whether policymakers are successful when introducing new initiatives. In many situations people can either make decisions based on their own intuitive signals or follow a social signal. Depending on the quality of the signals one might be more informative than the other. This project aims to better understand how people use social information to learn and imitate others in ambiguous situations, when both the private and the social signal are not perfectly informative. We conduct an experimental study that observes whether people are prone to imitate others in risky and ambiguous environments, and in gain and loss domain settings. We find that individuals do significantly learn from social information, independent of the framing. Social learning behaviour is not significantly affected by ambiguity.

JEL Classification: C91, D81, D82, D83

Keywords: risk; ambiguity; imitating; social learning

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1 Introduction

In many situations we observe a strong relationship between decisions made by an individual and her peers. These peer based effects are documented for example, for prosocial behaviour such as donating to charities, paying taxes or 'green' consumption decisions, for anti-social behaviour such as crime, vandalism and drug misuse and also for saving and investment decisions.[1]

These decision problems have in common that to a degree they involve unknown probabilities and thus, uncertainty can play an important role. The uncertainty can be both, either about the probability of an outcome or about not knowing what might be the best option for oneself. In this study, we want to explore the role of an uncertain environment on decision making and peer group effects.

Our starting point is the experimental study by Cooper and Rege (2011), who observe that with increasing uncertainty, subjects are more likely to imitate others. They focus on the role of social interaction based motives, where social interaction based motives include all motives in which the own utility is affected by the choices within a group, similar to other regarding preferences. For example losing a lottery is bad, but being the only one losing is worse and thus, as they describe it in their title, misery loves company.

Different to Cooper and Rege (2011), we do not look for an effect of uncertainty on social interaction based motives, but on the social learning motive. In contrast to accounting for an effect driven by other regarding preferences, a social learner imitates because of optimising the individual utility based on the outcome. We investigate whether people are more open to social learning if the environment is more uncertain or more ambiguous?

Knowing whether increased imitating behaviour under uncertainty can be attributed to both social learning and social interaction based motives is a relevant question. If a person imitates a group because of social interaction effects, for example to avoid social regret or social envy, the person might not repeat the decision if the reference group or strength of social interaction based motives changes. In contrast a social learner might without new information not adapt her choice. In our experiment, we remove social interaction effects from individuals' utility function and check if social learning takes place independent of social interaction.

The decision whether someone will imitate the group behaviour because of social learning, can be described as the scenario where a social signal is more informative in comparison to a private signal. The private signal could represent the individual's first intuitive preference. The social signal represents the most popular choice within a group. Obviously, if one signal, either the private or the social signal is getting more (or less) informative this has an effect on which signal to follow. For instance, if the social signal is based on an expert who is very well informed, it would be better to follow the social signal,

[1]see Hong et al. (2004); Duflo and Saez (2003, 2002); Falk and Fischbacher (2002); Madrian and Shea (2001); Kelly and O Grada (2000)

rather than a private one.

But what happens if both signals are of the same poor quality? This can be the case if subjective probabilities are hard to estimate and the situation is ambiguous and complex. In such a situation with just a private signal, an individual might be unsure about what to do and behave erratically. It might seem intuitive to follow the social signal (almost like a "wisdom of the crowd" scenario). But, the social signal may be based on the same kind of information as the individual has herself - so it is not clear whether she should follow this signal or not. Whether one would expect more openness for social learning under increased uncertainty depends on whether individuals put more weight on the social signal relative to the private one.

We conduct an experimental study to investigate such a scenario. We examine whether and to what extent, ambiguity affects social learning in groups. Using an experimental study allows us to construct comparable risk and ambiguity environments and thereby control and exclude potential confounding factors. Most importantly, we exclude social interaction based motives by implementing a strict independent payoff rule. This allows us to observe an as pure as possible effect of the uncertain environment on social learning. Additionally, we account for framing effects, by using both a loss and a gain frame.

We find evidence for the initial choices to be affected by ambiguity and we do observe social learning in our experiment. Interestingly, we observe that the level of ambiguity does not significantly affect social learning behaviour. In contrast we report that ambiguity is very unlikely to affect social learning (p-value=0.98). We conclude that the openness for social learning is relatively robust in the presence of ambiguity. This indicates that if (as in other studies) observed ambiguity causes increased imitating behaviour, this effect is driven by different mechanisms such as social interaction effects and not by social learning.

1.1 Related Literature

Our research contributes to the literature of decision-making under risk and uncertainty and decision-making in groups. There already exists a number of studies showing that social interaction is affecting decision-making under risk (see Karakostas et al., 2021; Steiger and Pelster, 2020; Gantner and Kerschbamer, 2018; Lahno and Serra-Garcia, 2015; Fahr and Irlenbusch, 2011). These studies find that people change their behaviour, i.e. imitate others or conform to the group consensus once they learn the choices of others. Trying to better understand when and why people imitate others, one can classify the motives into social interaction based and social information based.

Duffy et al. (2021) highlights that both can be relevant motives. In their study, they test whether subjects are able to identify whether a social signal or a private signal is more informative. As in the real world, in this study, in some situations imitating is optimal while in other situations it is not. They find that some imitation could be classified as rational social learning and some might be due to social interaction motives. Similarly Heap (2014) and Cooper and Rege (2011) show that subjects update their choice and even change their preferences, even if there is nothing rational to learn as all information about the problem is already available.

Looking at ambiguous situations, we know that subjects react to ambiguity by significantly adapting their behaviour, compared to situations in which they are aware of the probabilities. There is a growing literature that considers how players react to ambiguous situations in lab settings. For instance, Calford (2021) and Kelsey and le Roux (2015) find that ambiguity-averse subjects display a preference for randomisation in game theoretic experiments. Studies by le Roux (2020); Kelsey and le Roux (2017a,b, 2015) show that if an ambiguity-safe option is available, individuals opt for it significantly more often than other options available to them. This is true in single-person decisions as well as in games. Eichberger et al. (2012) observe that subjects in a two-stage game, no longer prefer betting on events with known proportions if they no longer know the consequences, that is, fewer subjects prefer to bet on events with known proportions once a second source of ambiguity is in place. In our case, the social signal should have the reverse effect.

Cooper and Rege (2011) report that with increasing ambiguity one can also observe more imitating behaviour. However, the underlying mechanism for this effect is not clear because in their experimental design one cannot cleanly disentangle between pure social learning and social interaction effects. Thus it is not clear how imitating behaviour in the form of rational social learning is affected by the environment. Interestingly the question how social learning is affected by ambiguity is already raised by Cooper and Rege (2011) and more recently by Karakostas et al. (2021). One contribution of the current study is directly responding to this question.

The seminal paper of Kahneman and Tversky (1979) established that people also responded differently, depending on whether they were making a decision in a gain or loss domain. In particular, it has been documented that people generally react more acutely in the loss domain and are more sensitive to losses than to gains. This type of behaviour has been confirmed by a large number of experimental studies, in various different settings over the years (see Baumeister et al., 2001; Halek and Eisenhauer, 2001; Chandler et al., 2009; Binswanger and Sillers, 1970). In this paper, we test social learning in both the gain and loss domains, to check if there is any difference in subject behaviour and whether subjects are more likely to display social learning in the loss domain when compared to the gain domain.

2 Experimental Design

Our paper adapts the experimental design employed by Cooper and Rege (2011). In order to observe the effect of ambiguity on social learning we create two environments, a risky environment and an ambiguous one. The environments differ by the type of choice problems used. Subjects are presented with two matrices in which elements have different payoffs indicated by colour.[2] The expected value of the matrices differ by the frequency of colours contained.

The ambiguous setting differs from the risk environment in two ways. Firstly, in the risk setting, the payoff of all elements is visible to the subject, whereas in the ambiguous setting, the payoff of some elements is "hidden". We use the colour grey to indicate these unknown payoff elements. Secondly, in the risky environment, the elements are sorted by colour, whereas in the ambiguous environment the elements are scrambled. Thus in the risky environment, the approximate expected payoff of a matrix can be deduced more easily, compared with the ambiguous environment where the expected payoff and the variance may be harder to estimate within the given decision time of 30 seconds. Figure 1 presents an example for a lottery ticket from the risk environment on the left side and the ambiguous environment on the right side.

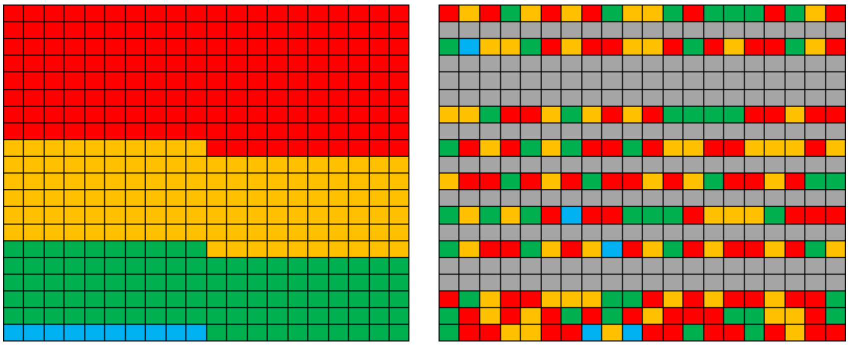

Figure 1: Example of risky and ambiguous lottery tickets

All subjects make decisions for both environments. The order of the environments in which each participant makes a decision is flipped across treatments. This allows us a between-subject and also a within-subject comparison, controlling for possible order effects in the environment presented second.[3]

Each environment consist of five rounds. Each round follows the same sequence, which consists of two parts. In the first part, subjects make individual choices between a set of two lotteries(see Figure 2): At the top of the page, subjects see a short description of their task and in the middle, a legend in form of a colour code reminds the subject about the value of each colour. The first part aims to elicit the initial preferences between the two lottery tickets presented in the problem.

In the second part, subjects learn what the majority of their group did in the previous part and have the opportunity to revise their choice. They receive this information using the following structure: "Most people in your group selected the (left/right) lottery". The information was graphically displayed (see Figure 3). We use groups of four subjects, to ensure the possibility of a majority choice within the

[2]The payoffs associated with the coloured cells are as follows: Red = 0 EUR, Yellow = 5 EUR, Green = 12 EUR and Blue = 60 EUR.

