Lahno, Amrei M. und Serra-Garcia, Marta:

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Munich Discussion Paper No. 2012-34

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Online at https://doi.org/10.5282/ubm/epub.14309

Peer Effects in Risk Taking

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This version: Dec 20, 2012

First version: July 13, 2012

Abstract

This paper examines the effect of peers on individual risk taking. In the absence of informational motives, we investigate why social utility concerns may drive peer effects. We test for two main channels: utility from payoff differences and from conforming to the peer. We show experimentally that social utility generates substantial peer effects in risk taking. These are mainly explained by utility from payoff differences, in line with outcome-based social preferences. Contrary to standard assumptions, we show that estimated social preference parameters change significantly when peers make active choices, compared to when lotteries are randomly assigned to them.

JEL codes: C91, C92, D03, D83, G02.

Keywords: Peer Effects, Decision Making under risk, Social Comparison, Social Preferences, Laboratory Experiment.

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1 Introduction

Peers have a large impact on many aspects of life. One of these aspects is risk taking: peers affect stock market participation (e.g., Shiller, 1984; Hong et al., 2004), the decision to insure (Cai, 2011), and other risky behaviors.[1] These effects can be broadly classified as being driven by social learning, i.e. information peers have, or social utility, i.e. a direct utility from social comparison. While recent studies have shown social utility is an important driver of peer effects in risk taking (e.g., Bursztyn et al., 2012) and recent decision theories have been developed to allow for others to affect risk taking (Maccheroni et al., 2012), there is little empirical evidence about what drives social utility effects. Existing theories of outcome–based social preferences (Fehr and Schmidt, 1999; Bolton and Ockenfels, 2000; Charness and Rabin, 2002) suggest that relative payoff comparisons drive peer effects, while evidence from social psychology highlights the role of conformism (Asch, 1956; for an overview, see Cialdini and Goldstein, 2004).

This paper provides experimental evidence showing that, in the absence of informational motives, peer effects in risk taking are mainly driven by relative payoff concerns. Importantly, our results indicate that the direction and strength of these concerns strongly depend on whether peers make active choices. If peers do not make active choices among lotteries, individuals display a strong dislike of payoff disadvantages; if they do, this dislike weakens and a dislike of payoff advantages arises.

We obtain our results using a lab experiment, in which peers are anonymous and where we carefully identify peer effects, among others, by eliciting individual choices twice: once individually and again in groups of two. Our experimental design overcomes difficulties faced with field data in identifying peer effects (Manski, 1993) and, at the same time, provides evidence that is most likely a lower bound for the role of peers in risky choices (Falk et al., 2011). Our results suggest that individual decisions under

[1] Peers also affect credit decisions (e.g., Banerjee et al., 2011; Georgarakos et al., 2012) as well as different teenager (risky) behaviors (for an overview, see Sacerdote, 2011). Generally, peer effects are important in education (e.g., Sacerdote, 2001; Duflo et al., 2011), in labor (e.g., Falk and Ichino, 2006; Card et al., 2010; Mas and Moretti, 2009), in savings decisions (e.g., Duflo and Saez, 2002; Kast et al., 2012) and pro-social behavior (e.g., Gächter et al., 2012).

risk should not ignore the role of social comparisons, as these may have important consequences for many economic decisions.

Existing models of social preferences assume that individuals suffer a disutility from earning less than their peer, i.e. "envy" (e.g., Fehr and Schmidt, 1999). This is also implicit when arguing that individuals care about "keeping up with the Joneses" (e.g., Galí, 1994). At the same time, in the inequity aversion model by Fehr and Schmidt (1999) individuals may feel a disutility from earning more than the peer, i.e. "guilt". While the strength of envy is supported by a variety of experimental data, there is mixed evidence regarding guilt. Some studies suggest that individuals may not care about, or even enjoy, being head of their peer (e.g., Fershtman et al., 2012). To the best of our knowledge, our experiment is the first to provide a direct test of outcome–based social preferences in risky choices.

We first compare behavior in two treatments in which individuals receive feedback about peers, and can condition their choices on them, relative to a baseline treatment, where individuals receive no information about others. We find strongly significant peer effects: the average rate of changes in choices more than quadruples, from 7% to 33%, in the presence of a peer. Across individuals we uncover substantial heterogeneity: while some remain unaffected by the presence of a peer, others exhibit large social utility effects. Second, to disentangle outcome–based social preferences from a desire to conform to the peer, we run a treatment where the peer is randomly allocated one of two possible lotteries. We compare it to a treatment where the peer actively chooses between lotteries. If outcome–based social preferences are important, even randomly allocated lotteries to the peer should matter. We find that they do, the rate of changes increases from 7% to 18% in this treatment. Hence, almost half of the social utility effect is driven by relative payoff concerns, even if the peer makes no choices, while slightly more than half is driven by active choices of the peer.

To precisely distinguish a peer effect from revisions of choices (e.g. due to mistakes in the first choice), we use the strategy method. We consider this an important methodological step as it allows us to (1) rule out the effect of differences in the feedback about others' choices, and (2) the effect of knowledge about others' consistency or risk preferences, as well as (3) to have a clear reference point in each choice. Using the strategy method, we show that, in the presence of a peer, the most frequent decision of peers who change their choices is to imitate. Further, we find that active choices by the peer have a significant effect on the likelihood to imitate, while not affecting the rate of revisions.

Although an increase in imitation with active choices by the peer is in line with a desire to conform, this increase may be driven by a change in the strength of preferences with respect to payoff comparisons. If peers choose actively, envy and guilt may change, in a similar vein as intentions matter for pro-social behavior (e.g., Falk and Fischbacher, 2006). To examine which effect is empirically at play we estimate the strength of envy, guilt and conformism. In particular, we estimate a finite mixture model (e.g., Harrison and Rutström, 2009; von Gaudecker et al., 2011; Conte et al., 2011), in which we allow individuals to be either selfish, display no social utility concerns, or social, display a concern about others.

Our results show that almost half of the sample is of a social type, while the rest are selfish. For the social type, we find that if the peer is randomly allocated a lottery, individuals' behavior is best explained by a strong feeling of envy, while there is no significant feeling of guilt. Additionally, there is no evidence of a concern for conformism, as we would have expected. In contrast, if the peer actively chooses a lottery, three results are observed: first, the feeling of envy is reduced, while still significantly positive; second, the feeling of guilt becomes significantly positive; and third, the concern for conformism remains insignificant.

This evidence suggests that outcome–based social preferences are important in risk taking, but substantially depend on whether the peer makes active choices. If the peer is randomly allocated a lottery and he gets lucky, this appears to generate strong feelings of envy among individuals, but no guilt. Instead, if the peer chooses between lotteries, individuals feel more guilt from being ahead, potentially since this advantage stems from their better choice compared to the peers' and they may feel more responsible for it.

Within our setting, the desire to conform does not play a significant role. One potential explanation for this result is that decisions were extremely simple. Conformism may play a more important role when decisions are more complex and simply copying the peer avoids a costly decision–making process.

In addition to social utility, social learning is considered a main driver of peer effects (e.g., Bikhchandani et al., 1998; Banerjee, 1992; Ellison and Fudenberg, 1993).[2] To compare the importance of the social utility effect observed in our experiment to the potential role of social learning, we run a treatment in which the peer is perfectly informed about the payoff of the two lotteries that individuals have to choose from, while the individual has incomplete information, and only knows the payoffs of one lottery. In this treatment, changes of individual decisions increase significantly relative to all other treatments. Further, it is no longer the case that some individuals choose not to change a single choice, but all subjects now revise their choices more than once. Hence, we show that informational motives can significantly strengthen peer effects in our framework.

Our findings have important implications for the development of risky behaviors. Even in a very simple environment, receiving feedback about others' outcomes can generate a substantial increase in imitative behavior and can hence lead to the spread of risky choices. This has implications, for example, for the advertising campaigns of lotteries, such as the Dutch Postcode Lottery, where winners are very clearly announced within a neighborhood. Our results indicate that this may impact the choice to participate.[3] Further, policy–makers or marketers trying to increase the spread of a product can have some success by providing it as a gift to important individuals within a social group. However, obtaining the endorsement of these individuals through their active choices is likely to have a much larger impact. Hence, efforts to convince some indi-

[2] Anderson and Holt (1997) and Huck and Oechssler (2000), among others, observe informational cascades in the laboratory. Other laboratory studies on social learning include Çelen and Kariv (2004) or Goeree and Yariv (2007).

[3] Kuhn et al. (2011) show that the lottery has consequences ex–post: individual consumption patterns, especially of luxury cars, are significantly altered when a neighbor wins in the Dutch Postcode Lottery.

viduals to buy a product, such as an insurance or investment product, should be made with care, as these may be viewed by others as impositions rather than active choices.

Recent evidence from the field focusing on particular risky choices is in line with our results. Two recent field experiments have examined the effect of peers for buying insurance Cai (2011) and buying an investment product Bursztyn et al. (2012). For these particular products, they find substantial peer effects, but different drivers of peer effects. In the study by Cai (2011), peers exert most influence through the transmission of information, while in Bursztyn et al. (2012) both social and informational motives play a role. Our controlled laboratory evidence contributes to these studies by showing that social utility may be especially important when peers are considered as having chosen the product actively, while they may be hard to detect if individuals perceive choices as induced by others. While we cannot evaluate to what extent perceptions differed across the two studies, it may be an explanation for the differences in their results.

Our results are broadly in line with the few existing studies on social comparison effects in risk taking. We find substantial peer effects as they do (Bault et al., 2008; Linde and Sonnemans, 2012; Cooper and Rege, 2011). Our study differs from them in that we use different treatments to test for the direct impact of payoff differences as well as a mixture model to estimate preference parameters.[4] Further, our finding that a dislike of payoff differences is most important for the social utility dimension of peer effects does not appear to be unique to risk, but is line with the results of Gächter et al. (2012), who examine peer effects in a gift-exchange game experiment. They find social preferences play a stronger role than social norms.[5]

The remainder of the paper is organized as follows. In the next section we describe the experimental design and procedures in detail. In Section 3 we setup the theoretical

[4]Further, in Bault et al. (2008) there was either no peer, but a computer, the peer never made a choice in Linde and Sonnemans (2012) and only past choices of others were known Cooper and Rege (2011). See Trautmann and Vieider (2011) for an overview of studies on social risk.

[5]There are now a variety of studies considering social comparison effects in games such as public good games or coordination games (e.g., Falk and Fischbacher, 2002; Falk et al., 2013).

framework and derive testable hypotheses. Our main results are presented and discussed in Section 4. Section 5 concludes. The experimental instructions are presented in Appendix A. All proofs are presented in Appendix B, additional tables and results are presented in Appendix C.

2 Experimental Design

2.1 Treatments

Our experiment identifies peer effects by eliciting the same decisions twice. In Part I of the experiment, subjects make twenty choices among two lotteries, A and B, individually without any social interaction with other subjects. In Part II, they make the same choices, but in a different order, and in groups of two. In each group, one subject is assigned to be *first mover* and the other *second mover*. Depending on the treatment, the second mover may be given the option to condition his choice on that of the first mover.[6] Hence, we measure changes driven by the presence and choices of a first mover, by comparing the second mover's decision in Part I to the same decision in Part II of the experiment. We will also refer to the first mover as the *peer*. Note that this is a weak form of peer: the first mover is anonymous to the second mover throughout. The second mover only knows that he is a subject in the same session.[7]

We run a baseline treatment, BASE, where the second mover receives no information about the first mover's choices. The second mover cannot condition his choice on that of the first mover and no feedback is given at the end of the experiment about choices or payoffs. This allows us to measure how often switching, i.e. changes in choices between Part I and II, occurs in the absence of any feedback about others' choices. Second, we run two treatments to test for the presence of social utility motives. In the first treatment, RAND, the first mover does not make a decision in Part II of

[6] Groups were fixed for the whole of Part II. All choices were made without any feedback until the end of the experiment.

