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DEPARTMENT OF ECONOMICS

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SEIT 1386

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AWI DISCUSSION PAPER SERIES NO. 704
July 2021

Social Risk Effects:
The 'Experience of Social Risk' Factor*

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July 21, 2021

Abstract

Anticipating "social risk", or risk caused by humans, affects decision-making differently from anticipating natural risk. Drawing upon a large sample of the US population (n=3,982), we show that the phenomenon generalizes to risk experience. Experiencing adverse outcomes caused by another human reduces future risk-taking, but experiencing the same outcome caused by nature does not. While puzzling from a consequentialist perspective, the Experience of Social Risk Factor that we identify deepens our understanding of decision-making in settings in which outcomes are co-determined by different sources of uncertainty. Our findings imply that a unifying theory of social risk effects requires new explanations.

Keywords: Social risk, risk experience, decision-making under risk, behavioral economics, experiment.

JEL codes: C72, C90, D81, D91.

*This research has been funded by the European Research Council Project NATCOOP (ERC StGr 678049) and by the Norwegian Research Council Project FISHCOM (NFR-280467). Correspondence: diekert@uni-heidelberg.de. Instructions, data, and analysis files are available online at `https://osf.io/yncvk/?view_only=b341aa6425cb4b22b10188b94c584803`.

1 Introduction

People are "generally less willing to take risks when the source of the risk is another person rather than nature" (Bohnet et al., 2008). This is the key message from experiments that manipulate the source of risk in the trust game (Bohnet and Zeckhauser, 2004; Bohnet et al., 2008; Lauharatanahirun et al., 2012; Aimone et al., 2014, 2015; Butler and Miller, 2018). Departing from the trust game paradigm, this paper re-investigates from a different angle the idea that the source of risk is a relevant determinant of decision-making. That specific angle is the effect on decision-making of risk *experience*. In particular, it investigates whether the source, natural or social, that caused an adverse event in a past interaction makes a difference to how decisions about a future interaction are made.

The suspicion that experience of social risk, or risk caused by other humans, might impact on decision-making differently from experience of natural risk is not new. Policy-makers and regulators, for example, are aware that the general population responds differently to terrorism and to weather extremes, even when they cause damage and disruptions of comparable scale (Sunstein et al., 2002). Organizational studies find managers frequently taking excessive precaution after experiencing losses caused by employee misbehavior (Dalal et al., 2009; Li and Cropanzano, 2009) and too little after experiencing losses caused by natural events (Poirier and Quinn, 2004; Oetzel and Oh, 2021). These observations are suggestive of a social risk effect of experience, but little more. In each example, other differences between the sources of risk are equally capable of explaining the findings. For this reason, empirical evidence appears to show little promise of helping to establish conclusively that experience of social risk affects decision-making.

Previous research on social risk used experimental evidence with American (Bohnet and Zeckhauser, 2004) and international university students (Bohnet et al., 2008; Aimone et al., 2015; Butler and Miller, 2018), neuroeconomic evidence (Aimone et al., 2014; Lauharatanahirun et al., 2012) as well as animal experiments with chimpanzees (Calcutt et al., 2019). This research has established the existence of a 'social risk premium' (SRP) in the trust game: Subjects demand a premium for accepting a social risk with the same statistical properties as a natural risk. Our evidence on risk experience comes from online experiments in which participants play two separate rounds of a modified chicken game (MCG) against randomly matched co-players. In the MCG, the two players simultaneously take one of two actions, A or B. In addition, there is a randomization device. Both the actions of the players and the randomization device can cause an adverse event, which results in a $0-payoff outcome for both players. Adverse events occur under *at least* one of two conditions: (i) a red ball was randomly drawn from an urn (the randomization device); or (ii) both players took action B. The former condition means experiencing natural risk while the latter condition means experiencing social risk. Under all other conditions, the payoffs for a player are $1 for action A and $3 for action B. Both "social risk experiences" (adverse events uniquely caused by the actions of the players) and “natural risk experiences” (adverse events uniquely caused by the randomization device) are therefore possible. After the first round, players receive full feedback on the payoff outcome, the urn draw, and on the players’ actions. Participants with a risk experience can therefore attribute their experience to a materialization of either natural or social risk (or both jointly). After feedback, participants play an identical second round with another randomly matched co-player. The composition of the urn is calibrated such that the average game is about equally likely to result in a natural or social risk experience. The probabilities of social and natural risk experiences as well as the outcomes are identical across rounds and are announced before each round. In a ‘choices as lotteries’ framework, this design removes any payoff-related reason for a decision-maker to let the experience of an adverse event in round 1 affect the choice in round 2. At the same time, by allowing the researcher to isolate the causal effect of risk experience on subsequent choice, detecting the presence and direction of a new social risk effect becomes possible. This detection is the primary target of this paper.

Like the trust game, the MCG is a stylized setting. It captures a large class of economic settings in which parties compete for the use of an asset. The asset can deliver a flow of services under favorable states of nature (green ball), but has a finite capacity: It can accommodate all users at low use intensity (strategy combination $\{A, A\}$) and even some share of users that demand high use intensity (strategy combinations $\{A, B\}$, and $\{B, A\}$). The flow of services to users is disrupted, however, when user demand is excessive (strategy combination $\{B, B\}$) or when the state of nature is unfavorable (red ball). One example of economic settings that mirror these features are networks such as the Internet: There, outages can be caused by component failures (natural risk, Labovitz et al. (1999); He and Liu (2012)), but also by too many users requesting large amounts of bandwidth at the same time (social risk, Feldmann et al. (2020)). Another example are socio-ecological systems: Fisheries can collapse because of weather and climate extremes (Diamond, 2011; Cook et al., 2010), but also due to uncoordinated excessive exploitation by users (Diamond, 2011; Ostrom et al., 2002). Infrastructure such as airports (Ashley and Savage, 2010), roads (Cramton et al., 2018) and hospital emergency departments (Adams, 2013) are additional cases where unfavorable exogenous events and excess user demand cause disruption to the services provided by the asset. Decision-making by users who compete for a risky finite-capacity asset would therefore appear to merit researchers’ interest.