[3]We additionally ask subjects to make choices for 2 more rounds in a semi-ambiguous environment at the end of the experiment. In the semi-ambiguous environment, we only implement one feature to increase ambiguity - the matrices are scrambled but no grey elements are used.

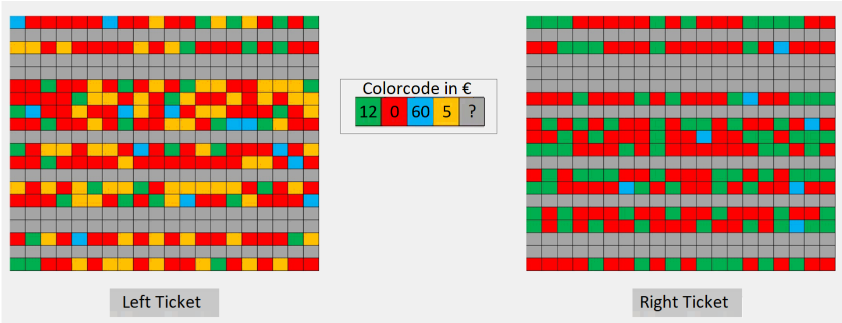

Figure 2: Initial choice between two tickets

group (example, 3 Left/1 Right or 1 Left/3 Right).

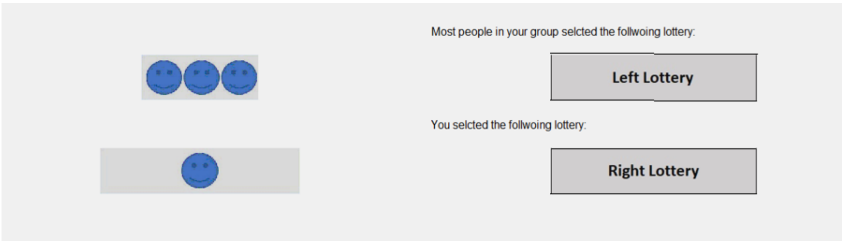

Figure 3: Learning the popular choice

In order to test for framing effects, we present the lottery tickets with either a loss or a gain frame. In the gain-framing, the values of the coloured elements are positive, with associated payoffs values as previously discussed. In the loss-framing, subjects receive an endowment of 60 EUR and the value of the coloured elements are negative.[4]

As we are only interested in strictly measuring the magnitude of social learning, we aim to exclude all confounding factors. To ensure salience and that each decision is equally relevant for everybody and to exclude subjects hedging between rounds, only one decision was selected to be payoff-relevant.

In order to exclude the effect of social interaction based motives such as envy or regret, where subjects might imitate the answer of others in the group in order to get the same level of payoff as they do, we implement a strictly independent payment mechanism. In our experiment, subjects were told that each question would be payoff-relevant for only one person in the group. By doing this, we take away a possible reference or comparison point, so no two people within a group get paid for the same problem, and can therefore not compare their outcomes/feel envy or regret about their choice.

After observing the subjects in the main experiment, we use a mixture of hypothetical choice problems and a questionnaire to learn more about their individual characteristics. Using three hypothetical choices, we elicit risk-aversion using Holt and Laury (2005) and ambiguity-aversion using Ellsberg (1961) style questions and then elicit their willingness to pay in our setting. These questions are only hypothetical

[4]The payoffs associated with the coloured cells in the loss-frame are as follows: Red = -60 EUR, Yellow = -55 EUR, Green = -48 EUR and Blue = -0 EUR.

for several reasons. The purpose of the questions is to get an independent measure of the subjects' risk and ambiguity attitude. If these decisions were payoff relevant, this could create hedging opportunities and diverge focus from the main experimental question. We believe the advantage of excluding hedging is bigger than the disadvantage of a reduced salience. In the questionnaire, we ask gather information on subjects' demographics. We also elicit the level of confidence, the subjects' learning type, the perceived difficulty and how useful they found the social signal within the environments.

2.1 Behavioural Predictions

In this section, we describe the question whether to adapt a choice due to social learning in an ambiguous environment, by using a simple theoretical model. After introducing the notation, we describe three necessary conditions for social learning: Agents have to believe that their inherent type is correlated, that the social signal is informative, and agents have to be able to update their beliefs when seeing a conflicting social signal. Understanding when an agent might adapt because of social learning, we can in the next step formulate our hypotheses.

Let us assume that the world creates types $r_i \in [x, y]$ with some distribution. The type could be interpreted as 'I will be most happy to invest in portfolio x' or 'I will be most happy to invest in portfolio y'.[5]

The agent does not have complete information about her own type, but has a private signal $s_i \in [x; y]$ hinting with some probability $p_i = Prob(r_i = x|s_i = x)$ to her type. Let's assume the signal is at least weakly informative. The first choice (c_1) is in an individual setting - so agent i can decide based on her own private signal ($c_{1,i} = s_i$). This should hold for all agents ($c_{1,-i} = s_{-i}$). Henceforth for simplicity, we use c_1 to depict the first choice.

Next, the agent learns the popular choice (c^{Mo}, the Mode of the choices) made by others, which directly reflects the majority of the others' signals, but she does not know firsthand the probabilities behind these signals. Based on this information, the agent can either stay with their initial choice ($c_2 = c_1$) or switch away from the initial choice ($c_2 \neq c_1$).

If an individual's beliefs about how her type is correlated with others' types[6] is given by $b(\rho)$, then:

$$Prob(r_i = x|c^{Mo} = x) \geq Prob(r_i = x|c^{Mo} = y), \text{ iff } b(\rho) \geq 0.5;$$
$$\text{else, } Prob(r_i = x|c^{Mo} = x) < Prob(r_i = x|c^{Mo} = y), \text{ for } b(\rho) < 0.5.$$

Therefore, if $c_1 = x$ and the agent sees the social signal $c^{Mo} = y$, then the agent should stick to her initial choice if she believes that her type is not correlated with her group ($b(\rho) < 0.5$), therefore $c_2 = c_1$.

[5]In a parallel universe, the decision may be whether to accept an experimental medicine/vaccine or not; whether to invest in green technology or a new business venture today or defer investment to the future; and so on.

[6]since they come from the same known distribution

Else if she believes that the types are correlated, she should change her decision, meaning that $c_2 \neq c_1$, i.e, the agent should switch away from the initial choice.

We use $\omega_P \in [0; 1]$ and $\omega_S \in [0; 1]$ to capture subjects' beliefs about the quality of the private signal and the social signal, where a higher ω indicates that a higher quality signal is perceived. If the $c_1 \neq c^{Mo}$ and $\omega_S > \omega_P$ subjects would change their decision, because the social signal is perceived to be of better quality than the private signal.

An agent may have a tendency to interpret or process the social signal as consistent with their prior belief ω_P and first choice c_1. Confirmation bias, as it is termed in the psychological literature describes agents' tendency to selectively gather or put an undue weight on new evidence that supports their original position, while neglecting, ignoring or discounting information that would point to the contrary (Nickerson, 1998). Studies of social judgement have found that agents often overweight positive confirmatory information and underweight negative discomfirmatory information that they can access, once they have made their initial decision or choice (Kuhn, 1989).

Let's consider what would happen to an agent in our model who may be affected by confirmation bias. Let $q \in [0, 1]$ be the probability with which the social signal is interpreted incorrectly, i.e., confirmation bias affects the agent's decision. If $c_1 = x$ and the agent gets a social signal $c^{Mo} = x$, she correctly interprets it. However, if she gets a social signal $c^{Mo} = y$, she incorrectly interprets it with probability q. Thus, $q = 0$, would indicate no bias; while $q = 1$ would indicate that no amount of other agents opting for 'y' can change her mind. An agent would be less likely to respond to the social signal and switch, as $q \to 1$.

We now consider how an agent's decisions can be modelled in the ambiguous environment. Her reaction to the endogenous ambiguity within the situation is modelled by $\delta_i \in [0, 1]$, with $\delta_i = 1$ denoting complete ignorance about the lottery choice c_1, and $\delta_i = 0$ denoting complete certainty about c_1. Her attitude to exogenous ambiguity (general ambiguity-attitude) is captured by $\alpha_i \in [0, 1]$, with $\alpha_i = 1$ denoting pure pessimism in the face of ambiguity or expecting the worst possible outcome will happen, and $\alpha_i = 0$ denoting pure optimism about the ambiguous outcome. If the decision-maker has $0 < \alpha_i < 1$, she is neither purely optimistic nor purely pessimistic (i.e., ambiguity-averse), but reacts to exogenous ambiguity in a partly pessimistic way by putting a weight on bad outcomes and in a partly optimistic way by putting a weight on good outcomes.

With ambiguity, a subject makes an initial choice based on their (ambiguous) belief about the quality of the private signal (ω_P). Let $c_1 = (r_1 = x | s_1 = x, \delta_P, \alpha_1)$, where $0 < \delta_P < 1$ captures the reaction to endogenous ambiguity and $0 < \alpha_1 < 1$ captures the reaction to exogenous ambiguity after receiving the private signal s_i. Following this, suppose the agent receives the social signal $c^{Mo} = y$ and forms her beliefs about it's quality (ω_S). She would update her ambiguous beliefs about which lottery to choose, depending on her beliefs about the other agents. In essence if she believes the other agents are more informed/capable of making a decision in this situation, i.e., $\omega_S > \omega_P$, the endogenous ambiguity or the δ_S she faces after viewing the social signal would be reduced, i.e., $\delta_S < \delta_P$, and she would switch from her initial choice. Thus, we would find that $c_2 \neq c_1$, where $c_2 = (r_1 = y | c^{Mo} = y, \delta_S, \alpha_1)$.[7]

Therefore the decision to switch, i.e. $c_2 \neq c_1$, would occur iff:

$$\text{i) } b(\rho) > 0.5 \text{ and } c^{Mo} \neq c_1;$$
$$\text{ii) } c^{Mo} \neq c_1 \text{ and } q < 1;$$
$$\text{iii) } c^{Mo} \neq c_1 \text{ and } \delta_S < \delta_P.$$

Only looking at the interesting case, where subjects see conflicting social and private signals $c_1 \neq c^{Mo}$, the problem reduces to the question, which signal ω_P or ω_S is more informative. As $q \to 1$, that is, as confirmation bias increases, ω_P would become more valuable and ω_S is less valued. As $\omega_S \to 1$, that is, as the belief about the quality of the social signal increases, $\delta_S \to 0$, or the endogenous ambiguity a subject perceives would fall. Agents would adapt their choice if they believe that the social signal ω_S is more informative.