[7] Throughout, we will refer to the first mover as "she" and the second mover as "he".

the experiment. Instead, she is randomly allocated a lottery. Here a concern about payoff differences can lead to switching by the second mover. In the second treatment, CHOICE, we allow the first mover to choose. The setup is the same as in RAND except for the fact that first movers now actively choose between the two lotteries. Here, a desire to conform, make the same choices as the first mover, can lead to switching, in addition to a concern about payoff differences.

In both treatments, the second mover is allowed to condition his choices on the lottery allocated to the first mover. We use the strategy method, which allows us to observe the choice of the second mover for both possible allocations or choices, A and B. It also allows us to obtain a clean identification of peer effects for several reasons. Let us define a peer effect. We say a peer effect occurs if an individual changes his or her choices due to the choices or allocations of a peer. Using the strategy method, we can rule out that the individual changes his choices because of what he learns about the risk preferences or consistency of the peer. Since, at the moment of making his decision, the individual has no information about the risk preferences or consistency of the peer, these cannot influence the peer effect. In addition, there are no differences in feedback, regarding the peer's choices, between RAND and CHOICE, which allows for a clean treatment comparison. The fact that individuals make choices twice, in Part I and II, could lead to changes in choices, due to, for example, revisions of earlier mistakes. The strategy method allows us to distinguish these revisions from the choice to imitate. In the existing literature, there is no consensus about the potential effect of the strategy method on choices, but a clear consensus that treatment effects observed with the strategy method remain robust using the direct-response method (Brandts and Charness, 2011).[8] Finally, note that in both treatments learning in general is not

[8] A difference between BASE and RAND or CHOICE is that the latter treatments use the strategy method. For the reasons mentioned above, however, the use of the strategy method is crucial for a clean identification of peer effects. Introducing the strategy method in BASE would have implied introducing peer effects, since, by design, the second mover would have been allowed to condition his choice on that of the first mover. Hence, BASE does not use the strategy method. We conducted an extra treatment, ANTI, with 40 subjects, where social feedback is only received at the end of the experiment and second movers could not condition their choices on first movers' (no strategy method). We find that peer effects, i.e. switching, significantly increase compared to BASE (MW-test, p-value<0.01;

likely to play any role, since all decision problems are very simple (as we will describe below).

2.2 Lotteries

In Part I and Part II of the experiment, subjects made 20 choices between a lottery A and a lottery B. Lottery A yields

$$m_A^g = 20 \quad \text{and} \quad m_A^b = 0, \tag{1}$$

where the good state, g, occurs with probability p, and the bad state b with probability $1 - p$. We label this lottery as the *risky* lottery. To keep comparability of choices constant, we generate the payoff of lottery B, similar to that of an insurance product, in the following way:

$$m_B^g = 20 - (1-p)cf \quad \text{and} \quad m_B^b = 0 + c - (1-p)cf, \tag{2}$$

where m_B^g and m_B^b denote the payoffs in the good and bad state, respectively. Compared to the payoffs of lottery A in each state a "premium" of $(1-p)cf$ is subtracted, while in the bad state B pays an additional coverage of c. If c is 20, B provides full certainty. Lottery B is labeled throughout as the *safe* lottery.[9]

All lotteries are summarized in Table 1. As can be seen, the lotteries vary with respect to the parameters p, f, and c. First, we divide 18 lotteries in the experiment into three groups: first, lotteries with $p = 0.2$ (20/80 lotteries); second, $p = 0.5$ (50/50 lotteries); and third $p = 0.8$ (80/20 lotteries). Within each group, there are six decision problems: Two with $f = 1.2$, two with $f = 1$ and two with $f = 0.8$. Throughout the paper, we will denote those lotteries with $f = 1.2$ as those where B has a higher expected value than A ($EV_B > EV_A$), while those with $f = 1$ as $EV_B = EV_A$ and those

Marginal effect, stemming from logit regression, p-value<0.01). This indicates that peer effects are significant, even without using the strategy method.

[9] In terms of risk preferences B cannot be labeled as safe since it does not necessarily yield a certain payoff. In comparison to A, we still label it as safe, for simplicity, as its variance is always smaller. But note that a risk averse individual does not necessarily prefer B over A.

with $f = 0.8$ as $EV_B < EV_A$.[10] Within each pair of decisions with the same f, c is either 20 or 15. We label lotteries with $c = 20$ as *certainty lotteries*, and those with $c = 15$ as *uncertainty lotteries*.[11]

Nr.	Lottery A	Lottery B	c	f	EV_A	EV_B
		Panel A: 20/80 Lotteries				
1	(20,0.2 ; 0,0.8)	(0.80,1)	20	1.2	4.00	0.80
2	(20,0.2 ; 0,0.8)	(5.60,0.2 ; 0.60,0.8)	15	1.2	4.00	1.60
3	(20,0.2 ; 0,0.8)	(4,00,1)	20	1.0	4.00	4.00
4	(20,0.2 ; 0,0.8)	(8.00,0.2 ; 3.00,0.8)	15	1.0	4.00	4.00
5	(20,0.2 ; 0,0.8)	(7.20,1)	20	0.8	4.00	7.20
6	(20,0.2 ; 0,0.8)	(10.40,0.2 ; 5.40,0.8)	15	0.8	4.00	6.40
		Panel B: 50/50 Lotteries				
7	(20,0.5 ; 0,0.5)	(8.00,1)	20	1.2	10.00	8.00
8	(20,0.5 ; 0,0.5)	(11.00,0.5 ; 6.00,0.5)	15	1.2	10.00	8.50
9	(20,0.5 ; 0,0.5)	(10.00,1)	20	1.0	10.00	10.00
10	(20,0.5 ; 0,0.5)	(12.50,0.5 ; 7.50,0.5)	15	1.0	10.00	10.00
11	(20,0.5 ; 0,0.5)	(12.00,1)	20	0.8	10.00	12.00
12	(20,0.5 ; 0,0.5)	(14.00,0.5 ; 9.00,0.5)	15	0.8	10.00	11.50
		Panel C: 80/20 Lotteries				
13	(20,0.8 ; 0,0.2)	(15.20,1)	20	1.2	16.00	15.20
14	(20,0.8 ; 0,0.2)	(16.40,0.8 ; 11.40,0.2)	15	1.2	16.00	15.40
15	(20,0.8 ; 0,0.2)	(16.00,1)	20	1.0	16.00	16.00
16	(20,0.8 ; 0,0.2)	(17.00,0.8 ; 12.00,0.2)	15	1.0	16.00	16.00
17	(20,0.8 ; 0,0.2)	(16.80,1)	20	0.8	16.00	16.80
18	(20,0.8 ; 0,0.2)	(17.60,0.8 ; 12.60,0.2)	15	0.8	16.00	16.60

Table 1: Decision Problems

Each panel in Table 1, especially if divided by the level of c, can be seen as a multiple decision list (e.g., Holt and Laury, 2002). We presented choices individually, instead of using a list format, to have maximum control over the individuals' information and potential reference point. By focusing on individual choices, we make sure the second

[10] We will use the terms expected value and f interchangeably, though what we exactly observe is the effect of changes in f.

[11] Additionally, we included two choices to serve as controls for the certainty effect (Kahneman and Tversky, 1979; Andreoni and Sprenger, 2009). We analyze these two decisions and the role of peer effects, in Lahno and Serra-Garcia (2012).

mover does not have information about the consistency of the first mover. Though this potentially increases inconsistencies, it allows us to provide a clean answer to our main research question, is an individual's risky choice affected by the risky choice of a peer?

The order of the lotteries was randomized across Part I and II. The position of lottery A and B on the screen (left or right) was also randomized across subjects to avoid systematic reference point effects (Sprenger, 2012). Lastly, in Part II risks are *perfectly correlated* across group members: one single draw of nature determines the payoffs of both members of a group. This implies that if they both choose the same lottery, they will certainly obtain the same payoff. We believe this type of risks to be especially relevant for peer effects, and hence concentrate on them as several papers in the literature do. Among others, risks are perfectly correlated in the Dutch Postcode Lottery, examined by Kuhn et al. (2011), and in the investment product considered by Bursztyn et al. (2012). They are also almost perfectly correlated in the weather insurance considered by Cai (2011).

2.3 Experimental procedures

Sessions were run in MELESSA (Munich Experimental Laboratory for Economic and Social Sciences), the laboratory of the University of Munich. Each session lasted approximately one hour. Instructions were handed out in printed form and read aloud by the experimenter at the beginning of each session.[12,13] Questions were answered in private by the experimenter. The experiment was computerized using zTree (Fischbacher, 2007). In total, 160 subjects participated in the main treatments of the experiment (40 in BASE, 60 in RAND, and 60 in CHOICE). Their average age was 24 years and roughly 65% of all participants were female. Fields of study were almost equally distributed over 20 different fields, ranging from medicine, through cultural studies to business and

[12]The instructions of the BASE treatment can be found in Appendix A, the instructions of the other treatments can be obtained upon request from the authors.

[13]In every treatment, subjects were provided with an answer sheet at the beginning of Part I, which displays every decision problem in the same order as presented in Part I and on which they could record their decisions made in Part I.

economics.

One choice from one part was randomly selected at the end of the experiment for payment. If Part I was selected for payment, then one decision problem was determined for each participant. If Part II was drawn, one decision problem was selected for each and every group only. Thus, for both group members the same decision problem was payoff-relevant. To ensure credibility, one participant was randomly selected as assistant at the end of the experiment. The assistant drew one ball from an opaque bag containing two balls, labeled with numbers 1 and 2, corresponding to Part I and II, and then balls from an opaque bag containing 20 balls, labeled 1 to 20. For each decision problem, the corresponding combination of black and white balls (representing each state) was put in an opaque bag and the assistant again drew one ball. Once all draws were done, payoffs were computed and subjects were paid out in cash. Subjects were paid a show-up fee of 4 Euro additionally to their earnings from their lottery choices, yielding in total an average of 15 Euro per subject.

3 Theoretical Framework

We present a simple theoretical framework that allows for social utility in risk taking. We leave all proofs to Appendix B.1. In line with our experimental design, we focus on the case where two lotteries are available, A and B, each yielding payoff m_i^j, as defined by (1) and (2), in state of nature j, where $j \in \{g, b\}$ and $i \in \{A, B\}$.

We assume all individuals derive an *individual* utility from their lottery choices. The expected individual utility from lottery i is $U_i = \sum_j p_j u(m_i^j)$. The only assumption made about the utility of a given outcome is that $u(\cdot)$ is increasing and continuous.

3.1 Social Utility

In addition to caring about their own payoffs, some individuals may derive utility depending on the payoffs and choices of others. We consider two motivations, a concern about payoff differences with respect to their peer, and a desire to conform to their peer. In particular, let $i, k \in \{A, B\}$ denote the lottery of the individual and his peer, respectively. The individual's expected utility is

$$V_{i,k} = U_i + \eta \left[\sum_j p_j R(m_i^j - m_k^j) + \gamma \cdot \mathbf{1}_{\{i=k\}} \right], \tag{3}$$

where $\mathbf{1}_{\{i=k\}}$ denotes the indicator function that takes value 1 if the lottery chosen by the first and second mover coincide, and 0 otherwise. The parameter η determines whether an individual experiences social utility. We assume $\eta \in \{0, 1\}$, i.e. some types, labeled as "selfish types", do not care about others, while others care and are labeled as "social types".

Social types care about payoff differences relative to their peers, as in the inequity aversion model of Fehr and Schmidt (1999). In state $j \in \{g, b\}$ obtaining m_i^j, compared to the peer's outcome of m_k^j, yields a utility of $R(m_i^j - m_k^j)$, where

$$R(x) = \begin{cases} -\beta x & \text{if } x \geq 0, \\ \alpha x & \text{if } x < 0. \end{cases}$$

In line with the inequity aversion model, and with existing empirical evidence, we assume that individuals dislike earning less than their peers, i.e. $\alpha > 0$. In Fehr and Schmidt (1999), individuals also dislike being ahead, i.e. $\beta \geq 0$. In other models, however, individuals are assumed enjoy being ahead (e.g., in the main model of Maccheroni et al., 2012), i.e. $\beta < 0$.[14] Existing evidence is mixed: while some find individuals dislike payoff advantages on an aggregate level (e.g., Blanco et al., 2011), others do not (e.g., Fershtman et al., 2012). As a starting point and assumption, we assume that $\beta > 0$. In our results section, we will estimate β and test whether it is positive.