We conducted four treatments in which 3,982 participants interacted within the MCG paradigm in an online environment. The ’human co-player’ (HC) treatment ($N = 986$) was an implementation of the MCG exactly as described above. A second ’computer co-player’ (CC) treatment ($N = 1,025$) replaced the human co-player in the pairwise interaction with a computer. The computer played the two actions, A and B, with the same probabilities as the population of human players in the HC treatment. A third ‘assigned action’ (AA) treatment ($N = 996$) was identical to the HC treatment except that in the first round, participants only reported their preferred action, but were customarily assigned action B. A fourth (AA/CC) treatment ($N = 975$) was identical to the AA treatment, except that participants faced the computer co-player. The online environment (MTurk) allowed not only to recruit a large pool of participants. Its size and track record was also critical for making it obvious to participants that both the random re-matching procedure and the announcements about event probabilities were credible.

The treatments reaffirm existing results and – more importantly – generate new insights. First, comparing behavior in the HC and the CC treatments, we find evidence consistent with the SRP: When taking action B exposes participants to social risk (HC) rather than natural risk (CC), they are 18 percentage points less likely to choose that action. Second, the HC treatment also shows that participants with a social risk experience were twice as likely to switch behavior in the second round (37%) as participants with a natural risk experience (19%). This doubling of the frequency of behavioral change after experiencing social risk constitutes a previously undocumented social risk effect, which we term the 'experience of social risk factor' (ESRF). Third, replacing the human co-player with a statistically equivalent computer player in treatment CC, we no longer find a difference in how participants respond to experiencing an adverse event: Those with a natural risk experience due to the computer co-player's action are as likely to change behavior (20%) as those with a natural risk experience due to the urn (20%). In other words, the CC treatment returns behavioral patterns consistent with the 'choices as lotteries' framework: The human co-player is a necessary requirement for the ESRF to arise. Finally, the AA treatment, which forces all participants to be exposed to social risk irrespective of preferences for action A or B, shows that the ESRF only affects those individuals ready to be exposed to social risk: Among subjects that preferred action B, 32% changed behavior following a social risk experience and only 8% changed behavior following a natural risk experience. Subjects that preferred action A changed behavior with the same frequency, irrespective of whether they had a natural or social risk experience. This re-affirms previous evidence that intentions matter for social risk (Butler and Miller, 2018). Here, however, the relevant intentions are not those of a co-player (trustee) in a trust game, but the player's own intentions. Jointly, the three treatments establish the ESRF as a new social risk effect. In contrast to the SRP, it is driven by the social source of an adverse *experience* and depends on a subject's own prior intentions of being exposed to social risk.

Our results are significant for three reasons. First, the results highlight that social risk experience can have a measurable impact on decision-making under risk. Important economic decisions may therefore well be influenced by decision-makers' experiences of social sources of economic losses. How the ESRF affects decision-making in other paradigms is a matter of future research. Second, the results suggest that SRP has thrown open the door to what may well be a class of distinct social risk effects. Further research employing alternative paradigms could uncover additional manifestations of social risk effects that affect decision-making under risk in different ways. Third, due to its origins in the MCG, the ESRF is a social risk effect that arises under very different conditions from the SRP and plays out in different economic settings. This complicates attempts to explain social risk effects solely by reference to features of the trust game such as 'betrayal aversion' (Bohnet and Zeckhauser, 2004; Birnberg et al., 2008) or 'loss of control aversion' (Owens et al., 2014; Bartling et al., 2014) that are not present in the MCG. A unifying theory of social risk effects will likely need to rely on other mechanisms than those currently prominent in the debate about social risk.

2 Experimental Design

2.1 Game form

At the core of the experiment is a game form that could be described as a 'Modified Chicken Game' (MCG). The four treatments all rely on the MCG, with small variations on the HC treatment that is explained here.

The MCG couples a standard chicken game and a randomization device. Each participant plays two rounds of the MCG in pairs of two, with random partner matching before each round. Figure 1 presents the normal form of the chicken game used within the MCG. If both players 1 and 2 choose action A, they both receive a payoff of x. If both players choose action B, they both receive a payoff of zero. When actions do not coincide, the player playing action A receives x, while the player playing action B receives $x + y$. The randomization device (nature) is a virtual urn that contains a known distribution of red and green balls. If a red ball is drawn, both players receive a payoff of zero, irrespective of the outcome of the chicken game. If a green ball is drawn, both players receive the payoff associated with the outcome of the chicken game. At the end of each round, players receive full feedback about the actions and outcome of the chicken game as well as the color of the ball drawn from the urn. The combination determines their round payoffs. One of the two rounds is later randomly selected to determine the final payment to participants.

		Player 2 A	*Player 2* B
Player 1	A	x , x	x , $x+y$
	B	$x+y$, x	0 , 0

Figure 1: Normal form of the chicken game

The MCG shares some commonalities with the binary trust game paradigm in which the social risk premium has been shown to arise: In both paradigms, the setting involves two players and participants can avoid social risk, in the trust game by choosing the outside option, here by taking action A. Another common element is that exposure to social risk potentially increases a participant's payoff, but also the possibility of a lower payoff than when avoiding the social risk. Finally, in both game forms inequality-averse players must form beliefs over the co-player's actions if they want to minimize differences in payoffs between participants.

There are also a number of important differences between the MCG and the trust game: The MCG is a symmetric simultaneous-move game rather than an asymmetric sequential-move game. Economic situations that the MCG structurally resembles are therefore very different from those captured by the trust game. In the MCG, natural risk is irreducible, even when playing action A, while risk can be completely avoided in the trust game. The adverse outcome generated by both social and natural risk has more drastic payoff consequences for the player in the MCG (a zero payoff) than a trustee that behaves selfishly in the trust game (typically a positive payoff). In the MCG, choosing to be exposed to social risk can only generate benefits for themselves, but it generates net benefits for the other player in the trust game. Finally, in our experiment the MCG is played repeatedly rather than once.