After making an initial choice, if an agent learns that the majority of her group preferred the other option and adapts her choice to the majority, we classify this behaviour as 'social learning'. Based on this definition, we'd like to check how many of our subjects can be classified as 'social learners'. Accounting for switching due to erratic behaviour, we compare the number of subjects who switch when they learn that they are in the minority, with those that switch when they learn that their choice is in line with the majority.

Proposition 1. *We expect a higher share of switching when subjects are in the minority, compared to the majority.*

$$Proportion(c_2 \neq c_1 | c_1 \neq c^{Mo}) > Proportion(c_2 \neq c_1 | c_1 = c^{Mo})$$

The choices are designed such that one ticket does not strictly dominate the other and not all subjects will be likely to pick the same ticket. The design and selection of each choice are the result of multiple pilots. Still it may be possible that one ticket is preferred by a larger majority. In the ambiguity environment where the lotteries are more complicated, we expect participants to have a more difficult decision and be less likely to cluster in their choice. Thus, we expect more balanced initial choices in the ambiguity environment.

[7]Note: the agent's exogenous ambiguity-attitude or α_1 would not be affected by receiving more information specific to the decision-making situation.

Table 1: Characteristics of lottery tickets

	Risk (R)		Ambiguity (A)	
	E[EUR]	Variance	E[EUR]	Variance
Problem 1 Left	5	34.7	4.97	34.8
Problem 1 Right	5	8.4	4.98	8.6
Problem 2 Left	10.8	13	10.8	13
Problem 2 Right	7.23	81.3	7.23	81.5
Problem 3 Left	5.75	171.6	6.4	182.5
Problem 3 Right	6.6	122.3	6.6	127.8
Problem 4 Left	6	97.7	6	98
Problem 4 Right	9	315.7	9	316.6
Problem 5 Left	5.51	31.9	5.54	33.4
Problem 5 Right	5.58	95.5	5.62	97.7

Table 1 presents the expected value and variance of the tickets for both environments Risk and Ambiguity. While designing, we tried to hold these characteristics as constant as possible. In the ambiguity setting the variance is calculated based on the non-grey elements. By the reduction of the sample, obviously the variance has slightly increased.

Proposition 2 directly follows from the idea that a subject facing an ambiguous environment is less certain about what decision to make. In our framework this is represented by the private signal in the ambiguity environment being worse when compared to the risk environment, because of the increased uncertainty:

$$(\omega_P^A|\delta_P^A) < (\omega_P^R|\delta_P^R)$$

For any possible non-equal distribution of types the following holds: If the signal is perfectly informative ($\omega_P = 1$), the distribution of signals is identical with the distribution of types. Generally, if the private signal is not informative, or the closer $\omega_P \to 0$, we could expect subjects to randomise between the two lotteries and for their choices to be closer to a 50-50 distribution. In contrast, in the risky situation, we would expect choices to deviate from the 50-50 distribution. In the binary case, the proportion of the most popular choice (the mode), is expected to be smaller under ambiguity.

Proposition 2. *The initial preferences in the ambiguity environment are more balanced compared to the risk environment.*

$$Proportion(mode(c_1)^A|\omega_P^A) < Proportion(mode(c_1)^R|\omega_P^R)$$

Looking at our main question, we compare the share of subjects that are switching when they are in the minority within both environments. As we try to exclude all motives other than social learning, a change in the switching rate indicates that subjects in an environment are relatively putting more weight on the social signal ($\omega_S > \omega_P$). We expect that the social signal would be more influential in the ambiguous environment than in the risk environment ($\omega_S^A > \omega_S^R$), thus switching due to social learning becomes more likely in the ambiguous situation.

Proposition 3. *We expect a higher share of switching behaviour of minority subjects in the ambiguity environment compared with the risk environment.*

$$Proportion(c_2 \neq c_1 | c_1 \neq c^{Mo}, \omega_S^A, \omega_P^A) > Proportion(c_2 \neq c_1 | c_1 \neq c^{Mo}, \omega_S^R, \omega_P^R)$$

2.2 Experimental Procedures

The experiment was conducted online, supported by the Business and Economics Research Laboratory (BaER-Lab) of Paderborn University. The experiment was approved by the ethical board of Paderborn University and preregistered using the American Economic Association's registry for randomized controlled trials (AEARCTR-0007747).

The sessions took place between September and October 2021. All sessions were conducted using the z-Tree experimental software (Fischbacher (2007)) and have been coordinated via ORSEE (Greiner, 2015). We used z-Tree-unleashed (Duch et al. 2020) to conduct the sessions online.

Subjects were given a comprehensive set of instructions (see Appendix) and their understanding was ensured using control questions. Subjects then took part in the main experiment and submitted their decisions anonymously. In addition to the main experiment, we elicit details on demographics via a questionnaire after the experiment.[8]

An average session lasted 50 minutes and the average earnings were €9.49, including a show-up fee of €2.5.[9]

3 Results and Discussion

The results are structured into three subsections. Section 3.1 presents demographics and randomisation checks. Section 3.2 investigates the effect of ambiguity on initial choices. Section 3.3 investigates the effect of an ambiguous environment on social learning.

[8]Unlike lab experiments, we do not have full control and technical issues on the participant side could appear. We address this issue by documenting inactivity as a proxy within the experimental software.

[9]At the time of conducting the exchange-rate was approximately 1EUR=1.17 USD.

3.1 Demographic Statistics and Randomisation Checks

We conducted 8 Sessions with a total of 184 Subjects. Sessions 1-4 had a gain framing and sessions 5-8 were framed in a loss domain. Subjects were randomly assigned to the risk or ambiguity group within a session. In the gain-framed sessions we have slightly fewer observations due to subjects not showing up to the online experiment. In the loss-frame we adjusted the number of subjects who were invited to account for this no-show rate. Most of the subjects were students. 54% reported themselves as undergraduate students, while 34% were postgraduate students. 43% of the subjects reported studying Economics. The average subject age is 24.8 years. 58% of the subjects were female and 42% male. Table 2 reports the demographic characteristics by treatment.

Table 2: Demographics and Pearson χ^2 goodness of fit test

	Risk		Ambiguity		
	Gain (n=40)	Loss (n=48)	Gain (n=48)	Loss (n=46)	Pr.
Female	27 (67.5%)	29 (60.4%)	29 (60.4%)	20 (43.5%)	.128
Economics Student	17 (42.5%)	27 (56.3%)	11 (22.9%)	23 (50%)	.007
Graduated	15 (37.5%)	19 (39.6%)	11 (22.9%)	18 (39.1%)	.263
Average Age	24.67	25.10	25.16	24.34	.209

We conducted a series of χ^2 tests to check whether the characteristics are equally distributed between the treatment groups. We do not observe any significant difference for gender, being a graduate, and/or age. The share of economics students is significantly different between the groups.[10] In the analysis we will control for potential effects using a regression.

3.2 Effect of Ambiguity on Initial Choices

In order to verify whether the manipulation of the environments was successful, we first look at our survey data and in a next step on the initial choices in the experiment. An indicator of success would be that as stated in Proposition 2 the initial choices are more balanced and subjects are less confident about their initial choices.

[10]In the loss frame we observe more economics students with a strong significance ($p = 0.004$) and in the ambiguity treatment we observe less economics students with a weak significance ($p = 0.052$).

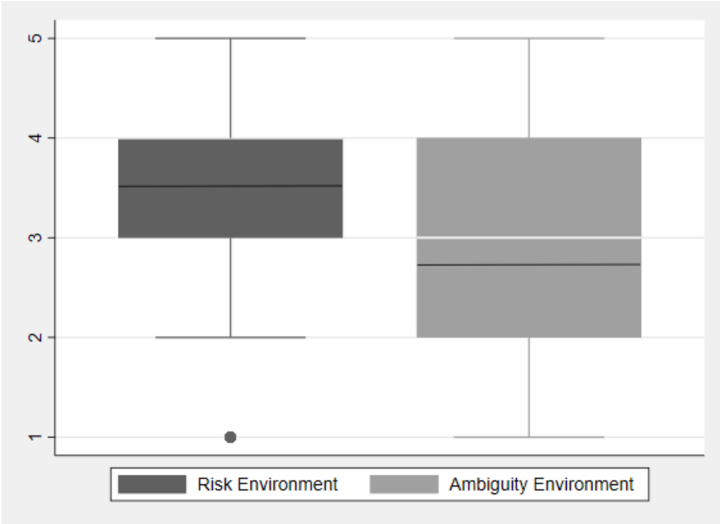

Figure 4: Box-plot of confidence level by environment

In the post experimental questionnaire, we asked the subjects how difficult the decision-making for each environment was and how confident they felt about their choices. We used a Likert-scale with a range from 1 to 5, in which higher values indicate a higher level of confidence. Figure 4 describes the self-reported level of choice-confidence. In the box-plot we see that decision-making in the ambiguity environment was perceived more difficult and subjects were less confident about their decisions. The average confidence on the Likert-scale for the risk environment is 3.5 and for the ambiguity environment is 2.75 points. The difference is highly significant (χ^2 p-value< 0.001). This is already a first indicator that our implementation of ambiguity has an effect. Next, we test whether, as predicted in Proposition 2, the initial preferences in the ambiguity environment are more balanced when compared to the risk environment. Observing more balanced choices can be seen as an behavioural indicator for subjects being less confident in their decision.