In the context of risky decisions, the utility from payoff comparisons may be considered from an ex-ante or ex-post perspective. Ex-ante comparison refers to differences

[14] This is in line with reference-dependent preferences (Kahneman and Tversky, 1979; Köszegi and Rabin, 2007), assuming the reference point to be the peer's payoff.

in expected utilities, while ex-post comparison refers to differences in utilities after the realization of outcomes.[15] We assume subjects to make ex-post comparisons. This is more likely in our setting, where subjects are shown their payoffs in each state and not the expected value of each lottery.

In addition to payoff differences, the individual may also care about *making* the same choice as the peer. As suggested in the seminal paper by Asch (1956), individuals may feel a disutility when they deviate from choices of others, or equivalently, feel better when making the same choices as others. A taste for conformism may generally stem from a desire to avoid blaming one-self or being *responsible* for one's own outcome. We model this preference as an extra utility $\gamma \geq 0$ from conforming to the choice of the peer (as in Cooper and Rege, 2011).

In what follows we examine the implications of social utility motives on risk taking.

3.2 The impact of others

We start by considering the case where the first mover does not choose a lottery but is randomly assigned one, as in treatment RAND. In this case, we assume the utility of conforming is zero, since first movers do not choose among lotteries and, hence, second movers cannot imitate any choices. In RAND, payoff differences may play an important role for social types. In particular, higher values of α and β lead to more imitation. To see why, suppose, for example, that the first mover was randomly assigned lottery A. Individually, the second mover may prefer B, but he anticipates that when choosing B, he will experience a disutility in the good state, due to his lower payoff compared to the first mover's, and a disutility in the bad state, due to his relatively higher payoff. Thus, in the presence of a peer, he may switch to A.

In addition to α and β, two components will be important for switching to occur. First, the difference in individual utility between the two lotteries. Second, the expected cost or benefit in direct monetary terms from choosing a different lottery. These are

[15] See Trautmann (2009) for a discussion of the ex-ante and ex-post approach from a procedural fairness perspective.

important as they determine the payoff differences in each state. Their role is illustrated when examining the effect of a downward shift in the payoffs of B, i.e. an increase in f. As f increases, B becomes less attractive per se. Further, the difference in payoffs with respect to A increases, making a switch to A, if the first mover is randomly assigned A, more likely. By the same argument, a switch to B becomes less likely.

Let us now turn to the situation in which the first mover actually chooses a lottery as is the case in treatment CHOICE. In this case, the second mover can act as the first mover, making the utility from conformism, γ, more likely to play a role. A straightforward prediction is that imitation increases. Interestingly, imitation becomes less sensitive to the expected payoffs of the lottery chosen by the first mover. Intuitively, since γ is constant and independent of payoff differences, the decision to imitate depends less on the characteristics of the lottery.

Note, that according to Fehr and Schmidt (1999), the values of α and β do not change depending on whether the first mover is randomly allocated a lottery or if she chooses a lottery. However, empirically it may be the case that their values change, potentially increase, when the first mover chooses a lottery. This would not change our predictions in RAND and, if α or β increase in CHOICE, this would yield the same predictions as with conformism. Whether social preferences change is an open question, which we address in our Results section.

Two main hypotheses can be derived from our model of social utility. First, we can focus on the treatment differences in switching. In BASE switches may occur if second movers wish to revise the choices made individually. In RAND and CHOICE, social types may have an additional motive to switch: to imitate the first mover's lottery allocation or choice. Since the first mover does not actively choose in RAND, we expect switching to be more frequent in CHOICE.

Hypothesis 1.

a) *Switching in BASE is less frequent than in RAND and CHOICE.*

b) *Switching in CHOICE is more frequent than in RAND.*

The different motives to switch also imply different strategies used in Part II. A second mover who revises her choice does so independently of the first mover. In contrast, a second mover who wishes to imitate the first mover's choice, switches only if the first mover chose a different lottery than he did individually. Since we use the strategy method to elicit choices of second movers, we can identify the direction of switches and, more precisely, the strategies used by second movers. Our model predicts that second movers should imitate, and not switch irrespective of the first movers. Further, it also predicts imitation to increase in CHOICE and to depend on the expected value of A relative to B (on f). This leads to our second hypothesis.

Hypothesis 2.

a) *Imitation is the most frequently used strategy in RAND and CHOICE.*

b) *Imitation increases in CHOICE compared to RAND.*

c) *As the payoffs of B shift downwards (f increases), imitation of A increases and that of B decreases.*

d) *The effect of f is weaker in CHOICE.*

In the discussion until now, we have focused on second movers. They are our main focus of interest in this paper, as they can condition their choices on the first mover's and hence allow for a clean observation of peer effects - independent of beliefs about the first mover's decision. We will also briefly address switching by the first mover in our empirical analysis and show that first movers' switches are in line with an anticipation of second mover's choices.[16]

[16] A game-theoretic literature has focused on the implications of social comparison and status concerns on conspicuous consumption (see, e.g., Hopkins and Kornienko, 2004). We abstract from this because existing evidence on social preferences suggests a stronger desire to avoid falling behind a peer than being ahead. Hence, we focus on the question of whether second movers will imitate first movers. This implies that, if social concerns are strong enough and beliefs are rational, individuals will in equilibrium make the same choices.

4 Results

4.1 Decisions in Part I

In order to examine peer effects across treatments, we first ensure that individual decisions in Part I do not vary across treatments. Table 2 describes the average frequency with which A was chosen, over all lotteries, by first and second movers, respectively, in each treatment. First movers choose A on average between 17.8% and 23.3% of the time, second movers choose A between 17.0% and 22.5% of the time. No differences across treatments are found, for first and second movers.

	% of A choices in Part I	
	First Mover	Second Mover
BASE	17.8%	22.5%
RAND	20.2%	21.7%
CHOICE	23.3%	17.0%
Mann-Whitney test, p-values:		
BASE vs. RAND	0.3883	0.9839
BASE vs. CHOICE	0.2070	0.4604
RAND vs. CHOICE	0.5607	0.3783

Table 2: Average Frequency of A choices in Part I

Choices in Part I display a strong variance depending on the kind of decision problem. While a vast majority of individuals chooses lottery A among the 20/80 lotteries if B has a lower expected payoff (88.8% and 70.2%; $f > 1$), this frequency drops to 22.1% and 21.7% for the 50/50 lotteries and to 16.7% for the 80/20 lotteries. Instead, when B has a higher expected payoff ($f < 1$), it is chosen in the majority of all cases. In the intermediate cases, where A and B have the same expected payoff ($f = 1$), the frequency with which A is chosen again varies from over 30% in the 20/80 lotteries down to 7.4% in the 50/50 lotteries.[17] Hence, on average individuals are risk averse, as is usually observed in experiments.[18]

[17]A detailed overview of choices in Part I is provided in Appendix C.

[18]We also controlled for consistency of decisions in Part I. We find across different probability panels, controlling for certainty, that at most 13% of decisions patterns are inconsistent. If we exclude

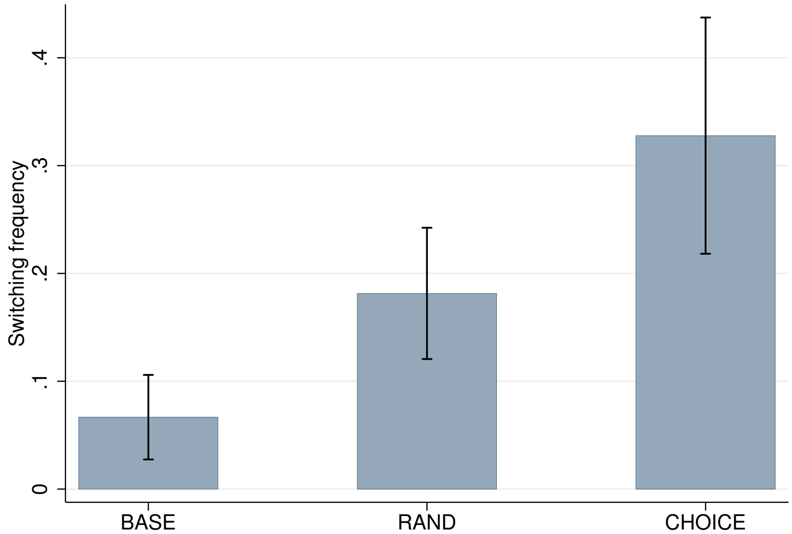
4.2 Peer Effects by Treatment

Peer effects in risk taking are significant. In the absence of any feedback, second movers revise on average 6.7% of their choices, as shown in Figure 1a. This frequency increases significantly in the presence of a peer. When the second mover can condition his choices on the first mover's allocated or chosen lottery, switching increases to 18.1% in RAND and to 32.8% in CHOICE.[19] These frequencies reveal two results: (1) at least some second movers care about first movers' payoffs relative to their own, even if the first mover does not actively choose, as the switching frequency in RAND almost triples compared to BASE; (2) however, lotteries *chosen* by first movers are substantially more important to second movers than lotteries *allocated* to first movers, as the switching frequency is higher in CHOICE. The difference between RAND and CHOICE is significant (Mann-Whitney (MW)-test, p-value=0.071). Of the total peer effect in CHOICE, we hence find that slightly less than half (44%) is generated independent of first mover's choices, while slightly more than half (56%) is driven by the fact that first movers choose between lotteries.

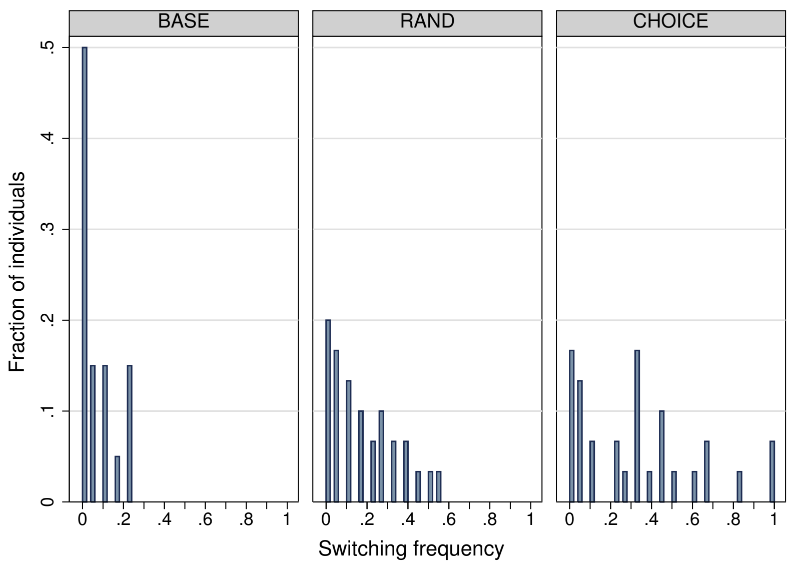
Figure 1b reveals that our population consists of different types. First, in BASE 50.0% of second movers do not revise a single choice in Part II. This frequency is 20.0% in RAND and 16.7% CHOICE. These individuals remain unaffected by the presence of a first mover, i.e. act as selfish types according to our model. Since the fraction does not change much in CHOICE compared to RAND, this suggests that the fact that the peer chooses plays a minor role on the *extensive* margin. However, whether choices of peers are actively made has an important impact on the *intensive* margin: the fraction of subjects who do switch do so more often in CHOICE compared to RAND. Note that, among those that switch, there could be selfish types who made a mistake in Part I, as those who switch in BASE. In the next subsections we will examine strategies,

inconsistent second movers from our sample our results presented in what follows remain qualitatively the same.