The repeat play is a central component of the design because it generates different histories of risk experience after round 1 to affect behavior in round 2. Before moving to round 2, each of the participant has one of eight histories, which are shown in Table 1. To fix notation, we write the action of player i in round t as $C_{i,t} = \{\mathrm{A}; \mathrm{B}\}$ (analogous for player j). The realization of natural risk (urn draw) is denoted by $U_t = \{\mathrm{red}; \mathrm{green}\}$. The payoff of player i for round t is given by $\pi_{i,t}$. We denote the probability that a red ball is drawn by p (that is, $p = \Pr(U = \mathrm{red})$) and the probability that a player takes action B by q. This means, for example, that the history according to which a green ball is drawn from the urn and both players take action A, occurs with probability $(1-p)(1-q)^2$. For easier reference, we adopt the following convention to label the histories: $H_i = \{\mathrm{AAg}\}$ refers to a possible history from the vantage point of player i in which player i took action A, the matched co-player j took action A, and the ball was green. Likewise, "AAr" refers to a history where player i took action A, the matched co-player j took action A, and the ball was red, etc. The histories, their corresponding actions, urn draws, as well as payoffs and probabilities are shown in Table 1.

2.2 Payoffs and parameters

The parameters x, y, and p jointly determine the expected payoffs, thus affecting subjects' choices and determining the population averages that subjects are made aware of at the beginning of each round.

We first fix the two payoff components x and y such that $x = \$1$ and $y = \$2$. This implies that the reward for taking social risk is a potential tripling of the payoff. To calibrate p, we considered two balancing conditions between natural and social risk. One condition ensures a balance of adverse events (zero payoff) across sources in the population of players. This means setting p such that it is equally likely that the adverse event is

Table 1: The eight different histories of the first round

H_i	$C_{i,1}$	$C_{j,1}$	U	$\pi_{i,1}$	$\Pr(H_i{=}\mathrm{h}n)$
AAg	A	A	green	x	$(1-p)(1-q)^2$
AAr	A	A	red	0	$p(1-q)^2$
ABg	A	B	green	x	$(1-p)(1-q)q$
ABr	A	B	red	0	$p(1-q)q$
BAg	B	A	green	$x+y$	$(1-p)q(1-q)$
BAr	B	A	red	0	$pq(1-q)$
BBg	B	B	green	0	$(1-p)q^2$
BBr	B	B	red	0	pq^2

uniquely caused by the urn draw returning a red ball and by both players taking action B. This requires $p = q^2$. An alternative condition ensures a balance of zero payoffs events across sources, conditional on a subject choosing option B. This requires $p = q$. We opt for the former balancing condition in order to maintain a population level perspective, even though prior piloting indicated that empirically, p and q are not tightly coupled.[1] Specifically, we fix p at 0.2, leading to an empirical population average of q at around 0.4.

2.3 Treatments

The experimental treatments vary two dimensions. One is the type of co-player that participants interact with. The second is how action choices are implemented in the MCG.

In the HC treatment, participants are in both rounds randomly matched with human co-players and actively decide whether to take action A or B. Before subjects take their actions in round 1 and round 2, they are instructed about the natural and social risk. Specifically, participants learn as part of the instructions that "The urn from which the ball is drawn contains 20 red balls and 80 green balls" and "In a previous experiment, the co-players action was A in about 60 out of 100 cases and B in about 40 out of 100 cases". The large population and matching procedures ensure that these instructions are truthful.

The CC treatment is identical to the HC treatment with the exception that participants always play against a computerized co-player that selects actions A or B with the same probabilities as the first-round participants of treatment HC. Accordingly, participants in the CC treatment learn that "The urn from which the ball is drawn contains

[1] A risk-neutral decision-maker's propensity to choose action B would be predicted not to be influenced by natural risk p. Experimental subjects are likely to deviate from this prediction. We therefore conducted three pilots in order to relate different values for p to the empirical distribution of q. At the population level, the relationship between p and q was weak. Specifically, we observed a value of q=0.36 in the pilot with p=0.4 (N=81), a value of q=0.38 in the pilot with p=0.2 (N=107), and a value of q=0.47 in the pilot with p=0.1 (N=92). The values of q were statistically indistinguishable from each other and from 0.4.

20 red balls and 80 green balls." and "The co-players action is programmed to be A in about 60 out of 100 cases and B in about 40 out of 100 cases."

The AA treatment is also identical to the HC treatment with the exception of round 1. There, participants are asked which action (A or B) they prefer to play, having been made aware that a computer can assign them a different action from the one chosen. The computer in fact assigns action B to every participant and informs participants accordingly. Accordingly, this is referred to as the *assigned action* (AA) treatment.[2] Unless otherwise stated, the analyses for AA treatment are based on preferred actions, rather than implemented ones.

The AA/CC treatment implements the assigned action condition of the AA treatment in round 1, but differs in that the co-player is a computer, as in the CC treatment.[3]

2.4 Procedures

The experiment was conducted online on Amazon Mechanical Turk. This choice entailed two important benefits: One was access to the large and diverse pool of participants on MTurk. The other, more important benefit was that information about the random rematching procedure and the behavioral constants in the subject pool had high credibility for MTurkers. We used o-Tree (Chen et al., 2016) to program and conduct the experiment. Participants received an unconditional participation fee of $0.50 plus the payoff of a randomly selected round (1 or 2). Final payments are comparatively high for a short online study that only took 10 to 15 minutes to complete.

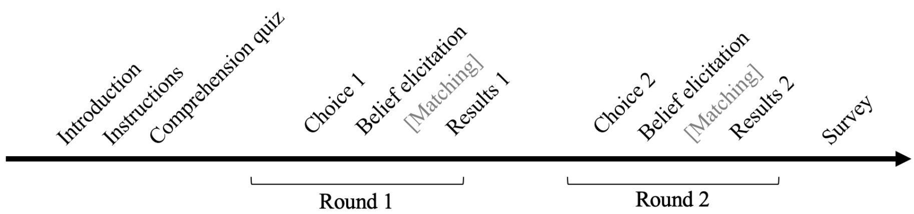

Figure 2: Stages of the experiment

Figure 2 illustrates the flow of the experiment. After reading the study description on Amazon Mechanical Turk and giving their consent to participate in the study, participants were first given general instructions on payoff calculation, duration, and the different stages of the experiment. Next, they proceeded to the instructions. We employed comprehension checks to make sure participants read and understood the instructions. In combination with an easy mental calculation task on the general instructions screen, this

[2]All announcements in the AA treatment are truthful, including the population averages of actions. To maintain truthfulness, the computer co-player chooses actions according to the distribution of choices of participants in round 1 of the HC treatment.