Table 3: Share of preferred ticket and difference to equal share

	Risk (p-value)	Ambiguity (p-value)
Problem 1	.67 (.008)	.52 (.906)
Problem 2	.73 (.001)	.80 (.001)
Problem 3	.60 (.097)	.60 (.073)
Problem 4	.65 (.006)	.56 (.294)
Problem 5	.63 (.022)	.56 (.256)

In Table 3 we report the share of the more often preferred ticket in the risk environment and the ambiguity environment. We test the null that the share of decisions is significantly different to 50:50 randomisation, which one might expect if subjects randomise between their choices in an adhoc fashion.

In the risk environment using a binomial test, we reject the null overall at 10%. We observe choices to be significantly different to a 50:50 share, in particular 4 out of the 5 problems are significantly different at the 5% level. Under ambiguity we fail to reject the null. The only problem where we see a strong deviation from 50:50 share is problem 2. This observation is in line with Kelsey and le Roux (2015) hinting that subjects are more likely to simply randomise between the lotteries in an ambiguous setting.

Looking in more detail at problem 2, we interpret it as a special case. We believe this observation is driven by a switch of the rule of thumb or heuristic being applied as the main decision rule. Depending on the design of the problem it is easier or harder to apply specific rules such as maximising the expected outcome or minimising the risk of getting the lowest outcome. In the ambiguity environment version of problem 2, the main strategy seemingly was to minimise the risk of having a low payoff and most subjects selected the right ticket. In the risk environment more subjects seem to also focus on the expected value, which was in favour of the left ticket. This can explain, why in problem 2 the choices are less balanced in the ambiguity setting. This effect is not surprising, as consistent with Cooper and Rege (2011), in the ambiguity environments probabilities are harder to estimate and thus an orientation on an expected value might be less likely.

In total, the choices in the ambiguity environment are more balanced (with an average deviation of 0.10) compared to the choices in the risk environment (with an average deviation of 0.14). Accounting for problem 2 as a special case the real difference between the environments in terms of balanced choices seems to be even bigger.

Result 1. *In line with Proposition 2, in our data we observe that choices are more balanced in the ambiguity environment.*

Looking at the more balanced choices and the reduced self-reported level of choice-confidence, we believe that our implementation of ambiguity was successful. Similar to a manipulation check this is a necessary prerequisite for analysing the effect of ambiguity on social learning.

3.3 Effect of Ambiguity on Social Learning

Let us start with exploring whether we can observe social learning in our base setting, the risk environment. With social learning, we should observe more switching behaviour of subjects in the minority compared to the majority.

Table 4: Switching behaviour by majority and minority in the risk environment

	Majority	Minority	Total
Not Switching	488	298	786
Switching	11	61	72
Total	499	359	858

Note. The p-value resulting from a one-sided Fisher's exact test is $< .001$

Table 4 reports the absolute numbers of switching behaviour within the risk environment. We clearly observe that subjects in the minority are more likely to switch away from their initial choice. Thus, we are confident that we are able to observe social learning using our experimental design. This allows us to use the risk environment as a baseline condition to further explore the effect of ambiguity.

Result 2. *In line with Proposition 1, we observe a significantly ($p < .001$) higher share of switching when subjects are in the minority (16.99%), compared to the majority (2.2%), within the risk environment.*

We had expected that ($\omega_S > \omega_P$), that is, subjects would find the social signal more informative. Reflecting on the subjects in the minority who do not switch, their behaviour could be explained by being confident about their own choice ($\omega_P \to 1$) or by perceiving the social signal as rather uninformative ($\omega_S \to 0$), so for these subjects ($\omega_S < \omega_P$), and they do not change their initial decision. Another plausible reason for these subjects not switching when they are in the minority, might be that their $q \to 1$, that is, there is some confirmation bias, which makes ω_P more valuable and ω_S is less valued.

Next, we focus on the effect of ambiguity on switching behaviour. Our expectation was that subjects would be less confident about their own choices, which is in line with Result 1. Subjects know that their group members have been in the same situation and we expect them to assume that the social signal is also affected by the ambiguity they face. The question we want to explore is how subjects deal with these two signals and whether they will put more or less weight on the social signal in the ambiguity environment. In the Table 5 we report absolute numbers of subjects' switching behaviour when they are within a minority, broken down by the problems and environment.

Table 5: Switching behaviour in minority by environment

	Problem 1	Problem 2	Problem 3	Problem 4	Problem 5
Risk	21/76 (.27)	16/69(.23)	08/76 (.11)	09/79 (.11)	07/59 (.12)
Ambiguity	13/67 (.19)	09/51(.18)	15/92 (.16)	12/94 (.13)	21/92 (.23)
Fisher's exact p-value	0.33	0.50	0.37	0.82	0.13

Overall in the risk environment 61 of 359 (16.99%) subjects and in the ambiguity environment 70 of

396 (17.68%) subjects in the minority adapted their behaviour. Using a non-parametric test, we fail to report a significant effect of the level of ambiguity on the switching behaviour, on both, pooled-level as well as on problem-level data. Additional to the non-parametric test, we conduct a parametric analysis accounting for individual effects as we observe multiple observations per subject, demographics and problem specific effects.

Table 6: Regression on switching behaviour in the minority

	Model 1		Model 2		Model 3	
	Coef.	p-value	Coef.	p-value	Coef.	p-value
Ambiguity	-0.00	0.97	-0.01	0.95	0.00	0.98
Female			0.08*	0.01	0.09**	0.01
Economic Stud.			0.04	0.25	0.04	0.21
Age			0.00	0.86	0.00	0.76
Graduated			0.02	0.47	0.02	0.54
Loss Frame					-0.01	0.73
Later Environment					-0.04	0.20
Problem=2					-0.03	0.52
Problem=3					-0.10*	0.01
Problem=4					-0.11*	0.01
Problem=5					-0.05	0.24
Constant	0.17***	<0.001	0.11	0.10	0.17*	0.02

*p<0.05, **p<0.01, ***p<0.001; N=755

Model 1 presents the most simple model, model 2 accounts for demographics and model 3 for order and problem-specific effects. For all models, random effects are clustered on an individual level.[11] Looking at the demographics, we observe a strong gender-effect with females being more likely to switch. For other demographic factors we do not observe a significant effect. For age this could be explained by the missing heterogeneity within the student sample. Subjects seem to be more confident with their choices over time and thus are less likely to switch in the set of problems presented second. This is captured by the variable 'Later Environment'. The effect is rather small and non-significant, but should not be omitted. Looking at the variable 'Loss Frame', we find the the loss/gain framing did not have a significant effect on switching behaviour. Non surprisingly we also observe some problem-specific effect, in particular for Problem 2.

[11] We decided not to include additional individual measures for risk and ambiguity aversion as they fail to explain behaviour in our game. Looking at Kelsey and le Roux (2017b), this is not too surprising, as risk and ambiguity attitudes can be context dependent and may differ depending on the type of problem.

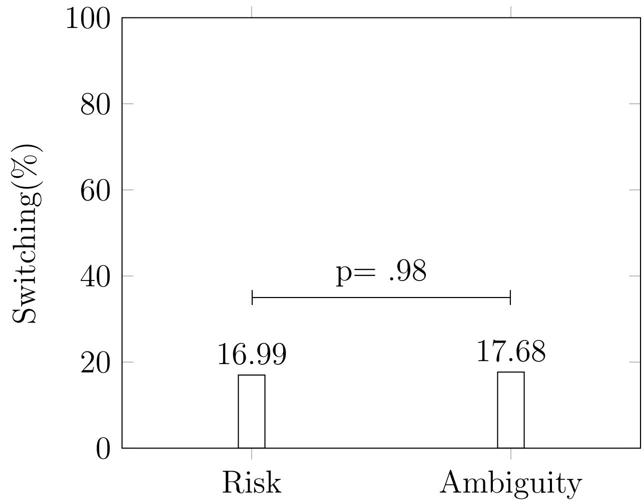

Figure 5: Share of switching behaviour within the minority by environment

As displayed in Figure 5, independent of the model specification, the effect of ambiguity is in line with the non-parametric test and seems to be non-existent or at most incremental but not significantly so. Our previous finding based on the non-parametric tests remains robust.

Result 3. *In contrast to Proposition 3, we do not observe a significantly different share of switching behaviour of minority subjects in the ambiguity environment compared with the risk environment.*

Reflecting on Proposition 3, which assumes that subjects in an uncertain environment might perceive the social signal (ω_S) to be of better quality ($\omega_S > \omega_P$), our results rather indicate that both the social (ω_S) and the private signal (ω_P) are by ambiguity. Whether someone follows the social signal, if the social signal is based on the same set of information, seems to be relatively robust towards the level of ambiguity.

4 Conclusion

In our study we aim to shed more light on environmental factors which could affect social learning. We observe that subjects in our experiments significantly respond to the social signal ($p < .001$) and display switching behaviour when they are in the minority (17%), compared to the majority (2%), within all treatments.

Our study was based on subjects making binary choices between lotteries, and in our data we observe that choices are more balanced in the ambiguity environment, indicating that players tend to randomise in a 50:50 way between the choices presented to them, without a particular preference. This is consistent with studies conducted by Calford (2021) and Kelsey and le Roux (2015) and hints that our implementation of an ambiguous environment has been successful.

Our experimental setup enables us to check whether social learning is affected by an ambiguous environment, and thereby respond to the questions raised by Karakostas et al. (2021) and Cooper and Rege (2011). As we are interested on the pure effect on social learning, we deliberately excluded other factors as social interaction based motives by implementing a strict independent outcome rule. Each decision problem could only be relevant for one person within the group. It follows that on a problem level one cannot therefore compare one's own outcomes with the outcome of group members.

Even though we tried to exclude peer group effects as much as possible in our experimental design, we are limited in our ability to fully exclude motives other than social learning. Subjects could interpret the social signal as a "norm". Thus, if we would observe an effect caused by ambiguity, we would not be able to cleanly separate, whether this would have been driven by social norms or by social learning. Given that we do not observe more imitating behaviour in the ambiguous situations, we do not see much scope for the salient norms-effect taking place. We are therefore confident that our results are not driven by social norm effects and to report a non-existing effect on social learning behaviour.