[19] A switch is said to occur if, for at least one of the lotteries of the first mover, the second mover changes his choice with respect to Part I. Alternative definitions, such as considering switches separately for each of the two possible lotteries of the first mover, do not affect results significantly. In Appendix C, Tables 9 and 10 display choices and switching frequencies separately (if the first mover has A or B).



(a) Average switching frequency



(b) Distribution of individual switching frequencies

Note: In BASE switching is a dummy variable that takes value 1 if the second mover changes his choice in Part II with respect to the choice made in Part I for the same decision problem. In RAND and CHOICE it takes value 1 if the second mover changes his choice in Part II for at least one of the possible choices of the first mover with respect to the choice made in Part I for the same decision.

Figure 1: Peer effects by treatment

to distinguish between those who revise their choices and those who imitate, and we will allow for errors in our estimation. All in all, the shifts in switching distributions between treatments are consistent with the assumption that some subjects are *selfish* and some of the *social* type.

The treatment differences described above remain significant in a regression analysis that controls for lottery characteristics, as reported in Table 3. As shown in all specifications, the likelihood of switching is significantly larger in all treatments compared to BASE. As already suggested above, marginal effects increase gradually and significantly, from RAND to CHOICE.[20] This leads to Result 1, in support of Hypothesis 1.

Result 1.

a) Peer effects are significant: the frequency of switching in RAND and CHOICE is significantly higher than that in BASE.

b) Not only payoffs but also active choices by the peer matter: switching is significantly more frequent in CHOICE than in RAND.

Further, in Table 3 we uncover three additional results. First, switching is more likely in decision problems where A's expected value (EV_A) is weakly larger than B's (EV_B). This is in line with the prevalence of risk aversion in our experiment. When $EV_A > EV_B$, the difference in expected individual utilities between A and B is small or negative and, hence, switches are more likely to occur in the presence of a peer. Interestingly, the average switching frequency in BASE is 6.7% for all lottery categories, irrespective of whether $EV_A > EV_B$, $EV_A = EV_B$, and $EV_A < EV_B$. This suggests that the presence of a peer in the other treatments drives the observed effect of expected values.

Additionally, if lottery B provides certainty, the likelihood of switching increases. This shows that switching cannot be solely attributed to mistakes by the second mover,

[20] The marginal effects are significantly different (p-value<0.01 comparing RAND and CHOICE).

	Probability of switching		
	(1)	(2)	(3)
RAND	0.115***	0.115***	0.116***
	[0.035]	[0.035]	[0.033]
CHOICE	0.261***	0.261***	0.258***
	[0.056]	[0.056]	[0.058]
$EV_A > EV_B$		0.091***	0.091***
		[0.026]	[0.026]
$EV_A = EV_B$		0.075***	0.075***
		[0.026]	[0.026]
Certainty		0.036**	0.036**
		[0.016]	[0.015]
p=0.5		-0.088***	-0.088***
		[0.027]	[0.027]
p=0.8		0.008	0.008
		[0.035]	[0.035]
N	1,440	1,440	1,440
Nr. of Subjects	80	80	80
Individual characteristics	No	No	Yes
Pseudo log–lik.	-685.5	-672.2	-667.5
Pseudo R–squared	0.068	0.0862	0.0926

Note: This table presents estimated marginal effects from logit regressions on the probability of switching, defined as in Figure 1 and in the text. RAND and CHOICE denote dummies for each treatment, where BASE is the omitted category. $EV_A > EV_B$ and $EV_A = EV_B$ are dummy variables for the expected value of A versus B. Certainty takes value 1 if lottery B is degenerate, 0 otherwise. The variables $p = 0.5$ and $p = 0.8$ refer to the lotteries with these probabilities, taking $p = 0.2$ as omitted category. Individual characteristics are gender, a dummy for business or economics student and age of the subject. Standard errors are presented in brackets and clustered at the individual level. ***, **,* indicate significance at the 1%, 5% and 10% level, respectively.

Table 3: Determinants of switching frequency

for example, due to difficulties in calculating the expected values of the lotteries, especially that of lottery B. If this were the case, we would expect switching to be more frequent when B is uncertain. Instead, the data suggests that a degenerate B lottery is a clearer reference point for second movers, which makes the comparison to the first mover's lottery more salient.

Third, we observe switching to be less likely when probabilities for good and bad states are equal, i.e. $p = 0.5$. This is also the case in BASE, which indicates that decision making may have been easier when the probability is 0.5. Even if this were the case, considering only lotteries with $p = 0.5$, we still observe the same treatment effects. Hence, peer effects in our data are *on top* of any "noise" in decision-making of second movers (in terms of revisions of their choices from Part I).

Before examining the strategies used by second movers, let us briefly mention the switching frequencies of first movers. First movers on average switch in 8% of the cases in BASE, 48% in RAND and 12% in CHOICE. The switching rate is close to 50% in RAND (48%), since the lotteries are randomly assigned to the first mover. Switching is (marginally) significantly different in CHOICE compared to BASE (MW-test p-value=0.095). This suggests that first movers anticipate the choices of the second mover and hence switching increases. We find further support for this by examining whether first movers' switches are towards the lottery chosen by the majority of second movers. In 10 out of 14 decisions, in which first movers switch, their switches are towards the lottery chosen by the majority of second movers.

4.3 Strategies and Comparative Statics

In what follows we examine social utility motives in detail. As has become clear from the discussion above, within each treatment, by considering the overall switching frequency only, we cannot disentangle a correction of mistakes in Part I from actual peer effects in Part II. A key advantage of our design is that we elicited choices with the strategy method.

We can distinguish three potential strategies of a second mover who switches in a given decision problem. First, he may switch to *imitate* the first mover's choice. This implies that, if the first mover has A, he chooses A, and if she has B, he chooses B $(A, A; B, B)$. Individuals who use this strategy, clearly do not revise their choice of Part I, but are affected by their peer. Second, a second mover may *deviate* from his first mover's choice: If the first mover has A, the second mover chooses B, and if she has B, the second mover chooses A $(B, A; A, B)$. Third, he may *change* his choice made in

Part I. This we also refer to as a revision. It implies that he chooses a different lottery compared to his Part I choice, *independent* of the first mover's lottery (e.g., $A, A; A, B$).

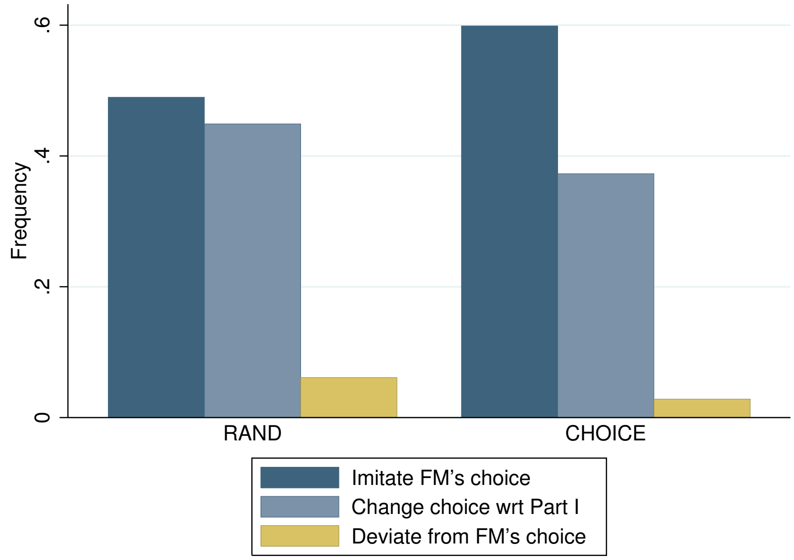


Figure 2: Strategies used by second movers when switching

Figure 2 presents the frequencies of these three strategies. It reveals that imitation is a dominant motive behind switching. Out of those second movers who switch, most imitate (49% in RAND and 60% in CHOICE), while only very few deviate (6% in RAND and 3% in CHOICE).

Further, we observe that 44.9% of switches are changes with respect to Part I in RAND. Given an average switching frequency of 18.1%, this is equivalent to 8% overall, which is in turn close to the switching frequency in BASE (6.7%). The difference is not significant (MW-test, p-value=0.2951). In CHOICE 37.3% of switches are changes with respect to Part I; out of 32.8% of choices this adds up to roughly a 12% of revisions, which is not significantly different to that in BASE (MW-test, p-value=0.2951).

Table 4 examines the determinants of imitation. We find that, in line with Figure 2, the rate of imitation increases significantly from RAND to CHOICE. Thus, when the peer chooses among lotteries, in contrast to being randomly allocated one, imitation increases. Further, Table 4 separates imitation into two possible directions, towards more or less risk. Columns (3) and (4) consider imitation of A, if the first mover has A, among second movers, who chose B in Part I (for a given decision problem). Similarly, columns (5) and (6) focus on the imitation of B choices.

According to our theoretical predictions, we would expect imitation of A to increase and imitation of B to decrease as the payoffs of B are shifted downwards (f increases). This is confirmed by the marginal effects of the dummy variables for $EV_A > EV_B$ and $EV_A = EV_B$. However, these are not significantly different from zero for imitation of B, potentially due to the limited number of observations. Further, we observe that the effect of B's payofs is moderated in CHOICE: the marginal effect of CHOICE$\cdot(EV_A > EV_B)$ in column (4) is negative and significant, and it is positive (but insignificant) in column (6). This is in line with a desire to conform to the first mover, but may also arise if concerns about payoff differences change, becoming more equality-seeking. To disentangle between these we estimate both the inequity aversion and conformism parameters and present the results in the next subsection.

Additionally, when B is a degenerate lottery, the likelihood of imitating B marginally increases, indicated by the significance of the dummy Certainty in columns (5) and (6). This again supports our argument above, that a lottery of the peer with a degenerate outcome may make the first mover's payoff a more salient reference point. This leads to Result 2, which is in line with Hypothesis 2.

Result 2.

a) In the presence of a peer, i.e. in RAND and CHOICE, the most frequently used strategy by the second mover is to imitate.

b) Peer effects generate more imitation in CHOICE.

c) Imitation depends on the expected value of the lotteries: as B's payoffs shift downwards, switching towards A is more likely, while switching towards B is less likely.

d) The above effect is moderated under CHOICE, significantly so if imitation is towards A.

	Imitate		Imitate A		Imitate B	
	(1)	(2)	(3)	(4)	(5)	(6)
CHOICE	0.111**	0.234***	0.123**	0.226**	0.097	0.149
	[0.059]	[0.094]	[0.062]	[0.109]	[0.075]	[0.231]
$EV_A > EV_B$	0.03	0.097	0.015	0.105**	-0.161	-0.185
	[0.026]	[0.063]	[0.030]	[0.056]	[0.111]	[0.196]
$EV_A = EV_B$	0.036	0.105**	0.039	0.094**	-0.126	-0.08
	[0.025]	[0.052]	[0.026]	[0.047]	[0.098]	[0.167]
Certainty	0.019	0.058**	-0.01	0.004	0.086*	0.131*
	[0.015]	[0.032]	[0.015]	[0.042]	[0.045]	[0.074]
$p = 0.5$	0.009	0.048	0.015	0.051	-0.059	-0.059
	[0.034]	[0.053]	[0.035]	[0.069]	[0.108]	[0.201]
$p = 0.8$	-0.011	0.016	-0.012	0.026	0.131*	0.095
	[0.031]	[0.033]	[0.031]	[0.055]	[0.063]	[0.101]
CHOICE$\cdot(EV_A > EV_B)$		-0.097		-0.132**		0.045
		[0.067]		[0.065]		[0.236]
CHOICE$\cdot(EV_A = EV_B)$		-0.100*		-0.074		-0.111
		[0.059]		[0.055]		[0.202]
CHOICE$\cdot$Certainty		-0.058*		-0.018		-0.084
		[0.035]		[0.044]		[0.100]
CHOICE$\cdot(p = 0.5)$		-0.042		-0.054		0.037
		[0.054]		[0.067]		[0.130]
CHOICE$\cdot(p = 0.8)$		-0.056		-0.049		-0.002
		[0.069]		[0.080]		[0.227]
Observations	1,080	1,080	864	864	216	216
Individual characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo log–lik.	-420.480	-418.014	-308.687	-305.965	-98.660	-97.700
Pseudo R–squared	0.0496	0.0552	0.0574	0.0657	0.107	0.116

Note: This table presents estimated marginal effects from logit regressions on the probability of imitation. CHOICE takes value 1 in this treatment, 0 in the RAND treatment. $EV_A > EV_B$ and $EV_A = EV_B$ are dummy variables for the expected value of A versus B. Certainty takes value 1 if lottery B is degenerate, 0 otherwise. The variables $p = 0.5$ and $p = 0.8$ refer to the lotteries with these probabilities, taking $p = 0.2$ as omitted category. Individual characteristics are gender, a dummy for business or economics student and age of the subject. The estimated marginal effects remain with the same sign and similar in size, if we use OLS regressions for the specifications with interaction effects (see Ai and Norton, 2003). Standard errors are presented in brackets and clustered at the individual level. ***, **,* indicate significance at the 1%, 5% and 10% level, respectively.