[3]The pre-registered study plan can be found at: `https://doi.org/10.1257/rct.3355-4.0`.

stage also served to filter out potential non-human (bot) participants. Participants then played two rounds of the MCG as described above.

After participants had made their in-round choices, but before they learned about the outcome of the MCG, we elicited subjects' perceptions about the cause of the outcome in a non-incentivized fashion.[4] Specifically, in each of the two rounds we asked participants whether they believed the color of the ball drawn to be green or red, and whether they believed their co-player's choice to be either A or B. To allow participants to express how confident they are in these beliefs, they were offered an unlabeled slider with inputs ranging from red to green (A to B) to give their answer. The sliders do not show a starting position. We treated the responses as believed probabilities of the ball being green (the co-player choosing B). In round 2, after the elicitation of beliefs, we also asked participants to state their motivation to switch (or not switch) actions from round 1 to round 2. Furthermore, participants filled in a short questionnaire before learning about their final payoff. There, we collect survey demographic information on age, gender, and the level of education. To control for risk attitudes, we also inquire about subjects' general willingness to take risks (Dohmen et al., 2011).

In total, 3982 participants were recruited across the four treatments. The mean age in our sample is 37 years and 48% of the participants are female (see Table A-1 in the Appendix). There are no differences in age, gender composition, education, or risk tolerance between the treatments, see Table A-1.

3 Hypotheses

We develop four hypotheses. The first hypothesis bridges to the existing literature and tests for the presence of a social risk premium in our experiment. The second hypothesis examines whether the experience of the same adverse event has a different impact on subsequent choice under risk, depending on which source caused the event. The third hypothesis examines if the effect of risk experience depends on whether the co-player is a person or nature. The fourth hypothesis examines whether the effect of risk experience is innate or depends on a participant's intent to be exposed to social risk.

3.1 The Social Risk Premium

The literature on the Social Risk Premium (SRP) predicts a violation of the 'choices as lotteries' framework: People treat statistically equivalent natural and social risks differently because they react differently to risk emanating from different sources. As a result, social risks tend to be avoided relative to natural risks or, conversely, the average subject needs to be paid a premium in order to accept a statistically equivalent risk when its source is the choice of another human.

[4] We do not incentivize the elicitation to keep it as unobtrusive and intuitive as possible.

In our experiment, the potential presence of the SRP can be found by comparing first-round behavior across treatments. The reason is that sources of risk differ between the different treatments HC and CC: In the HC treatment, taking action B exposes subjects to both natural (urn) and social (human co-player) risk. Taking action B in the CC treatment exposes subjects exclusively to natural risk, one caused by the urn and another caused by the computer co-player. The difference in the co-player between the HC (another human) and the CC treatment (a computer) changes the source of risk. The conservative hypothesis is that subjects treat statistically and materially equivalent natural and social risks as equivalent. If so, the same share of participants is predicted to take action B in the CC treatment as in the HC treatment.

Hypothesis 1 *The source of risk does not affect first-round choices over statistically equivalent risks.*

$$\mathrm{E}[C_{i,1}|T{=}\{HC, AA\}] \;=\; \mathrm{E}[C_{i,1}|T{=}CC]$$

If present, a SRP can lead to the rejection of Hypothesis 1 only if significantly more participants chose option B in the CC treatment, which only features natural risk, than in the HC treatment, where doing so exposes subjects to social risk.

3.2 The effect of social and natural risk experience

The core of the paper is dedicated to studying the effect of different sources of risk experience on behavior. The outcome variable is therefore behavioral change, in particular a change in the action, A or B, chosen in round 1 and in round 2 of the MCG. The indicator variable for a change in each subject i's choices between the two rounds $Y_i{=}\{0;1\}$ is defined by: $Y_i{=}0$ if $C_{i,1}{=}C_{i,2}$, i.e. the subject chose the same action in both rounds. $Y_i{=}1$ if $C_{i,1}{\neq}C_{i,2}$, i.e. the subject chose different actions in the two rounds.

We study the effect of social risk experience in the context of treatment HC, in which social risk arises in the form of a human co-player. To detect and estimate the effect of experience on behavioral change, we focus on the sub-sample of participants whose experimental histories differ only in the source that caused the zero payoff event, the urn draw (natural risk) or the combined play of the matched pair (social risk). Following our notation, this makes groups BAr and BBg, shown in rows 6 and 7 of Table 1, those with the relevant experimental histories. Having taken action B, subjects in both groups were exposed to the joint presence of natural and social risk. In both groups, the subjects also experienced a zero payoff event, $\pi_{i,1} = 0$. In history BAr, the unique source of the adverse event is nature: The urn draw returned a red ball, while the randomly matched co-player took action A. In history BBg, the unique source of the adverse event is social: The randomly matched co-player took action A, while the urn draw returned a green ball. The only difference between the subjects in the two groups is therefore whether they experienced social or natural risk. Despite this difference in the source of the risk, the behavioral change measured by the indicator variable Y_i is the same in both groups since their subjects all chose action B in round 1. Then Y_i=1 if subjects switch to action A in round 2.

In a 'choices as lotteries' framework, neither the arrival of the adverse event nor differences in its source can have a material effect on subjects' later decisions in this experimental design. To test whether a zero payoff outcome attributable to social or natural risk affects choices, we compare average changes in choice between the group of subjects that experienced history BBg (social risk) and the group that experienced history BAr (natural risk). We adopt the conservative hypothesis of no difference in behavioral change across groups.

Hypothesis 2 *The likelihood of behavioral change does not depend on whether the experience of the same adverse event was caused by social or natural risk.*

$$\mathrm{E}[Y_i|H_i{=}\mathrm{BBg} \wedge T{=}HC] \;=\; \mathrm{E}[Y_i|H_i{=}\mathrm{BAr} \wedge T{=}HC] \qquad (1)$$

Hypotheses 2 could be rejected only if a significant share of participants with history BBg (social risk) decided differently from participants with history BAr. This would be a first indication that experience of social risk impacts on subsequent decision-making under risk.