We do not find significant evidence that subjects display more pronounced social learning in the ambiguity environment compared with the risk environment. In addition, we also note that a switch from gain to loss framing does not significantly change subject behaviour in terms of social learning. The openness to social learning seem to be a relatively robust and independent of environmental factors such as the level of ambiguity or the framing context. Our interpretation is that whether a person is open for social learning is not driven by environmental factors. In contrast we believe that situational and individual factors may play their role. A study by Duffy et al. (2021) reports that individual types and characteristics can explain social learning and some people can be characterised as 'lone wolves' and some as 'herders'. Reflecting on Karakostas et al. (2021) and Cooper and Rege (2011), our results hint that if they observe more imitating behaviour under ambiguity, this effect should, even if social learning is not perfectly excluded, mainly be attributed to social interaction effects.

From a policy perspective our result has two implications. First, social learning is relatively robust and thus sharing information about other people's behaviour, can help to increase take-up of a 'preferred' action. This might be cheaper when compared to a policy-maker offering carrots (incentives) and/or imposing sticks (penalties) on a demographic. Second, social learning is robust towards uncertainty. Thus, in a very uncertain environment it can help to appeal to social learning, but it might be more effective to appeal to social interaction based motives instead.[12]

Looking at future research, it would be interesting to investigate whether there is a "wisdom of the crowd" effect taking place. In this study we do not directly measure how informative the social signal is

[12] An example for sequentially addressing social learning and social interactions motives could be observed during the pandemic. The German government in a first step communicated that a large share of the population is already vaccinated and thus social learning could become a relevant motive. After some time the communication strategy changed and the Government asked the population to talk about vaccination with family and friends, which could promote social interaction based motives.

perceived to be. We only observe whether people follow the social signal in relation to the private signal. This is related to the sensitivity of our measurement, where we observe binary choices as our design is based on Cooper and Rege (2011). It could be that people are actually more open for social learning due to their private signal having a worse quality. But at the same time people might be less open because of the social signal also being of unidentifiable quality. To exclude such an alternative explanation it would be interesting to see whether eliciting the willingness to pay for a signal is similarly affected. If the willingness to pay is not affected, this would hint that social learning is even more robust towards environmental factors as the level of uncertainty.

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5 Appendix

Translated Instructions

The original instructions are in German language. The layout of the screen is optimised for a screen resolution of 1440 x 900 or higher.

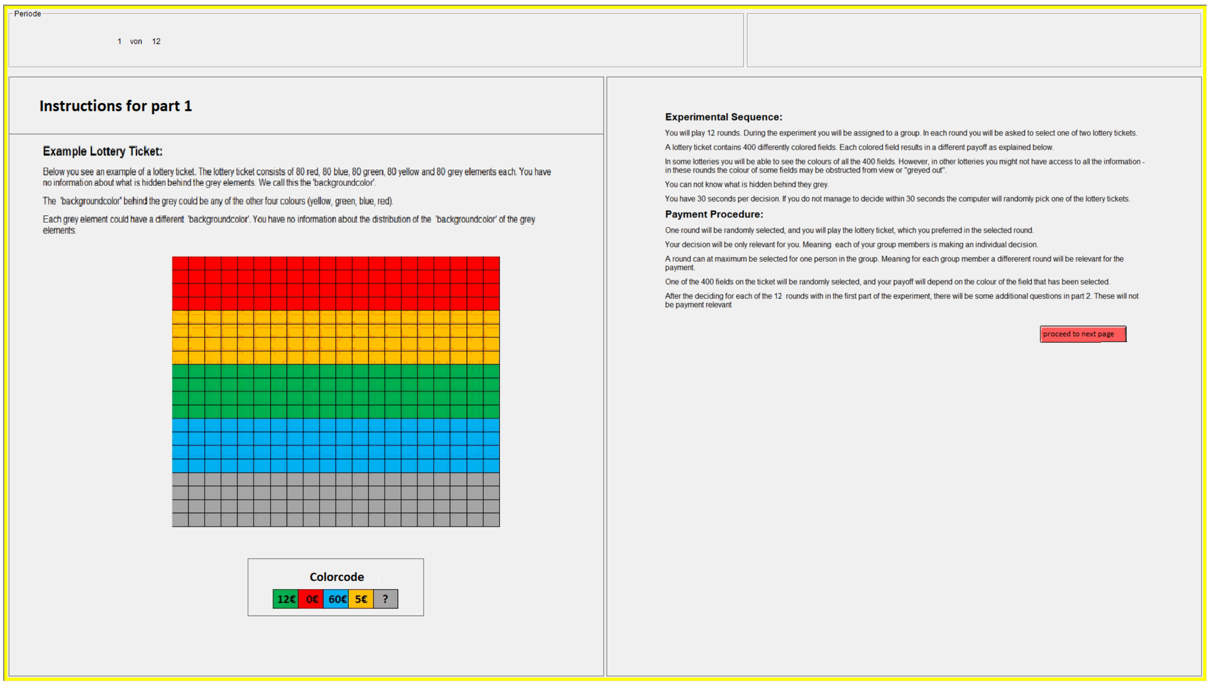

Figure 6: Instructions with gain-frame - translated into English

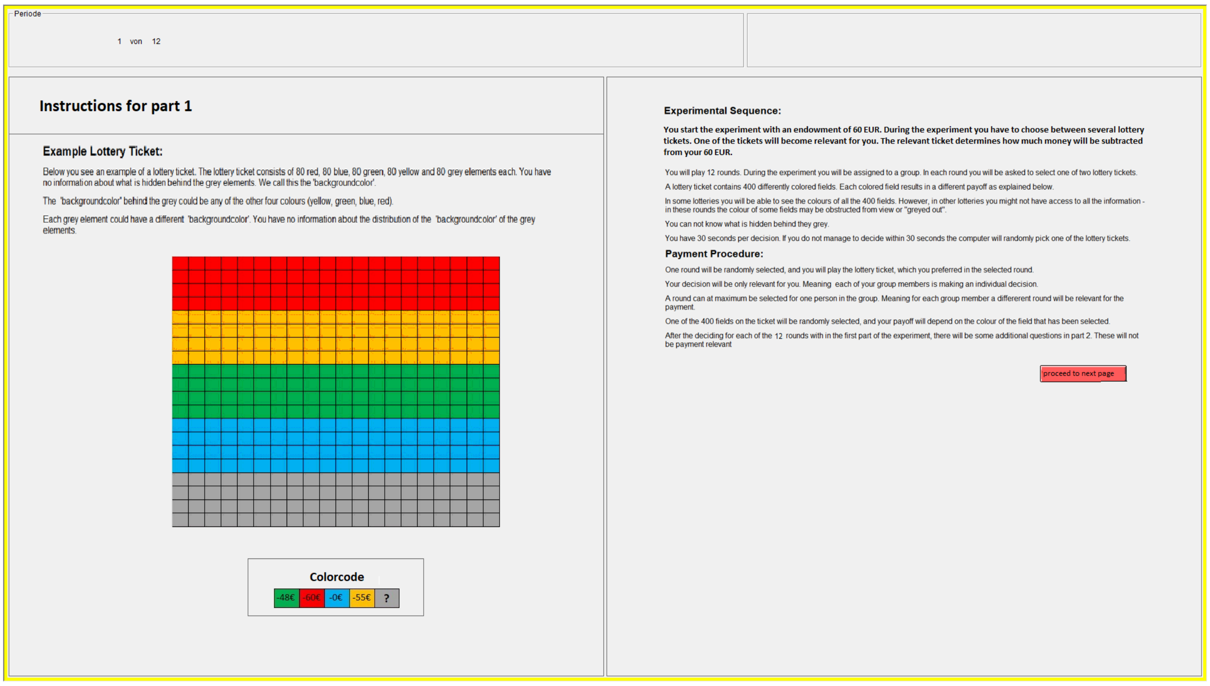

Figure 7: Instructions with lose-frame - translated into English

Figure 9: Example of individual choice between two lottery tickets in the ambiguity environment in the gain-frame - translated into English

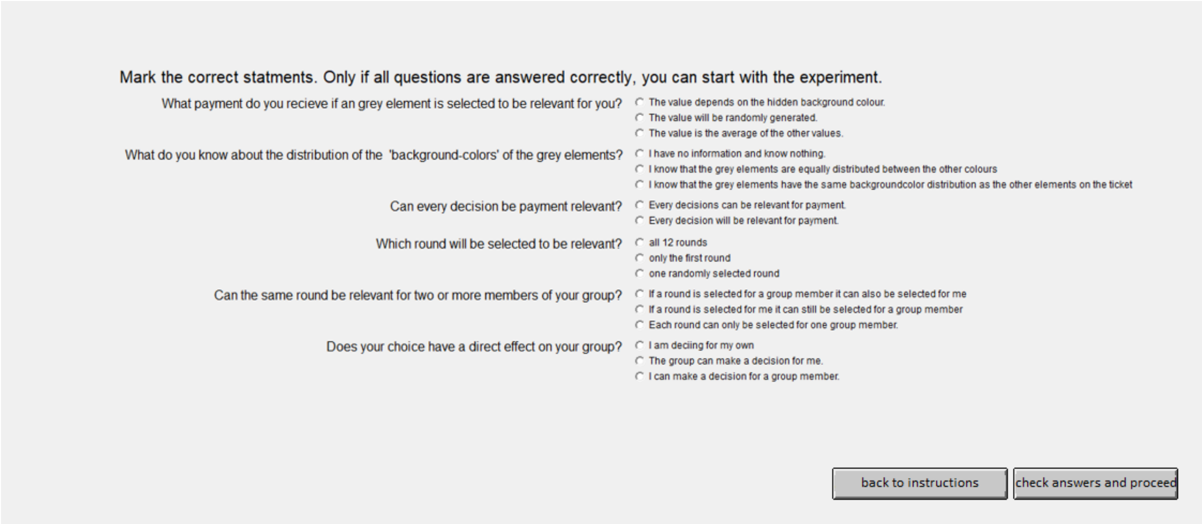

Figure 8: Questions to ensure understanding of the instructions - translated into English