Table 4: Determinants of imitation

4.4 Structural Estimation of Individual and Social Utility

The heterogeneity observed in second movers' switching suggests that, as hypothesized, there are social and selfish types in the population. At the same time, the switching frequency in BASE reveals that some individuals may be revising their choices. Hence, to be able to classify social and selfish types, errors need to be taken into account.[21] To this purpose, we estimate a finite mixture model to account for these two types and allow both types to make errors. We focus on the data of second movers from the treatments RAND and CHOICE. In particular, we assume that second movers might be of two different types, a selfish type (for which $\eta = 0$ in our model) and a social type ($\eta = 1$). We denote the fraction of selfish types among all second movers by $\kappa \in [0, 1]$. Further, we assume that individual utility is captured by a CRRA (consumption) utility function with parameter r, i.e. $u(x) = x^r$.

Following Hey and Orme (1994), we allow subjects to make so-called Fechner errors (also see, e.g. von Gaudecker et al., 2011; Loomes, 2005) when comparing expected utilities. Hence, a subject chooses lottery i if and only if $V_{i,k} - V_{-i,k} + \tau\epsilon > 0$, where $V_{i,k}$ is given in equation (3), Section 3, and ϵ is drawn from a standard logistic distribution and assumed to be independent between subjects and decisions. The expected utilities depend on the parameters $\theta = (r, \alpha, \beta, \gamma, \tau)$.

Then, the individual likelihood to choose A in decision problem t ($t = 1, \ldots, 18$) is determined by the *score* function

$$d^t(\theta) = \frac{1}{\tau}(V_{i,k}^t(r, \alpha, \beta, \gamma) - V_{-i,k}^t(r, \alpha, \beta, \gamma)).$$

Writing d_1 (d_2) for the selfish (social) type, the grand likelihood of choosing A in t is

[21] Mixture models have been used to estimate risk preferences in heterogeneous populations, amongst others by Conte et al. (2011) and Harrison and Rutström (2009). In these papers individuals are assumed to be heterogeneous with respect to their risk preference functionals: for some subjects, behavior might be explained by expected utility, for others by rank dependent expected utility or prospect theory.

determined by the weighted likelihood function

$$\mathcal{L}^t(\kappa, \theta) = \kappa \Lambda \left(d_1(\theta)\right) + (1-\kappa)\Lambda \left(d_2(\theta)\right),$$

where $\Lambda(x) = (1 + \exp(-x))^{-1}$ denotes the standard logistic cumulative distribution function. The log-likelihood function to be maximized is then simply $L(\kappa, \theta) = \sum_{n,t} \ln \mathcal{L}^t(\kappa, \theta)$, where we sum over all subjects $n = 1, \ldots, N$, and all decision problems $t = 1, \ldots, 18$. It is maximized using the Broyden-Fletcher-Goldfarb-Shanno (BFGS) algorithm (see, e.g., Broyden, 1970; Fletcher, 1970).

Table 5 reports the estimation results.[22] The first column shows a *single* model which is based on the assumption that everyone is of a selfish type. Next, in model (2) α and β for the social types are estimated setting $\gamma = 0$. In a last step, models (3) and (4) reflect our full model, allowing $\gamma \neq 0$.

Throughout, the estimated CRRA coefficient is close to 0.6, reflecting risk aversion in consumption utility, and highly statistically significant. Turning to the mixture models, the results support our hypothesis that preferences of second movers can be classified into two groups: In all models the fraction of selfish types κ, is highly significantly different from zero and one (Wald test p-values < 0.001). We find that between 46% and 48% of choices can be better explained by allowing for social utility rather than by assuming individual utility only.

Our results reveal that α is significantly different from zero, indicating that subjects envy their peer when being worse off. In contrast, β is weakly significant in model (2), but not significantly different from zero in (3). This changes when we allow α, β and γ to differ for treatments RAND and CHOICE. If the peer makes an active choice, β is (highly) significant. That is, subjects feel guilt when having *made* a better choice

[22]Table 11 in Appendix C reports estimated models in which we account for heterogeneity between subjects by controlling for subjects' gender and whether they are economics or business students, following the approach of Harrison and Rutström (2009) and Harrison et al. (2010). Results are qualitatively similar to these presented here. An alternative would be to control for unobservable heterogeneity by fitting a random coefficients model (Conte et al., 2011). This method is however computationally exhausting given the number of parameters and individual observations.

	(1)	(2)	(3)	(4)
Fraction of selfish types				
κ		0.5259***	0.5347***	0.5115***
		[0.0907]	[0.0921]	[0.0983]
Model 1: CRRA consumption utility				
r	0.6103***	0.6113***	0.6107***	0.6221***
	[0.0265]	[0.0161]	[0.0157]	[0.0292]
τ	0.5616***	0.0513***	0.0507***	0.0595**
	[0.0607]	[0.0178]	[0.0192]	[0.0260]
Model 2: CRRA consumption utility *and* social utility				
α		1.0477***	1.0640***	
		[0.1839]	[0.2266]	
α_R				1.3215***
				[0.4141]
α_C				0.7819***
				[0.0964]
β		0.1831*	0.1395	
		[0.1030]	[0.1380]	
β_R				-0.0505
				[0.2043]
β_C				0.4021***
				[0.1469]
γ			0.2997	
			[0.4742]	
γ_R				-0.4563
				[0.4401]
γ_C				0.6854
				[0.7579]
τ_{social}		1.1800**	1.3496*	1.1091**
		[0.4827]	[0.7549]	[0.5030]
Method	ML Model	ML Mixture Model		
Observations	2160	2160	2160	2160
Pseudo log–lik.	-1045.555	-952.295	-952.085	-934.554

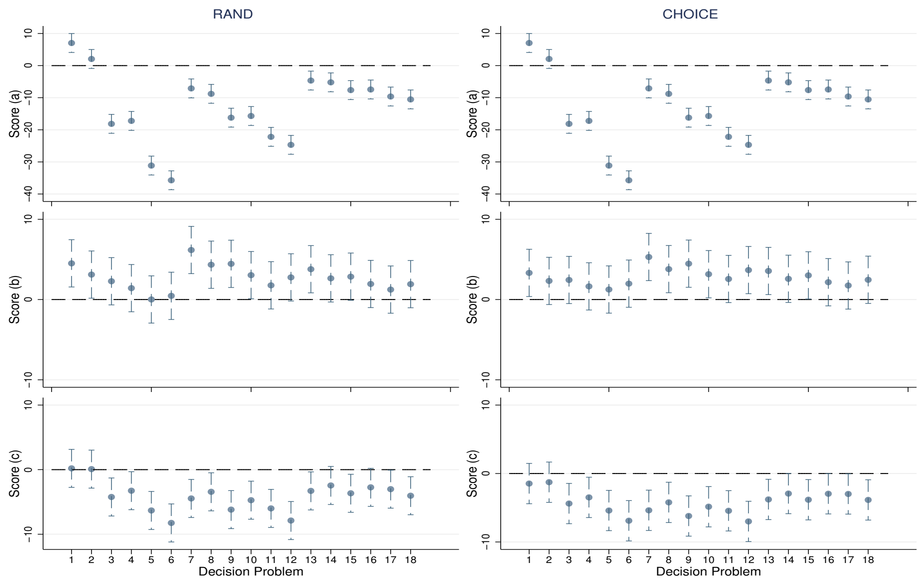
Table 5: In model (1) all individuals are assumed to be selfish. Models (2)-(4) are mixture models, in which κ denotes the probability that subjects are of the selfish type. We assume $r, \alpha, \tau > 0$ and $\kappa \in [0, 1]$ throughout; we assume $\gamma = 0$ in (2) and $\gamma \in \mathbb{R}$ in (3)-(4). In (4) we include treatment dummies for α, β and γ. Here, α_R, β_R, γ_R and α_C, β_C, γ_C denote the transformed estimates for RAND and CHOICE participants, respectively. Parameters τ and τ_{social} refer to the Fechner errors. Standard errors are reported in brackets and clustered on a subject level; *** (**, *) indicate significance at the 1% (5%, 10%) level.

than their peer, but not if the peer has simply been unlucky. At the same time α is significantly lower in CHOICE than in RAND. Hence, envy does not loom as large when the peer can be made accountable for her outcome, compared to when she has only been lucky.[23] The estimate of γ, the concern for conformism, is not statistically significant in (3) or in (4). This finding strongly suggests that when the peer makes active choices the concern for simply choosing the same is not strong, but that active choices significantly influence feelings of envy and guilt. The log-likelihoods improve also continuously from model (1) to (4). In summary, the fact that the peer makes an active choice has an considerable effect on the outcome-based social preferences of subjects. While subjects do not derive an extra utility from simply conforming, if the peer chooses for herself, envy turns out to be less and guilt to be more pronounced.

To complete this section we compute the value of the score function $d^t(\theta)$ for each decision problem t, using the estimates of model (4) for RAND and CHOICE, respectively. In Figure 3, $d^t(\theta)$ is plotted for each decision problem $t = 1, \ldots, 18$ (in the order of Table 1) for selfish types (upper row of Figure 3) and social types, given that the peer has lottery A (middle row of Figure 3) or B (lower row of Figure 3). If $d^t(\theta) > 0$ (< 0), then the second mover is very likely to choose A (B) in problem t.

Based on expected individual utility, a second mover frequently favors B, except for the first two decisions. But with social utility, second movers' choices coincide in expectation nearly with every choice of their peer. Clearly, due to the presence of a peer, preferences become less sensitive towards lottery characteristics of particular decision problems. Also, in RAND, the score function is in many decisions slightly closer to zero. This is in line with our observation of more imitation in CHOICE.

[23] Blanco et al. (2011) estimate the parameters of the inequity aversion model by Fehr and Schmidt (1999) on an aggregate level across different kinds of games and their results are very similar to ours ($\alpha = 0.91$; $\beta = 0.38$).



The score function is defined in (a) as $(U_A - U_B)/\tau$, in (b) as $(V_{A,A} - V_{B,A})/\tau$, and in (c) as $(V_{A,B} - V_{B,B})/\tau$. Vertical spikes indicate the 90% confidence interval of the standard logistic distributed random variable ϵ.

Figure 3: Score function for selfish and social types

4.5 Comparing Social Utility and Social Learning

Our results have shown that social utility motives generate substantial peer effects in risk taking within our setting. Additionally, there is substantial heterogeneity with respect to the importance of social utility motives across individuals. About 50% of our sample is selfish, and hence not subject to peer effects when social utility is the only mechanism at play, while 50% of our sample is social.

An open question is whether selfish types are affected by peers when there is a selfish motivation to imitate, i.e. when the peer has relevant information. When peers receive private signals about the state of nature, different to the ones of the decision maker, imitating can be in the interest of a selfish individual. A range of models focusing on observational learning have shown that this can allow for the transmission of information, generating cascades. Several experimental studies have in turn confirmed the predictions of these models (e.g., Anderson and Holt, 1997). In what follows, we do not aim at providing an additional test of these models, but at uncovering whether within our framework the possibility of learning through the first mover's decision increases peer effects and, if so, to which extent.