3.3 The effect of natural and natural risk experience

Rejecting Hypothesis 2 would constitute prima facie evidence for the existence of a social risk effect that affects choice under uncertainty through the pathway of experience, an effect that we call the 'Experience of Social Risk Factor' (ESRF). However, despite the symmetry in how and when natural and social risk affect the outcome, subjects might not just react to the different sources of risk, but also to asymmetries in the game form of the MCG: While the social risk arises within the chicken game component, the natural risk arises outside of it. To exclude this possibility, the CC treatment eliminates the social risk within the chicken game component and replaces it with another natural risk by substituting a computer for the human co-player. Both the urn draw and the "strategic choice" of the co-player action are now the result of computerized random draws and are parameterized in the same way as in the HC treatment.

To test whether the experience of a zero-payoff outcome attributable to the urn draw or the computer co-player action affects choices in the next round, we compare average changes in the choice between the group that experienced history BBg (natural co-player risk) and the group that experienced history BAr (natural urn risk). We adopt the conservative hypothesis of no difference in behavioral change.

Hypothesis 3 *The likelihood of behavioral change does not depend on whether the experience of the same adverse event was caused by the urn draw (natural risk) or the* *computer co-player (natural risk).*

$$\mathrm{E}[Y_i|H_i{=}\mathrm{BBg} \wedge T{=}CC] \;=\; \mathrm{E}[Y_i|H_i{=}\mathrm{BAr} \wedge T{=}CC] \tag{2}$$

Hypotheses 3 could be rejected only if a significant share of participants with history BBg (natural risk from computer co-player) decided differently from participants with history BAr (natural risk from urn). This would be an indication that some mechanism other than the experience of social risk impacts on subsequent decision-making under risk.

3.4 The effect of intent to social risk exposure

Evidence from the test of Hypotheses 2 sheds light on the effect of social versus natural risk experience on decision-making under risk. This test is conducted on data from treatment HC and therefore examines the effect among those subjects that intentionally expose themselves to social risk by taking action B in round 1. Empirically, these subjects form the relevant group of interest, both under controlled conditions and in the field.

For the purposes of theory-building, the relevant group of interest is wider, though. It also encompasses those in the population who choose not to expose themselves to social risk. Do these subjects respond to social risk experience in the same way as those who intentionally expose themselves to social risk? Answering this question helps the theorist decide whether to model a possible ESRF as an innate property of all decision-makers – or as a conditional property of 'social risk takers' who intentionally expose themselves to co-player action.

By eliciting preferences for action A or B, but then assigning an action B to all subjects in round 1, the AA treatment allows something of a test whether the effect of social risk experience differs by intent. It is immediately obvious that in a treatment with assigned round 1 actions that differ from subjects' preferred actions, a large share of subjects will revert to their preferred action in round 2. We hypothesize, however, that which action was preferred in round 1 does not matter for the presence and direction of an ESRF, should it be present. This is equivalent to predicting that the difference between the share of behavior-changing participants with natural and social risk experience is no different among those that prefer action A in round 1 and those that prefer action B. This can be stated more formally by letting Δ_P denote, conditional on subject i preferring action $P_i = \{A, B\}$, the difference between the share of behavior-changing participants with social risk and those with natural risk experience. For participants who preferred action A, for example, this difference is $\Delta_A = \mathrm{E}[Y|H{=}\mathrm{BBg} \wedge P_i{=}A \wedge T{=}AA] - \mathrm{E}[Y|H{=}\mathrm{BAr} \wedge P_i{=}A \wedge T{=}AA]$.

Hypothesis 4 *The difference between behavioral change driven social and natural risk experience is similar, irrespective of intent to social risk exposure.*

$$\Delta_A = \Delta_B$$

Comparing these Δ_P across the two groups in treatment AA, those who preferred action A and those who preferred action B, the observed differences-in-difference must be strong enough to reject the conservative hypothesis that the differences in the average treatment effects are zero.

For the computer co-player version of the AA treatment (AA/CC), the prediction is essentially identical, but with a semantic difference. Because the co-player in this treatment is not another person, participants are not exposed to or experience social risk. The co-player risk here has a natural source.

4 Results

4.1 The Social Risk Premium

Hypothesis 1 predicts that the average subject will express the same preference for first-round choices, A or B, across treatments HC and CC. This conservative hypothesis followed from the indifference, in a 'choices as lotteries' framework, between statistically and materially equivalent choices across the two treatments. A competing prediction comes from the 'social risk premium' framework: It predicts that fewer subjects will choose to expose themselves to the risk that the co-player also takes action B when that co-player is a randomly matched human compared to when the co-player is a randomizing computer.

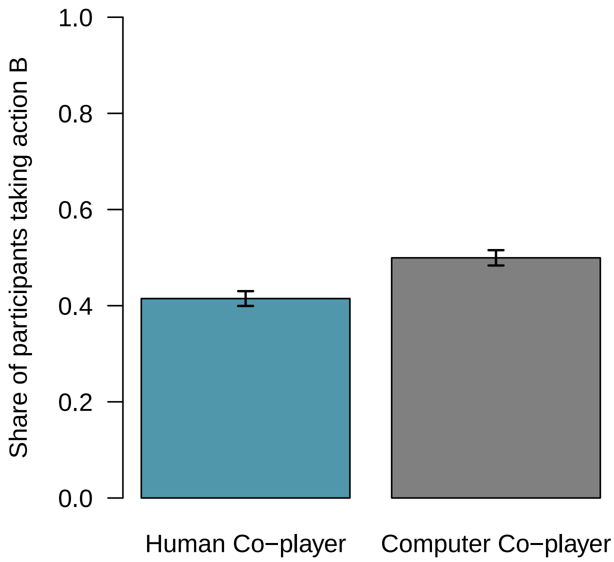

Figure 3: When it is associated with social risk, fewer participants choose to expose themselves to the co-player action than when it is associated with natural risk. The bar plot on the left shows the share of participants choosing the exposing action B when the co-player is another person (Human Co-player). The bar plot on the right shows the share when the co-player is nature (Computer Co-player). The share is significantly lower when the co-player is another person. Error bars, mean $\pm$ s.e.m.