Figure 10: Example of individual choice between two lottery tickets in the ambiguity environment in the lose-frame - translated into English

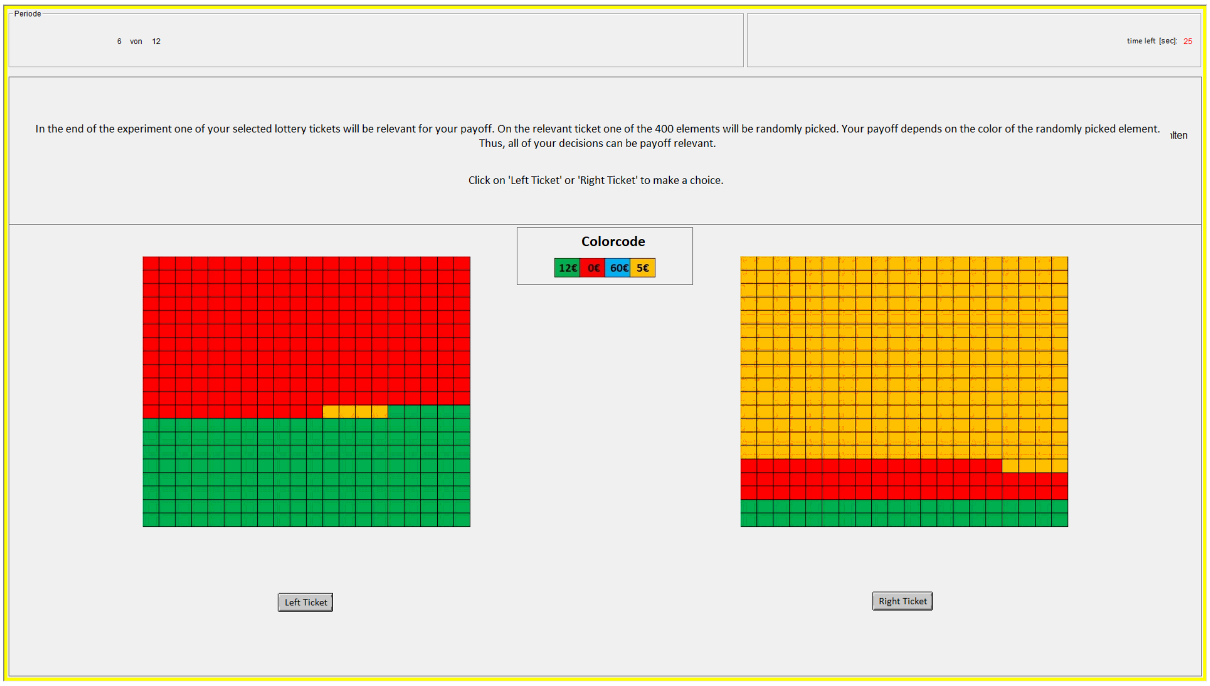

Figure 11: Example of individual choice between two lottery tickets in the risk environment in the gain-frame - translated into English

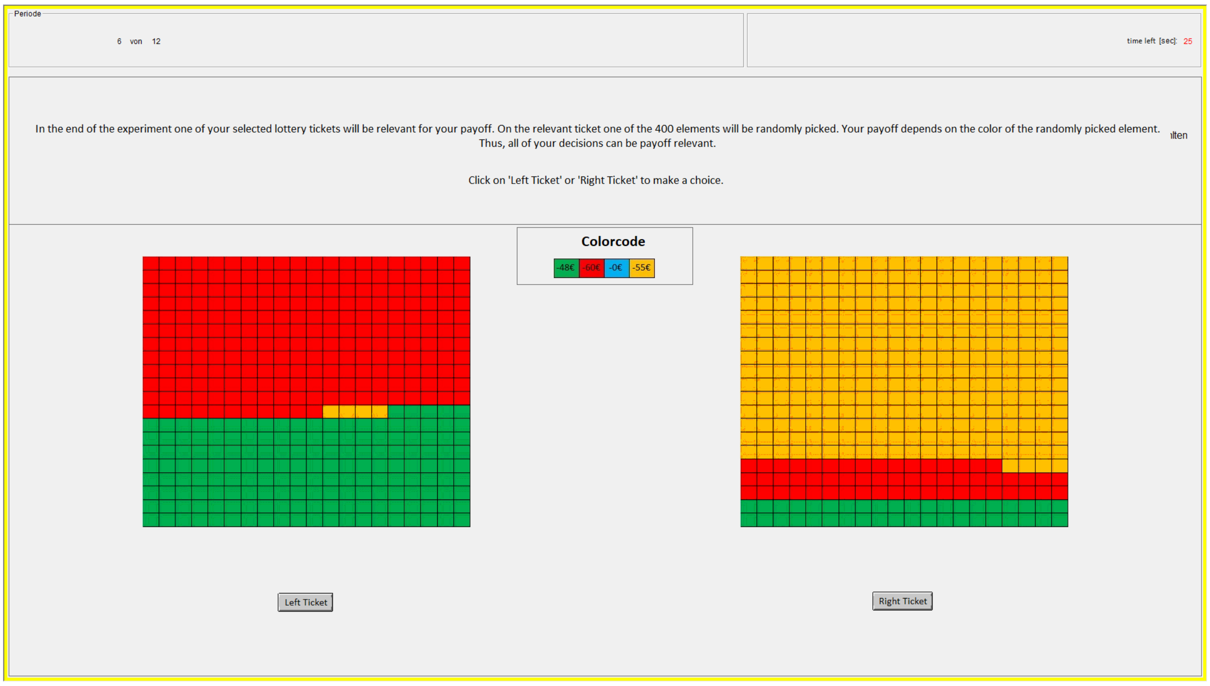

Figure 12: Example of individual choice between two lottery tickets in the risk environment in the lose-frame - translated into English

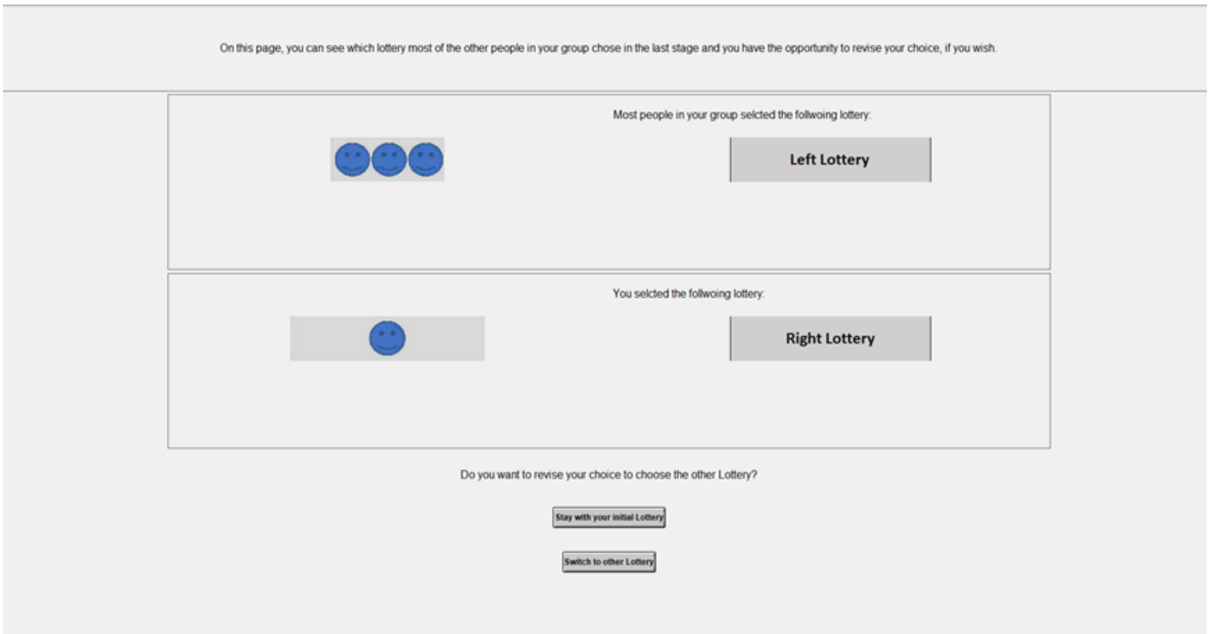

Figure 13: Social learning and possibility to switch the selected lottery ticket - translated into English

Original used Instructions in German Language

The layout of the screen is optimised for a screen resolution of 1440 x 900 or higher.