We setup the treatment LEARN, which introduces incomplete information about the lotteries. While the first mover knows the payoffs of both lotteries, the second mover only knows the payoffs of lottery A. Otherwise, LEARN follows the same structure as RAND and CHOICE.[24,25]

In LEARN, if the second mover's preferences are close enough to those of the first mover and the second mover is not too risk averse, the second mover has an incentive to imitate the first mover, due to the information contained in her choices. The details are reported in Appendix B.2. Intuitively, it is clear that, if the second mover is very risk averse, he will choose B in all decisions, both in Part I and II, and hence never imitate. In contrast, if the second mover is risk neutral and the first mover is as risk neutral, then she has an incentive to imitate all choices made by the first mover.

Our results are in line with these predictions. First, we find that LEARN leads to the highest switching rate. The average switching rate in LEARN, 46.9%, is significantly different to that in all other treatments (MW-test, p-value <0.01 comparing LEARN vs. BASE and RAND, and p-value=0.063 comparing LEARN vs. CHOICE). Second, in contrast to RAND and CHOICE, in LEARN *every* second mover switches at least one of his choices. Hence, given an informational motive for switching, *all* individuals indeed switch for some choices.

If we examine their strategies, we observe that over all choices, individuals stay with the same choice as in part I in 53.1% of the cases, imitate in 27.0%, deviate in 3.6% and change irrespective of the first mover's choice in 16.3% of the cases. The imitation

[24] It was common knowledge that the lotteries in Part II were identical to those in Part I, only presented in a different order. Participants had a complete list of all possible decision problems, since they received a decision sheet in Part I. The second mover knew in all cases the p of the lottery, and hence chose between lottery A and one of six possible B lotteries. We would therefore expect second movers to act consistently within a given p. If we compute the consistency of second movers in LEARN, we find that consistency is high: 68% of second movers make the same 6 choices for each panel p.

[25] In total 58 subjects participated in the experimental sessions for LEARN.

rate is higher than in CHOICE (MW-test, p-value=0.048).

A further test of our predictions is provided by examining the frequency of imitation depending on the A choices of the second mover in Part I. Under CRRA preferences, a second mover who chooses A more often is less risk averse. He should then have a stronger tendency to imitate. Table 6 reveals that this is indeed the case.

	Imitation		
	(1)	(2)	(3)
A choices	0.049***	0.048**	0.048**
	[0.018]	[0.022]	[0.022]
$p = 0.5$			-0.072
			[0.086]
$p = 0.8$			-0.078
			[0.081]
Observations	522	522	522
Individual Characteristics	No	Yes	Yes
Pseudo log–lik.	-293	-286.4	-284.5
Pseudo R–squared	0.0379	0.0596	0.0658

Note: This table reports estimated marginal effects from logit regressions on the probability of imitation; standard errors are presented in brackets, clustered at the individual level. A choices is the number of A choices in Part I. The variables $p = 0.5$ and $p = 0.8$, individual characteristics and significance levels are defined as in Table 4.

Table 6: Imitation in LEARN

The likelihood to imitate increases the more the second mover chose A in Part I.[26] We do not find that the probability of the lottery p, the only information available to the second mover, plays an important role for imitation. Hence, peer effects in LEARN increase, indicating that social learning can play an important role for peer effects also within our setting. Our setting therefore is able to capture both social utility and social learning motives caused by the presence of peers in risky choices.

[26] Alternatively, one can also estimate r for Part I choices using a random utility model with Fechner errors, scaled by τ, as in section 4.4. This yields similar results. Further it reveals that $\hat{r}_1 = 0.728$ for first movers and $\hat{r}_2 = 0.655$ for second movers. The distribution of r does not differ significantly between first and second movers (Kolmogorov-Smirnov test, p-value=0.680). Hence, the condition that first and second movers' risk preferences need to be similar for imitation to occur is fulfilled.

5 Conclusion

Peers are important for many economic decisions. They affect important educational decisions, work decisions as well as financial decisions. Existing evidence suggests that peer effects are driven by informational motives, social learning, as well as social motives, social utility. Within risk taking, both channels appear to be important, but little is known about what drives social utility. Existing theories of social preferences would suggest that a dislike of payoff differences, with respect to the peer, leads to peer effects. At the same time, evidence from social psychology suggests that the desire to conform to peers may also be a main driver of peer effects.

This paper examines peer effects in risk taking, testing to what extent and why social utility matters. We set up a simple theoretical framework, in which we allow subjects to be either of a selfish or a social type, where the latter derives social utility on top of individual utility. We then investigate experimentally two channels that potentially drive social utility: (1) outcome-based social preferences, and (2) a concern about conforming with others.

Our experiment reveals that outcome-based social preferences are most important. Even if the peer does not choose a lottery, significant peer effects are observed. These are then almost doubled when the peer actively makes choices. Our design allows us to identify which changes in choices in the presence of a peer can be defined as peer effects. We find that changes in choices that are irrespective of the first mover, between Part I and Part II of the experiment, which do not reflect peer effects, do not change with respect to the baseline. Instead, in the presence of a peer, most changes by second movers are imitative: they choose the same lottery as the first mover.

Within our sample, we uncover substantial individual heterogeneity in the role of social utility. There is an almost even split between selfish and social types. Among social types, we find a significant dislike of payoff disadvantages, as is common in the literature. In addition, if the first mover chooses among the lotteries, a significant dislike of payoff advantages is observed. Hence, we do not only uncover that outcome-based social preferences matter, but also that their effect may depend on whether the peer chooses a lottery, even if final payoffs remain unchanged. In contrast, within our setup, we do not find evidence of a concern for conformism. This may be driven by the fact that decisions were very simple and, hence, avoiding the decision–making process by imitating others may not be as attractive.

Understanding the presence of social utility motives in risk taking has important implications. First, our results suggest that communicating others' choices may have large consequences even in environments where all individuals are equally well informed. Taking as an example the Dutch Postcode Lottery, our results would suggest that receiving information about whether others won in your neighborhood, as is done in a weekly TV show, is likely to have an important effect ex-ante on the likelihood to participate in the lottery.

Second, our results reveal that peer effects become stronger when the peer actively chooses a product. Hence, campaigns that give "gifts" to some individuals to start the usage of a product, such as an investment product or an insurance policy, may have a limited success. Instead, if they can achieve the endorsement through active choices of important individuals within a social group, success is likely to be much stronger.

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Appendix A: Instructions for the BASE treatment

Welcome to the experiment.

Thank you very much for participating. Please refrain from talking to any other participants until the experiment is finished.

General Information

The purpose of this experiment is the analysis of economic decision making. During the course of the experiment you can earn money which will be paid out to you at the end of the experiment.

The experiment lasts about 1 hour and consists of two parts. At the beginning of each part you receive detailed instructions. If you have questions after the instructions or during the experiment please raise your hand. One of the experimenters will come to your place and answer your questions in private.

While you take your decisions a small clock will count down at the upper right corner of your computer screen. This clock serves as an orientation for how much time you should need to take your decision. However, the countdown will not be enforced in the case that you need more time to come to a decision. Especially in the beginning you might need more time.

Payoff

In both parts of the experiment your income is directly calculated in Euro. This amount will be paid out to you at the end of the experiment. For your punctual arrival you receive an additional 4 euro.

Anonymity

The experimental data will only be analyzed in the aggregate. Names will never be connected with the data from the experiment. At the end of the experiment you have to sign a receipt, confirming that you received your payoff. This receipt only serves our sponsor's accounting purposes. The sponsor does not receive any further data from the experiment.

Auxiliaries

At your place you find a pen. Please leave the pen at your place at the end of the experiment.

Part I

Task

You will be presented 20 decision situations. In every situation you can choose between two options, option A and option B. Consider your choice carefully, as your choice can - as described below - affect your payoff.

On the screen your will be shown one or two urns which contain white and black balls. The screen will further inform you about the number of white balls and the number of black balls in each urn. Furthermore you will be informed about the value of each white ball and the value of each black ball, in the case that you choose option A or option B, respectively. From each urn one ball will be randomly drawn. If there is only one urn the ball which was drawn is relevant for both options, A and B. If there are two urns the ball will be drawn from the urn which belongs to your chosen option. Figure 4 shows how your screen might look like.

In this example there is only one urn which contains 10 balls: 5 white balls and 5 black balls, i.e. the probability that a white ball is drawn amounts to 50

Should a white ball be drawn from the urn you receive 20 Euro if you chose option A or 15 Euro if you chose option B. If a black ball is drawn from the urn you receive 0 Euro if you chose option A or 5 Euro if you cchose Option B.

The urns in the 20 decision situations are always filled according to one of the following types:

- Type 1: 5 white balls and 5 black balls
- Type 2: 8 white balls and 2 black balls

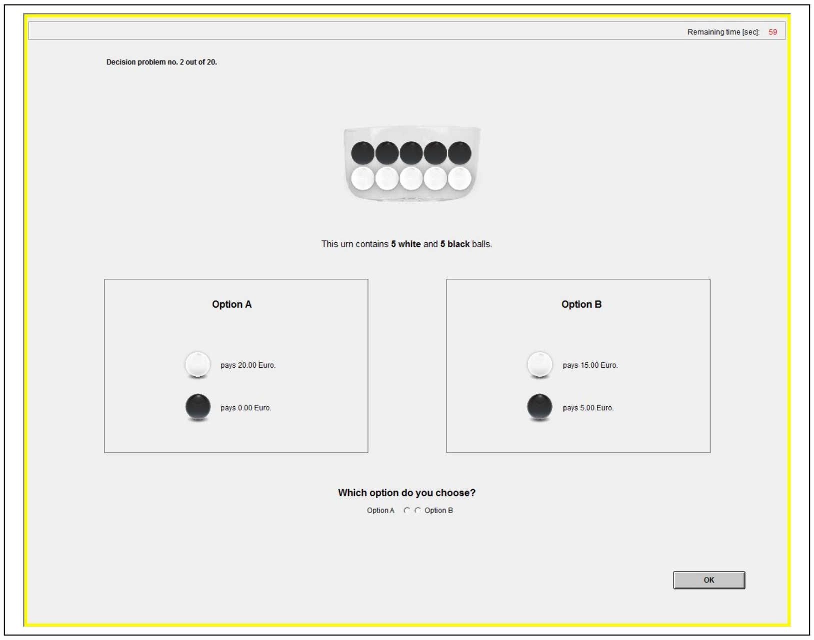

Figure 4: Example - Decision Problem

- Type 3: 2 white balls and 8 black balls
- Type 4: 2 white balls and 6 black balls

You take your decision by marking either option A or option B on the screen. Your decision is final once you clicked the OK-button in the lower part of the screen. In addition to these instructions you are given a sheet of paper on which all decision situations are printed out. Please note on this paper which decisions you have taken.

Payoff

At the end of part II of this experiment one participant will be chosen randomly by the computer. This participant will be assigned the role of an assistant. You will be shown on your screen whether you have been assigned this role or not. The assistant will help the experimenter to randomly determine which part and which decision situations are payoff-relevant.

For this purpose the assistant will first draw one ball out of a nontransparent pouch which contains 2 balls - marked with the numbers 1 and 2. This ball decides whether part I or part II of the experiment is payoff-relevant for all participants. The experimenter will type in this number at the assistant's computer.

Assume that part I is drawn as being payoff-relevant. Then, for each participant, the assistant draws one ball out of a nontransparent pouch which contains 20 balls numbered from 1 to 20. This ball decides which decision situation becomes payoff-relevant for the respective participant. Every decision situation is drawn with the same probability. The experimenter will type in this number at the assistant's computer.

Finally the assistant draws one ball out of each of four nontransparent pouches. Every pouch corresponds to one of the four types of urns.