To test Hypothesis 1, we compare the share of subjects taking action B in the human co-player treatment HC with the share of subjects taking action B in computer co-player treatment CC. In the HC treatment, 41.5% of subjects are willing to expose themselves to the co-player's action by choosing action B. When the human co-player is replaced with a computer co-player in treatment CC, 50.0% of subjects are willing to expose themselves to the co-player's action. This difference of 8.5 percentage points is substantial and statistically significant (two-sided test of proportions, $\chi^2 = 14.187$, $p < 0.001$, Cohen's $h = 0.170$). The evidence therefore leads us to reject Hypothesis 1.

Result 1 *The source of risk affects first-round choices over statistically equivalent risks: Subjects choose to expose themselves less to statistically equivalent co-player action when the co-player is human.*

The cross-treatment evidence on subjects' first-round choices affirms the presence of a social risk premium in the MCG: Subjects behave as if they attach a greater weight to the potential adverse outcome arising under the future history BBg when the co-player is human.

4.2 The effect of social and natural risk experience

Hypothesis 2 posits that participants that experienced an adverse event will switch action at the same rate, irrespective of the source. We first test Hypothesis 2 for the HC treatment, which directly implements the MCG.

Figure 4 shows, for subjects having experienced social or natural risk materializing in treatment HC, the fraction that changes behavior between rounds 1 and 2 following the adverse event. Experiencing the zero-payoff event when its source is natural risk induced 19.4% of subjects to switch action. By comparison, experiencing the same zero-payoff event when its source is social risk led 36.6% of subjects to change behavior. This difference in behavioral change is both large and statistically significant (two-sided test of proportions, $\chi^2 = 5.225$, $p = 0.022$, Cohen's $h = 0.387$). The evidence therefore leads us to reject Hypothesis 2.

Result 2 *The experience of social risk affects decision-making more than the experience of natural risk: Subjects exhibit a greater propensity to change behavior after experiencing an adverse event when the source was another person compared to experiencing the same adverse event when the source was nature.*

Result 2 also holds up under multivariate analysis (see Table A-2, columns 1 and 2, in the appendix). There, demographic control variables such as age and gender as well as self-reported propensity to take risks account for differences in individual characteristics that conceivably affect the propensity to switch, independent of risk experience. The coefficient associated with social risk experience returns consistently positive and statistically significant estimates of its impact on the propensity to switch behavior.

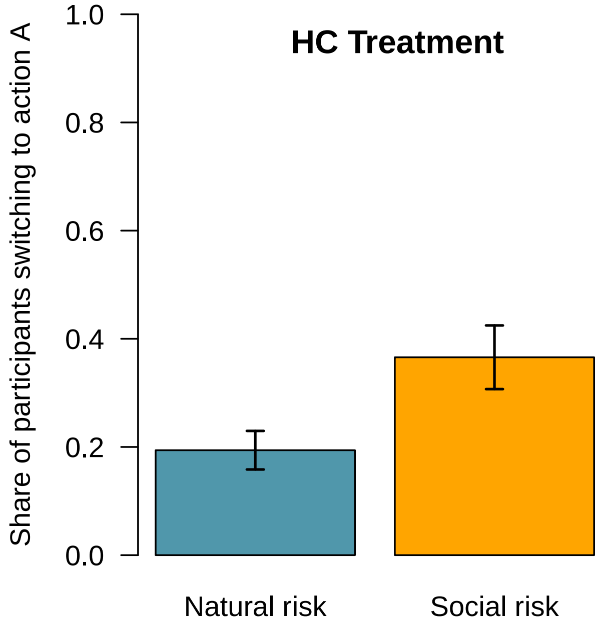

Figure 4: Experiencing social risk has a different behavioral impact compared to experiencing natural risk. The bar plot shows the share of participants switching action between rounds 1 and 2 in treatment HC. The switching propensity for those that experienced an adverse event due to an unfavorable urn draw is on the left (natural risk). It is significantly lower than the propensity of those that experienced an unfavorable co-player action (social risk). Error bars, mean ± s.e.m.

4.3 The effect of natural and natural risk experience

In a treatment in which the co-player is nature (a randomization device), subjects face two natural sources of risk experience. We hypothesized (Hypothesis 3) that the experience of an adverse event has the same effect on behavioral change, irrespective of whether the urn draw or the computer co-player led to the experience of an adverse event.

Figure 5 shows the share of players switching action after experiencing an adverse event that can be uniquely attributed to each of the two sources of natural risk. When the source is the urn draw, then 20.1% of subjects change their behavior. When the source is the computer co-player, then 19.7% of subjects switch to a different action. To test Hypothesis 3, we compare these two shares and find that the difference is statistically not significant (two-sided test of proportions, $\chi^2 < 0.001$, $p > 0.999$, Cohen's $h = 0.011$).

Result 3 *The experience of natural risk through a computer co-player affects decision-making in the same way as the experience of natural risk through an urn draw: Subjects exhibit the same propensity to change behavior after experiencing an adverse event when the source was nature in the form of a computer co-player as when experiencing the same adverse event when the source was nature in the form of an urn draw.*

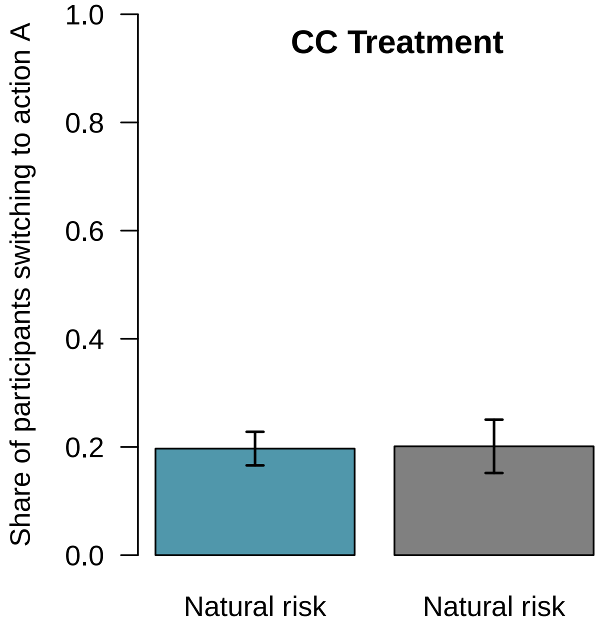

Figure 5: When the co-player is a computer, then experiencing an adverse event caused by co-player action does not lead to a higher propensity to switch action. The bar plot shows the share of participants switching action between rounds 1 and 2 in treatment CC. The switching propensity for those that experienced an unfavorable urn draw is on the left; the propensity of those that experienced unfavorable co-player action is on the right. The difference is not significant. Error bars, mean ± s.e.m.