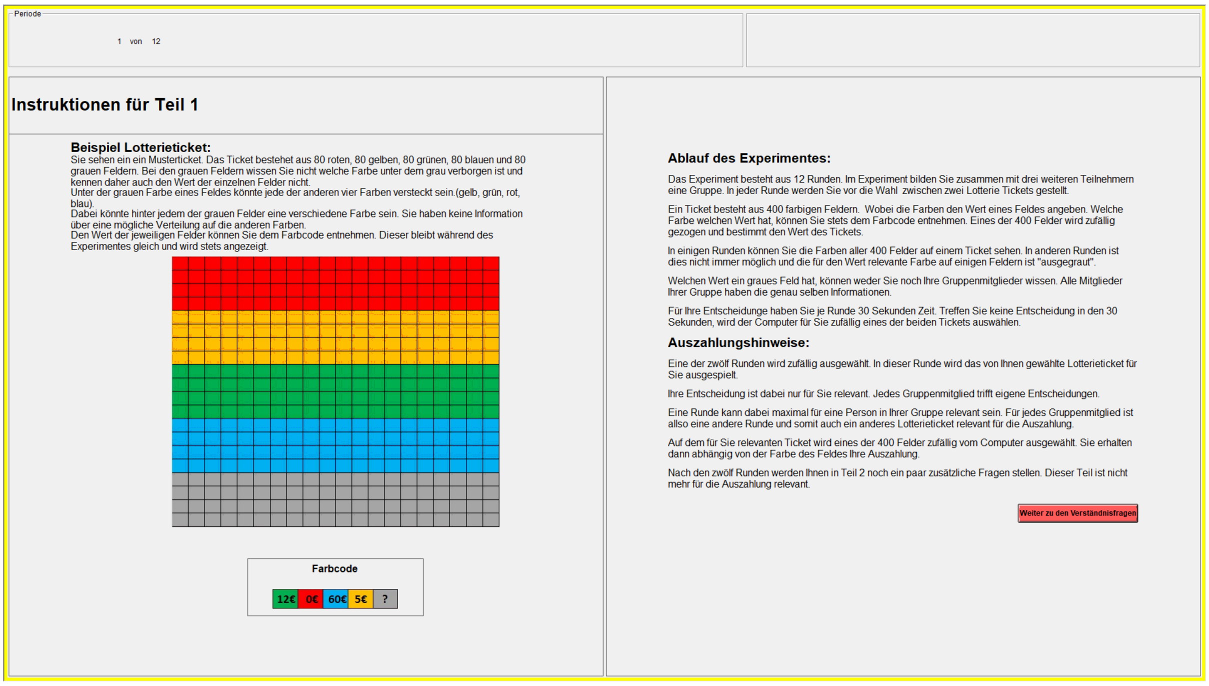

Figure 14: Instructions with gain-frame

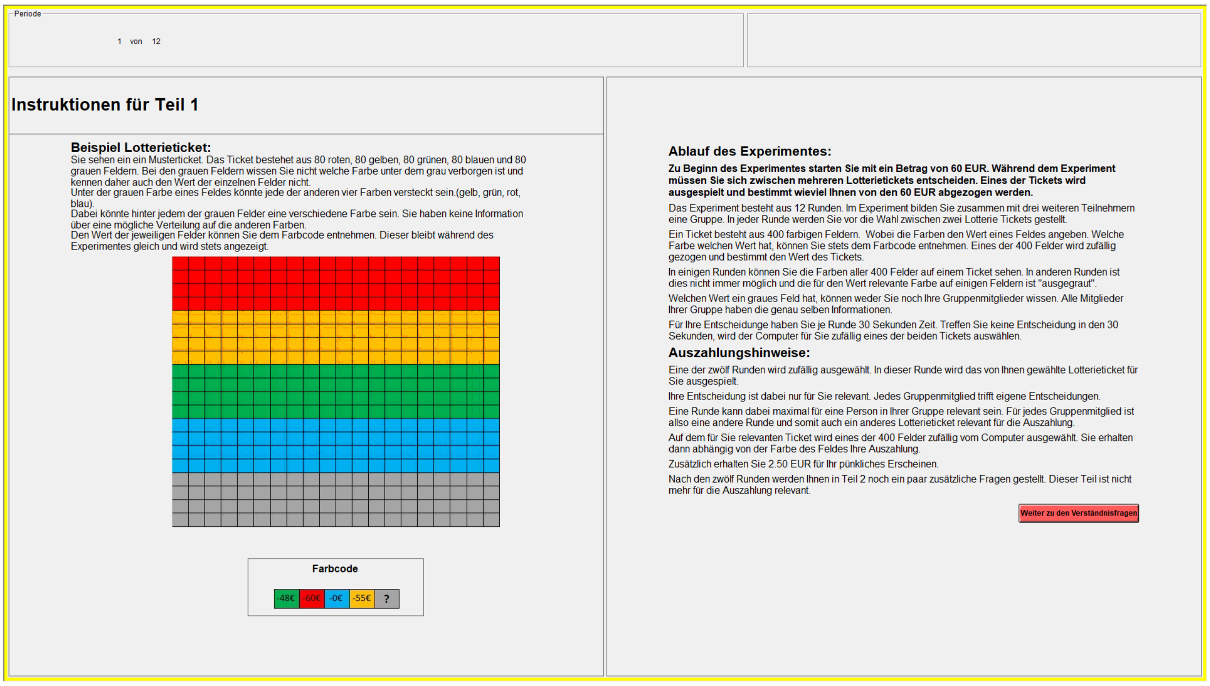

Figure 15: Instructions with lose-frame

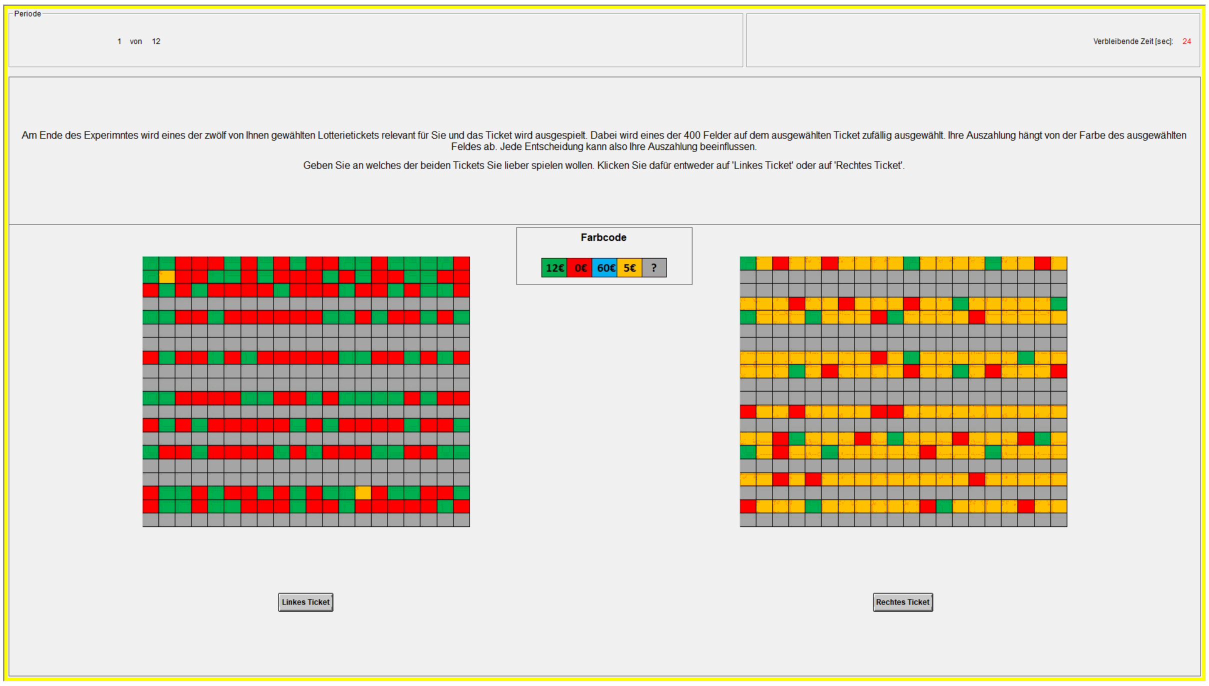

Figure 17: Example of individual choice between two lottery tickets in the ambiguity environment in the gain-frame

Figure 16: Questions to ensure understanding of the instructions

Figure 18: Example of individual choice between two lottery tickets in the ambiguity environment in the lose-frame

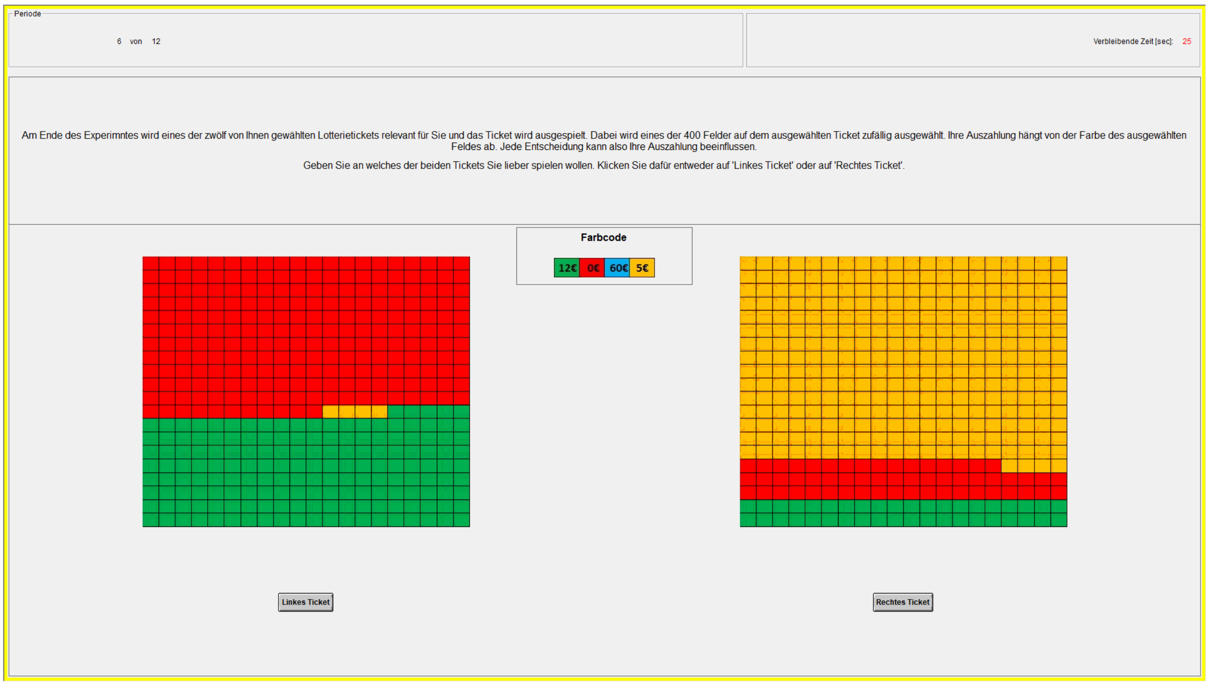

Figure 19: Example of individual choice between two lottery tickets in the risk environment in the gain-frame