- Bag 1 contains 5 white balls and 5 black balls; corresponds to an urn of type 1
- Bag 2 contains 8 white balls and 2 black balls; corresponds to an urn of type 2
- Bag 3 contains 2 white balls and 8 black balls; corresponds to an urn of type 3
- Bag 4 contains 2 white balls and 6 black balls; corresponds to an urn of type 4

The draw from bag 1 (2,3,4) decides which color will be paid out for an urn of the type 1 (2,3,4). At the assistant's computer the experimenter types in which color has been drawn from the four bags.

For example: If, in the third draw, the assistant draws a ball with the number 2, the decision situation 2 becomes payoff-relevant for participant 3. If, in decision situation 2, there is only one urn which is of type 1, the colour of the ball which has been drawn from bag one pins down the payoff of participant 3.

Assume this decision situation is exactly the decision situation depicted above, which is of type 1. If the assistant has drawn a white ball from bag 1, participant 3 earns 20 Euro if he chose option A in this decision situation; he earns 15 Euro if he chose option B. If the assistant has drawn a black ball from bag 1, the participant earns 0 Euro if he chose option A and 5 Euro if he chose option B.

Please note: As every decision situation will be drawn with the same probability, it is in your interest to take every decision carefully.

Subsequently the computer computes your income, which will be shown to you on your screen. Furthermore you will be informed, which part and which decision situation have been drawn for you as well as which color decides your income.

Part II

Groups

At the beginning of part II you will be randomly matched with another participant of this experiment. The two of you will form one group in part II. Groups will remain unchanged for the rest of part II.

Every participant will be randomly assigned by the computer one of two roles in his group. We call these roles person 1 and person 2. At the beginning you will be informed on your screen whether you will be person 1 or person 2 for the rest of part II.

Task

In this part person 1 and person 2 will be presented 20 decision situations. These decision situations will be identical to the decision situations from part I. The sequence of decision situation however, will be different from part I. As in part I, both as person 1 and person 2, you will be informed on your screen about the value of a black ball and the value of a white ball in the case you choose option A and option B.

In every decision situation each participant chooses one of the two options. You will take your decisions as in part I. Person 1 and person 2 decide simultaneously and person 2 will not be informed about the decision of person 1 in this decision situation.

This is how the screen of person 1 might look like:

This is how the screen of person 2 might look like:

You take your decision by marking either option A or option B on the screen. Your decision is final once you clicked the OK-button in the lower part of the screen.

Please consider your decision carefully as your choice can - as described below - affect your payoff.

Payoff

After all participants completed their decision problems the assistant will be selected randomly by the computer. As described in the instructions of part I, for deciding whether part I or part II becomes payoff relevant, the assistant draws one ball from a nontransparent bag containing two balls.

Assume that part II is drawn as being payoff-relevant. Then, for each group, the assistant draws one ball out of a nontransparent bag which contains 20 balls numbered from 1 to 20. This ball decides which decision situation becomes payoff-relevant for the participants of the respective group. Every decision situation is drawn with the same probability. The experimenter will type in this number at the assistant's computer.

Finally the assistant draws one ball out of each of four nontransparent bags. Every bag corresponds to one of the four types of urns.

- Bag 1 contains 5 white balls and 5 black balls; corresponds to an urn of type 1
- Bag 2 contains 8 white balls and 2 black balls; corresponds to an urn of type 2
- Bag 3 contains 2 white balls and 8 black balls; corresponds to an urn of type 3
- Bag 4 contains 2 white balls and 6 black balls; corresponds to an urn of type 4

The draw from bag 1 (2,3,4) decides which color will be paid out for an urn of the type 1 (2,3,4). At the assistant's computer the experimenter types in which color has been drawn from the four pouches.

For example: If, in the fifth draw, the assistant draws a ball with the number 2, the decision situation 2 becomes payoff-relevant for group number five. If, in decision situation 2, there is only one urn which is of type 1, the color of the ball which has been drawn from bag one pins down the payoff of group 5.

Assume this decision situation is exactly the decision situation depicted above, which is of type 1. If the assistant has drawn a white ball from bag 1, person 1 and person 2 of group 5 receive the following income: If person 1 and person 2 both chose option A, each receives 20 EUR. If both chose option B, each receives 15 EUR. If person 1 chose option A and person 2 chose option B, person 1 receives 20 EUR and Person 2 15 EUR. Analogously, if person 1 chose option B and person 2 chose option A, person 1 receives 15 EUR and person 2 receives 20 EUR.

If the assistant has drawn a black ball from bag 1, person 1 and person 2 of group 5 receive the following income: If person 1 and person 2 both chose option A, each receives 0 EUR. If both chose option B, each receives 5 EUR. If person 1 chose option A and person 2 chose option B, person 1 receives 0 EUR and Person 2 5 EUR. Analogously, if person 1 chose option B and person 2 chose option A, person 1 receives 5 EUR and person 2 receives 0 EUR.

Subsequently the computer computes your income. You will be informed on your screen, which part and which decision situation have been drawn for you as well as which color defines your income. Additionally both options, your decision and the resulting income will be shown to you on your screen.

You will then be informed about the amount of Euro you have earned in this experiment. You will not be informed about how much your group member earned in the experiment.

Appendix B: Theoretical Framework

B.1. Social Utility

In the following we start by considering the case where the firt mover is randomly assigned a lottery. Since the second mover cannot conform to his choice, but only equalize payoffs by choosing the same lottery, we set γ to zero. Alternatively, we could assume that γ increases when the first mover actively chooses a lottery. The results would be qualitatively the same.

If the first mover is randomly allocated a lottery, it is straightforward that the second mover chooses to switch if the following conditions are satisfied:

i) If the first mover is randomly allocated lottery A and the social second mover did not choose A individually, he will switch to choosing A when

$$U_A > U_B - \alpha(p(1-p)cf) - \beta(1-p)c(1-(1-p)f); \tag{4}$$

ii) If the first mover is randomly allocated lottery B and the social second mover did not choose B individually, he will switch to choosing B when

$$U_B > U_A - \alpha((1-p)c(1-(1-p)f)) - \beta p(1-p)cf. \tag{5}$$

Hence, a large set of posible values of α and β can lead to switching. With our estimation in the Results section we will search for the combination of values of α and β that best fits the data. In what follows, we briefly examine the comparative statics. We will in particular focus on the effect of f, i.e. on the effect of shifting the payoffs of B downwards. This allows us to test whether the comparative statics observed experimentally are consistent with our model of social utility.

As the payoffs of B shift downwards, if the first mover is allocated A, a second mover who switches to A mainly reduces potential payoff disadvantages. Hence, if α is large enough relative to β, we expect switching towards A to become more likely as f

increases and that towards B to become less likely. This is summarized in Proposition 1.

Proposition 1. If $\alpha > \beta \max\{\frac{1-p}{p}; \frac{p}{1-p}\}$, as f increases switching to A becomes more likely and switching to B becomes less likely.

Proof. We start with the condition stated in equation (4). We have that, by the payoffs of A and B, $\frac{\partial U_A}{\partial f} = 0$ and $\frac{\partial U_B}{\partial f} < 0$. Further, $\frac{\partial \alpha(p(1-p)cf)}{\partial f} = \alpha p(1-p)c$ and $\frac{\partial \beta(1-p)c(1-(1-p)f)}{\partial f} = -\beta(1-p)^2 c$. Hence, if $\alpha > \beta\frac{1-p}{p}$, this condition becomes less binding and switching to A more likely.

Similarly, take the condition stated in equation (5). We have that $\frac{\partial \alpha((1-p)c(1-(1-p)f)}{\partial f} = -\alpha(1-p)^2 c$ and $\frac{\partial \beta p(1-p)c)}{\partial f} = \beta p(1-p)c$. Hence, if $\alpha > \beta\frac{p}{1-p}$, this condition becomes less binding and switching to B more likely.

Note that, if $p = 0.5$, Proposition 1 only requires $\alpha > \beta$, which is the assumption made by Fehr and Schmidt (1999).

We now turn to the case where the first mover chooses between lottery A and B. It is straightforward that, should the value of α and β remain unchanged, as assumed in Fehr and Schmidt (1999), and if $\gamma > 0$, the conditions above become less binding. The utility from conforming, γ, makes it more attractive to switch to the lottery chosen by the first mover. In particular, for switching to occur, the following conditions apply:

iii) If the first mover choose A and the social second mover did not choose A individually, he will switch to choosing A when

$$U_A + \gamma > U_B - \alpha(p(1-p)cf) - \beta(1-p)c(1-(1-p)f); \tag{6}$$

iv) If the first mover chooses B and the social second mover did not choose B individually, he will switch to choosing B when

$$U_B + \gamma > U_A - \alpha((1-p)c(1-(1-p)f)) - \beta p(1-p)cf. \tag{7}$$

Since switching is more likely, it follows that a downward shift in the payoffs of B (in all states), i.e. an increase in f, will have a weakly smaller effect on the likelihood of switching.

Lemma 1. When the first mover chooses a lottery, the effect of f on the likelihood of switching is weakly smaller than that when she is randomly allocated a lottery.

Proof. This follows from the fact that conditions (6) and (7) are less binding than (4) and (5), and the effect of f, in (6) and (7), is the same.

B.2. Social Learning

If learning motives are present, we would expect imitation to be more frequent under incomplete information than under complete information for the second mover. Without making additional assumptions, however, this need not be the case. To see why, consider the following situation. Under complete information, the second mover only imitates the first mover in one of her decisions, say number 1 for $p = 0.2$. In the rest of his decisions, he always chooses A. Under incomplete information, the same second mover does not know which decision she is facing out of the six for $p = 0.2$. Hence, upon observing the first mover choose B, if the second mover believes it to be sufficiently likely that the first mover chooses B for other decisions, say 2 to 6, he will not imitate. In this case, we obtain no imitation under incomplete information, while there was imitation under complete information.

To find conditions under which social learning may lead to imitation, we need to make further assumptions on the consumption utility of first and second movers. Let us assume they have a power utility function: $u(x) = x^r$, where r is the coefficient of constant relative risk aversion. Moreover, let us first abstract from social utility.

To clarify the notation let us add p as a superscript to B_m, where $m = 1, ..., 6$, and A to denote the lotteries for a given p. For each m, the first mover chooses A^p or B^p_m depending on his r. The bounds on r, determining for which values the first mover chooses A, can be easily calculated. For simplicity, we will focus on three groups of two lotteries, as the bounds on r are very similar for B_1^p and B_2^p, B_3^p and B_4^p, and B_5^p and B_6^p, respectively. The first one is determined by the first movers who never choose A^p. The second group chooses A^p when compared to B_1^p and B_2^p. We label this group as the *slightly risk averse*. Then, there are first movers who choose A^p when compared B_3^p and B_4^p as well. These first movers have a r of at least one. We label them as *risk loving*. A further group could be considered taking those second movers who always choose A^p. Since the latter group is rare (never occurs in our experiment), we concentrate on the first three groups.

Suppose the share of *very risk averse* first movers is q_1^p, that of *slightly risk averse* q_2^p and that of *risk loving* q_3. Note that q_1 and q_2 depend on p, since the bounds of these groups depend on the probability of the good state. Assume that second movers hold correct beliefs about these shares. After the first mover chooses A^p, i.e. $k = A$, the probability that the lottery is B_m^p is as follows,

$$\begin{aligned}
\mu_{A,1} = \mu_{A,2} &= \frac{q_2^p + q_3}{2q_2^p + 4q_3}, \\
\mu_{A,3} = \mu_{A,4} &= \frac{q_3}{2q_2^p + 4q_3}, \\
\mu_{A,5} = \mu_{A,6} &= 0,
\end{aligned}$$

while if she chooses B, i.e. $k = B$, the probability is,

$$\begin{aligned}
\mu_{B,1} = \mu_{B,2} &= \frac{q_1^p}{4q_1^p + 2q_2^p + 2}, \\
\mu_{B,3} = \mu_{B,4} &= \frac{q_1^p + q_2^p}{4q_1^p + 2q_2^p + 2}, \\
\mu_{B,5} = \mu_{B,6} &= \frac{1}{4q_1^p + 2q_2^p + 2}.
\end{aligned}$$

Then, the second mover will imitate if the following incentive compatibility constraints are satisfied:

$$U_A > \sum_{m=1}^{6} \mu_{A,m} U_{B_m^p}, \quad \text{and} \quad U_A \leq \sum_{m=1}^{6} \mu_{B,m} U_{B_m^p}.$$

As the share of slightly risk averse first movers increases, towards 1, the likelihood that a slightly risk averse second mover imitates converges to 1. This leads to the following Proposition.