Like Result 2, Result 3 survives multivariate analysis.[5] The analysis for the computer co-player returns a coefficient associated with a co-player risk experience that is an order of magnitude smaller than that for the human co-player in Result 2 and statistically insignificant.

The switching propensities in the CC treatment are not only statistically indistinguishable from each other. They are also statistically indistinguishable from the 19.4% propensity to switch action following an adverse event attributable to nature in the HC treatment (two-sided test of proportions, $\chi^2 < 0.001$, $p > 0.999$, Cohen's $h = 0.007$). This evidence leads us not to reject Hypothesis 3. Behavior in the CC treatment is, in other words, the evidence that Hypothesis 2 predicted the HC treatment to return. The contrast between the two treatments is striking: The point estimate of the rate of behavioral change after experiencing an adverse event caused by the human co-player in the HC treatment and that estimate for the computer co-player is almost twice the magnitude (20.1% vs. 36.6%, two-sided test of proportions, $\chi^2 = 8.812$, $p = 0.003$, Cohen's $h = 0.369$).

[5]Appendix, Table A-2, columns 3 and 4.

4.4 The effect of intent to social risk exposure

To support theory-building, treatment AA is designed to shed light on whether a possible ESRF is a phenomenon specific to 'social risk takers' that intentionally expose themselves to a co-player's action or a general trait. This is accomplished by eliciting subjects' preference for the first-round action, but assigning action B in round 1.

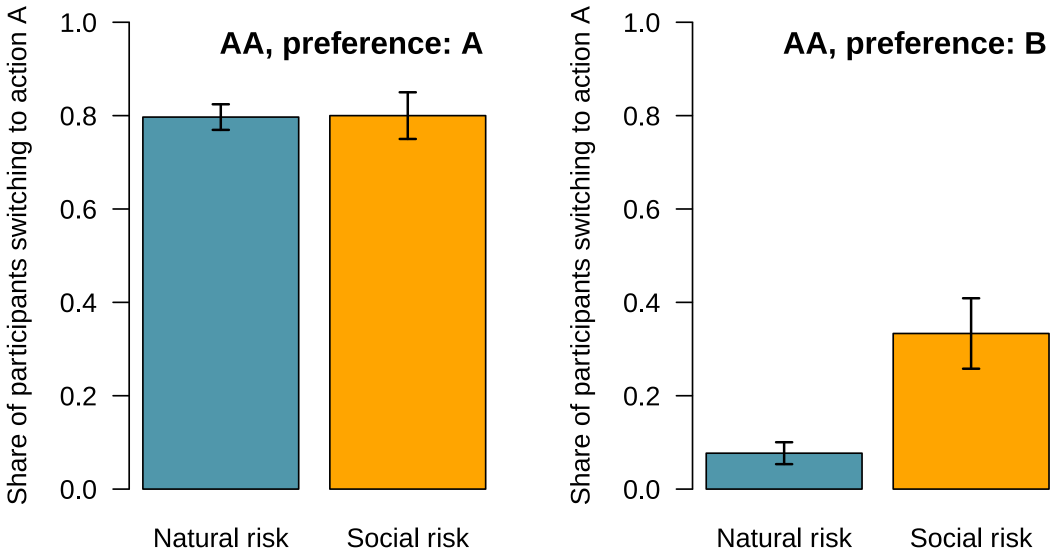

Figure 6: The experience of social risk has a significant behavioral impact. The bar plots show the shares of participants switching action between rounds 1 and 2 in treatment AA. **a** The switching propensity for those that preferred action A in round 1 is unaffected by the cause of the adverse event. **b** Participants that preferred action B in round 1 and experience social risk have a substantially higher propensity to switch action than those who experience natural risk. Error bars, mean s.e.m.

Figure 6 shows, in left panel, the share of participants preferring action A in round 1 that switched action following a natural (blue) or social (orange) risk experience. By visual inspection, the source of risk experience appears to be immaterial for behavioral change: Among those who preferred not to be exposed to social risk, experiencing social risk (orange) led 80.0% to choose action A in round 2 and 20.0% to choose action B. Since these subjects preferred action A to begin with, this pattern is unsurprising. Among those experiencing natural risk (blue), 79.7% chose action A in round 2 and 20.3% action B. These shares are statistically indistinguishable ($\chi^2 < 0.001$, $p > 0.999$, Cohen's $h = 0.008$) and are consistent with the absence of an ESRF among 'social risk avoiders'. The right panel of Figure 6, on the other hand, is consistent with Result 2. 7.7% of subjects who preferred to be exposed to social risk in round 1 switched action in round 2 after experiencing natural risk (blue) while 33.3% switched action after experiencing social risk (orange). This indicates the presence of a ESRF among social risk takers that is highly significant ($\chi^2 = 8.654$, $p = 0.003$, $h = 0.669$).

Testing Hypothesis 4 requires a test of the difference-in-differences between the natural and social risk experience by intent to expose oneself to social risk. Among those who preferred action A in round 1, the difference between natural and social risk experience is 0.3%; among those who preferred action B, the difference of 25.6%. The difference-in-differences is highly significant (interaction term in linear model: $p = 0.009$, probit model: $p = 0.009$, Tables A-4 and A-5 in the Appendix). This leads us to reject Hypothesis 4.

Result 4 *The experience of social risk only affects decision-making of those choosing to be exposed to it: The difference between behavioral change driven social and natural risk experience differs significantly by intent to social risk exposure revealed before round 1.*

Like Results 2 and 3, Result 4 is robust to a multivariate analysis.[6] It both reaffirms the presence of an ESRF (Result 2) and characterizes it as conditional on intent. While this conditionality is of limited empirical relevance, it is important for theorizing about the nature of the experience of social risk effect and for model agent behavior.