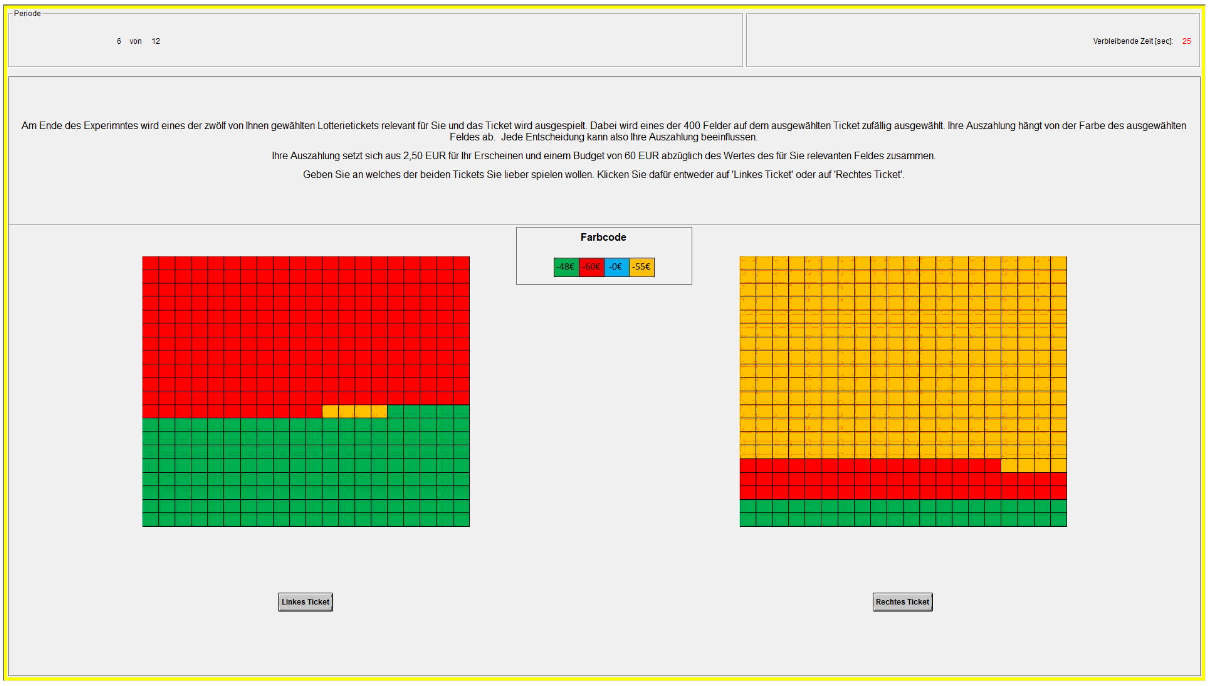

Figure 20: Example of individual choice between two lottery tickets in the risk environment in the lose-frame

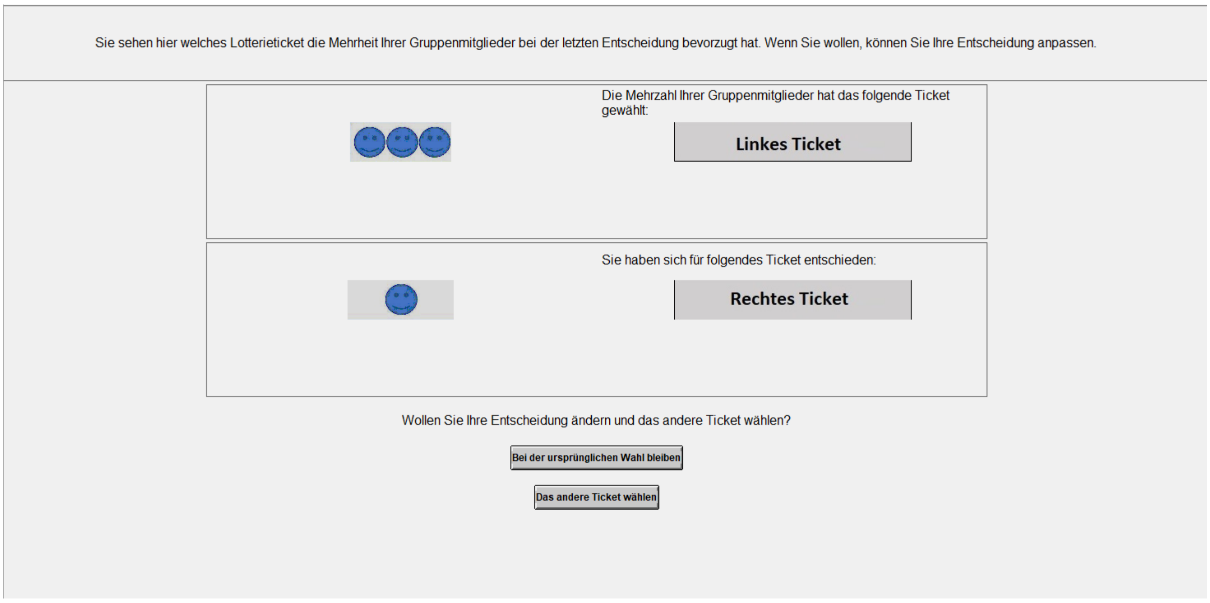

Figure 21: Social learning and possibility to switch the selected lottery ticket

Lottery Tickets

In table 7 the lottery tickets used are displayed. The expected value and variance is always referring to the observable elements.

Table 7: Lottery tickets with full details

	0EUR	5EUR	12EUR	60EUR	?EUR	E[EUR]	σ^2
Ticket 1L	231	4	165	0	0	5	34.7
Ticket 1R	56	304	40	0	0	5	8.4
Ticket 2L	40	0	360	0	0	10.80	13
Ticket 2R	30	290	70	10	0	7.23	81.3
Ticket 3L	230	100	50	20	0	5.75	171.6
Ticket 3R	228	0	160	12	0	6.6	122.3
Ticket 4L	170	120	100	10	0	6.00	97.7
Ticket 4R	260	0	100	40	0	9.00	315.7
Ticket 5L	190	45	165	0	0	5.51	31.9
Ticket 5R	170	144	76	10	0	5.58	95.5
Ticket 1L(Amb.)	116	2	82	0	200	4.97	34.8
Ticket 1R(Amb.)	29	151	20	0	200	4.98	8.6
Ticket 2L(Amb.)	20	0	180	0	200	10.80	13
Ticket 2R(Amb.)	15	145	35	5	200	7.23	81.5
Ticket 3L(Amb.)	123	69	35	13	160	6.40	182.5
Ticket 3R(Amb.)	127	0	86	7	180	6.60	127.8
Ticket 4L(Amb.)	85	60	50	5	200	6	98
Ticket 4R(Amb.)	130	0	50	20	200	9	316.6
Ticket 5L(Amb.)	92	27	81	0	200	5.54	33.4
Ticket 5R(Amb.)	82	76	37	5	200	5.62	97.7

Can we pool the data?

All subjects made decisions in both risk and ambiguity environments. To test whether we can pool the data or whether we observe order effects, we compare the individual choices as well as the switching behaviour of the treatments for each environment. If either the choices or the switching behaviour is significantly different depending on the order they faced the environment, we can not pool the data without accounting for possible effects. We find that for some choice problems the share of individuals preferring one ticket over the other and also the share of switching behaviour is significantly affected by the order[13]. We believe that this effect may be due to subjects getting more confident about their own preference when making repeatedly similar choices or due to an increasing consistency bias. Thus for the non parametric analysis, we decide not to pool the data and only use data from the environment observed first.

Table 8, 9, 10, and 11 presents a serious of χ^2 tests. We test whether the choices or the switching behaviour from the same environment and the same problem set differ, if they have been presented in the first or the second environmental block.

Table 8: Share of left ticket selected under ambiguity by order and problem

	Problem 1	Problem 2	Problem 3	Problem 4	Problem 5
1st Environment	.328	.731	.402	.651	.372
2nd Environment	.457	.637	.478	.521	.330
Pearson χ^2 p-value	.108	.183	.320	.077	.554

Table 9: Share of left ticket selected under risk by order and problem

	Problem 1	Problem 2	Problem 3	Problem 4	Problem 5
1st Environment	.514	.802	.400	.440	.564
2nd Environment	.280	.736	.455	.425	.557
Pearson χ^2	.003	.292	.462	.848	.924

Table 10: Switching under ambiguity by order and problem

	Problem 1	Problem 2	Problem 3	Problem 4	Problem 5
1st Environment	.323	.304	.167	.227	.154
2nd Environment	.244	.196	.050	.070	.091
Pearson χ^2	.454	.313	.098	.049	.458

[13] for details see Table 9 and Table 10 affected by the order in the appendix

Table 11: Switching under risk by order and problem

	Problem 1	Problem 2	Problem 3	Problem 4	Problem 5
1st Environment	.303	.278	.143	.022	.185
2nd Environment	.088	.121	.186	.229	.290
Pearson χ^2	.026	.161	.576	.003	.241

Preferred Ticket by Decision Rule

Table 12: Preferred tickets by decision rules

	Left Ticket	Right Ticket
Problem 1	MaxMax; MaxE	MaxMin; MaxE; MinVar
Problem 2	MaxE; MinVar	MaxMin; MaxMax
Problem 3	MaxMin; MaxMax	MaxMin; MaxE; MinVar
Problem 4	MaxMin; MinVar	MaxMax; MaxE
Problem 5	MaxE; MinVar	MaxMin; MaxMax; MaxE

Table 12 describes whether specific decision rules which could motivate the choice of each problem. Subjects who follow the MaxMax-Rule would choose the ticket with the higher probability of receiving the maximal payoff. In comparison the MaxMin rule describes the strategy of reducing the probability of the worst possible outcome. The MaxE rule describes the strategy of maximising the expected payoff and the MinVar describes the strategy of reducing the variance. Accounting for complexity of the decision problem, we only describe choosing a ticket as not in line with a specific rule if this is obvious. Therefore, if the expected payoff in problem 5 differs by less than 10 cents, we would still describe both tickets as in line with the MaxE rule.