Proposition 2. *Under incomplete information a slightly risk averse second mover who maximizes consumption utility will imitate the choice of the first mover, if he believes the share of slightly risk averse subjects to be sufficiently large.*

Proof. This follows from the equations of $\mu_{A,m}$ and $\mu_{B,m}$ when $q_2^p \to 1$, and $q_1^p, q_3 \to 0$.

If the second mover is of a social type, the same result can be obtained by simply adapting U_i to $V_{i,k}^{\mu}$.

Appendix C: Additional Results

Choices in Part I - First & Second Movers

A: 20,0 vs. B:	BASE	RAND	CHOICE	χ^2 p-value
Panel A: 20/80 Lotteries				
(0.8,1)	75.0%	95.0%	86.7%	0.015
(5.6,0.2;0.6,0.8)	70.0%	73.3%	68.3%	0.830
(4,1)	30.0%	41.7%	28.3%	0.257
(8,0.2;3,0.8)	27.5%	43.3%	18.3%	0.011
(7.2,1)	7.5%	3.3%	3.3%	0.537
(10.4,0.2;5.4,0.8)	2.5%	5.0%	6.7%	0.645
Panel B: 50/50 Lotteries				
A: 20,0 vs. B:	BASE	RAND	CHOICE	χ^2 p-value
(8,1)	10.0%	20.0%	28.3%	0.084
(11,0.5;6,0.5)	25.0%	16.7%	23.3%	0.537
(10,1)	10.0%	13.3%	3.3%	0.145
(12.5,0.5;7.5,0.5)	7.5%	10.0%	8.3%	0.901
(12,1)	5.0%	3.3%	6.7%	0.704
(14,0.5;9,0.5)	7.5%	1.7%	5.0%	0.360
Panel C: 80/20 Lotteries				
A: 20,0 vs. B:	BASE	RAND	CHOICE	χ^2 p-value
(15.2,1)	20.0%	13.3%	18.3%	0.636
(16.4,0.8;11.4,0.2)	20.0%	11.7%	15.0%	0.520
(16,1)	12.5%	8.3%	11.7%	0.760
(17,0.8;12,0.2)	12.5%	11.7%	16.7%	0.704
(16.8,1)	15.0%	1.7%	11.7%	0.041
(17.6,0.8;12.6,0.2)	10.0%	5.0%	11.7%	0.412

Table 7: Frequency of Lottery A choices of First and Second Mover in Part I

Note: χ^2 test is used to test for differences between choices in treatments BASE, RAND and CHOICE.

Choices in Part II - First Movers

Panel A: 20/80 Lotteries			
A: (20,0) vs. B:	BASE	RAND	CHOICE
(0.8,1)	75.0%	43.3%	86.7%
(5.6,0.2;0.6,0.8)	70.0%	66.7%	80.0%
(4,1)	15.0%	50.0%	20.0%
(8,0.2;3,0.8)	20.0%	60.0%	20.0%
(7.2,1)	5.0%	53.3%	0.0%
(10.4,0.2;5.4,0.8)	10.0%	33.3%	3.3%
Panel B: 50/50 Lotteries			
A: (20,0) vs. B:	BASE	RAND	CHOICE
(8,1)	5.0%	50.0%	33.3%
(11,0.5;6,0.5)	10.0%	46.7%	16.7%
(10,1)	5.0%	40.0%	10.0%
(12.5,0.5;7.5,0.5)	0.0%	50.0%	13.3%
(12,1)	0.0%	40.0%	10.0%
(14,0.5;9,0.5)	0.0%	36.7%	13.3%
Panel C: 80/20 Lotteries			
A: (20,0) vs. B:	BASE	RAND	CHOICE
(15.2,1)	10.0%	46.7%	30.0%
(16.4,0.8;11.4,0.2)	20.0%	53.3%	23.3%
(16,1)	5.0%	43.3%	0.0%
(17,0.8;12,0.2)	15.0%	46.7%	10.0%
(16.8,1)	20.0%	63.3%	10.0%
(17.6,0.8;12.6,0.2)	5.0%	53.3%	10.0%

Table 8: Frequency of Lottery A choices of First Mover in Part II

Choices in Part II - Second Movers

Panel A: 20/80 Lotteries					
	BASE	RAND		CHOICE	
A: (20,0) vs. B:	Uncond.	FM has A	FM has B	FM has A	FM has B
(0.8,1)	85.0%	86.7%	76.7%	66.7%	50.0%
(5.6,0.2;0.6,0.8)	85.0%	83.3%	83.3%	60.0%	43.3%
(4,1)	25.0%	36.7%	23.3%	23.3%	6.7%
(8,0.2;3,0.8)	15.0%	46.7%	33.3%	33.3%	10.0%
(7.2,1)	0.0%	13.3%	3.3%	23.3%	0.0%
(10.4,0.2;5.4,0.8)	5.0%	6.7%	6.7%	23.3%	3.3%
Panel B: 50/50 Lotteries					
	BASE	RAND		CHOICE	
A: (20,0) vs. B:	Uncond.	FM has A	FM has B	FM has A	FM has B
(8,1)	15.0%	33.3%	13.3%	23.3%	6.7%
(11,0.5;6,0.5)	20.0%	26.7%	16.7%	20.0%	6.7%
(10,1)	5.0%	13.3%	6.7%	30.0%	3.3%
(12.5,0.5;7.5,0.5)	15.0%	13.3%	6.7%	20.0%	3.3%
(12,1)	5.0%	3.3%	3.3%	20.0%	3.3%
(14,0.5;9,0.5)	5.0%	6.7%	3.3%	16.7%	0.0%
Panel C: 80/20 Lotteries					
	BASE	RAND		CHOICE	
A: (20,0) vs. B:	Uncond.	FM has A	FM has B	FM has A	FM has B
(15.2,1)	30.0%	10.0%	10.0%	33.3%	16.7%
(16.4,0.8;11.4,0.2)	20.0%	20.0%	13.3%	36.7%	10.0%
(16,1)	20.0%	23.3%	6.7%	26.7%	13.3%
(17,0.8;12,0.2)	15.0%	23.3%	10.0%	23.3%	13.3%
(16.8,1)	15.0%	10.0%	6.7%	36.7%	13.3%
(17.6,0.8;12.6,0.2)	15.0%	16.7%	10.0%	33.3%	10.0%

Table 9: Frequency of Lottery A choices of Second Mover in Part II

Panel A: 20/80 Lotteries

	BASE	RAND		CHOICE	
A: 20,0 vs. B:	Uncond.	FM has A	FM has B	FM has A	FM has B
(0.8,1)	5.0%	10.0%	20.0%	26.7%	43.3%
(5.6,0.2;0.6,0.8)	5.0%	20.0%	20.0%	36.7%	40.0%
(4,1)	10.0%	26.7%	33.3%	30.0%	26.7%
(8,0.2;3,0.8)	10.0%	20.0%	26.7%	33.3%	16.7%
(7.2,1)	10.0%	10.0%	6.7%	23.3%	6.7%
(10.4,0.2;5.4,0.8)	10.0%	6.7%	6.7%	26.7%	6.7%

Panel B: 50/50 Lotteries

	BASE	RAND		CHOICE	
A: 20,0 vs. B:	Uncond.	FM has A	FM has B	FM has A	FM has B
(8,1)	5.0%	20.0%	13.3%	23.3%	26.7%
(11,0.5;6,0.5)	5.0%	16.7%	6.7%	16.7%	16.7%
(10,1)	5.0%	16.7%	10.0%	30.0%	3.3%
(12.5,0.5;7.5,0.5)	5.0%	6.7%	0.0%	23.3%	6.7%
(12,1)	5.0%	3.3%	3.3%	23.3%	6.7%
(14,0.5;9,0.5)	5.0%	3.3%	0.0%	13.3%	3.3%

Panel C: 80/20 Lotteries

	BASE	RAND		CHOICE	
A: 20,0 vs. B:	Uncond.	FM has A	FM has B	FM has A	FM has B
(15.2,1)	10.0%	20.0%	26.7%	20.0%	16.7%
(16.4,0.8;11.4,0.2)	10.0%	16.7%	16.7%	36.7%	16.7%
(16,1)	5.0%	10.0%	13.3%	33.3%	20.0%
(17,0.8;12,0.2)	5.0%	23.3%	10.0%	30.0%	13.3%
(16.8,1)	10.0%	6.7%	3.3%	30.0%	20.0%
(17.6,0.8;12.6,0.2)	0.0%	13.3%	6.7%	43.3%	20.0%

Table 10: Frequency of Switches of SM in Part II

This table summarizes the frequency of observed switches of the second mover in Part II of the experiment.

	(1)	(2)	(3)	(4)
Fraction of selfish types				
κ		0.5354***	0.5432***	0.5227***
		[0.0866]	[0.0927]	[0.0826]
Model 1: CRRA consumption utility				
r	0.5804***	0.5922***	0.6503***	0.6903***
	[0.0556]	[0.0277]	[0.0683]	[0.1466]
$r_f^\dagger$	1.0375	0.9921	0.9358	0.8511
	[0.1137]	[0.0257]	[0.1103]	[0.1836]
$r_e^\dagger$	1.4167†††	1.3597†††	1.1789	1.1666
	[0.1560]	[0.0633]	[0.1905]	[0.2476]
τ	0.5533***	0.0132	0.0599	0.0129
	[0.0596]	[0.0292]	[0.0514]	[0.0296]
Model 2: CRRA consumption utility *and* social utility				
α		1.0145***	0.8406***	
		[0.2260]	[0.2189]	
α_R				1.0761***
				[0.3037]
α_C				0.6062***
				[0.1760]
$\alpha_f^\dagger$		1.0035	1.2317	1.2571
		[0.2144]	[0.3762]	[0.3098]
$\alpha_e^\dagger$		1.1442	2.4384	1.6772
		[0.3767]	[3.7810]	[0.6558]
β		0.3176	0.2728	
		[0.2409]	[0.2992]	
β_R				0.0339
				[0.3460]
β_C				0.5328
				[0.3320]
β_f		-0.1191	-0.0658	-0.0549
		[0.2630]	[0.3218]	[0.3283]
β_e		-0.473	-0.8133	-0.514
		[0.4404]	[1.2750]	[0.3888]
γ			1.4018	
			[1.4613]	
γ_R				0.5339
				[0.8542]
γ_C				1.7462
				[1.4066]
γ_f			-1.3851	-1.2961
			[1.4140]	[1.0818]
γ_e			-2.2585	-1.7497
			[2.4208]	[1.4066]
τ_{social}		1.1357**	1.2866*	1.0526***
		[0.4423]	[0.6797]	[0.4011]
Method	ML Model	ML Mixture Model		
Observations	2160	2160	2160	2160
Pseudo log-lik.	-1038.317	-938.063	-937.193	-916.143

Table 11: This table reports the estimated models as in Table 5 in Section 4.4, in which we additionally include individual controls; subscripts f and e indicate female participants and economics or business students, respectively. Again, in model (4) we include treatment dummies for α, β and γ. Here, α_R, β_R, γ_R and α_C, β_C, γ_C denote the transformed estimates for RAND and CHOICE participants, respectively.

†: The observed controls enter multiplicatively due to the exponential transformation to ensure positivity. Coefficient values smaller (greater) than one indicate a negative (positive) effect on the parameter. † † † (††, †) indicate significant difference from 1 at the 1% (5%, 10%) level.