In contrast to Result 4, the prediction of Hypothesis 4 holds for the computer co-player version of the AA treatment (CC/AA). There, the impact of experience of co-player risk on decision making does not differ between intent to exposure. Among those who preferred action A in round 1, the difference between experiencing an adverse event on account of an unfavorable urn draw and an unfavorable co-player experience is 17.3% ($\chi^2 = 5.827$, $p = 0.016$, $h = 0.37$); among those who preferred action B, the difference of 9.7% ($\chi^2 = 1.846$, $p = 0.174$, $h = 0.25$). The difference-in-differences is insignificant (interaction term in linear model: $p = 0.407$, probit model: $p = 0.697$, Tables A-4 and A-5 in the Appendix). This is additional evidence that social risk experience impacts decision-making differently from natural risk experience.

5 Discussion

The core message of the 'experience of social risk' factor that our experimental evidence suggests is that people are generally less willing to take social risk again after experiencing an adverse event whose source was another person rather than nature. Subjects with a social risk experience were twice as likely to switch to action A compared to subjects with a natural risk experience in treatment HC (Result 2). When the 'social risk experience' was instead generated by a computer co-player in treatment CC, subjects switched at the same rate, irrespective of the source of experience (Result 3), and also at the same rate as after a natural risk experience in treatment HC. We therefore detect the presence of a new social risk effect, the ESRF, and find that its direction favors the avoidance of social risk in future interactions. In addition, we find that the ESRF selectively affects individuals

[6] Appendix, Table A-2, columns 5 and 6.

who chose to be exposed to social risk, but not those that avoided the experience of social risk (Result 4).

With a focus on detection, the experiment was not designed to test possible mechanisms behind the ESRF. Nevertheless, the experimental data provide a number of starting points to guide future research on what we believe is a promising topic of inquiry. The starting points in the data come from participants' demographic characteristics and from participants' beliefs about their co-player's action and the urn draw, elicited after every choice and before feedback.

A multivariate analysis provides first evidence that demographic characteristics hold little promise as explanatory variables for the ESRF. Neither age, gender nor education play a statistical role in determining propensity to switch action following an adverse event (see Table A-2 in the Appendix). Further analysis that interacts demographics with social risk experience also fails to yield clear insights (Table A-6). One possible line of research could follow tentative evidence that education attenuates the ESRF: Participants who self-report holding a college degree respond somewhat less to a social risk experience.

The experiment was designed to rule out the possibility that subjects can learn information in round 1 that could be decision-relevant in round 2. Despite these intentions, it cannot be excluded *a priori* that subjects erroneously believed to have gathered valuable information from round 1, influencing round 2 decisions. For example, it has been suggested that despite random re-assignment to a new co-player drawn from a vast pool of subjects, participants believe that the co-player action in round 1 contains information about the new co-player's action in round 2. This conjecture can be examined more closely by drawing on the beliefs data elicited after each of the two choices. Pooling across histories, we regressed changes in beliefs about co-player action between rounds 1 and 2 on participants' own action, co-player action, and urn draw in round 1, adding the co-variates demographic characteristics, risk attitude, and interaction terms. This analysis reveals no significant statistical relationships, either individually by treatment (HC and CC) nor pooled across treatment (Table A-7). As in the multivariate analysis of choice data, education appears to have some influence: College-educated participants change their beliefs slightly less.

A key piece of evidence against the "learning" conjecture comes from comparing the determinants of changes in beliefs in the HC and the CC treatment. In the CC treatment, participants confirm that they have understood the mechanistic nature of their co-player and then learn the probabilities of play for each action A and B. In the HC treatment, participants likewise confirm their understanding of a human co-player. They are, truthfully, informed about the probabilities of play in the population "from a previous experiment" (see instructions). One might reason that even though participants only observe a single co-player choice, the HC treatment provides more grounds for learning than the CC treatment. Yet, there are no significant differences between the HC and CC treatments in how beliefs are shaped by previous play (Table A-7, columns 5 and 6).

We further restricted the analysis to a subsample of changes in beliefs about co-player action that appear consistent with Bayesian updating (i.e. belief changes that positively correlate with observed co-player action, Table A-8). For this subsample, there are differences between the HC and CC treatment that are borderline significant: Beliefs in the HC treatment respond *less* to co-player action than in the CC treatment. This finding runs counter to the idea that the "learning" conjecture can explain the ESRF.

Instead of learning, there are at least two mechanisms that could contribute to the phenomenon of the ESRF and that appear to merit further investigation. Both mechanisms relate to the experiences and predispositions that participants apply when facing the experimental task (Cárdenas and Ostrom, 2004; Binmore, 2010).

One possible mechanism could revolve around norms, conformity, and co-player intent (Butler and Miller, 2018). There is renewed interest among experimental economists in the evolution of norms and norm-based behavior in social dilemmas. Experience of the consequences of norm-inconsistent behavior may well be a driver in this evolution, giving rise to a 'moral lesson effect'. In our experiment, it is important to note that those who experience social risk make this experience as a result of an intent to capture an own benefit of US$3 by choosing action B and encountering another player choosing the same. Given the announced probabilities of 60% of subject choosing A, participants know the modal behavior in this dilemma. In the HC treatment, this would be consistent with a descriptive norm and may well be interpreted by participants to imply also an injunctive norm about behavior in the MCG. Everyone taking action A has, after all, ethically attractive properties: It ensures equal positive payouts of US$1 for both participants under a favorable state of the world.[7] In the CC treatment, the announced probabilities can at most provide a description of behavior, but for obvious reasons cannot convey an ethical message. This implies that the normative context of the HC and the CC treatment differ. A participant choosing B in the HC treatment may feel that he is violating a norm. A participant choosing B in the CC treatment is not.[8] The adverse event could then have the same effect as experiencing punishment in other social dilemmas, thus reinforcing the norm-based message. This is particularly so because participants can reasonably attribute intent to their human co-players in the HC treatment. In the CC treatment, where the norm never existed, such a leveraging of experience to reinforce norms cannot take place. The 'experience of social risk' factor may therefore well be an endogenous reinforcement learning of norms among unlucky participants that leads, overall, to a better collective payoff outcome. To study the postulated mechanism underpinning the ESRF, future experiments could elicit participants' beliefs about behavioral norms in the MCG and administer new treatments that vary the normative content of the game, for example by changing the payoff matrix, or by explicitly framing the actions. Similarly, allowing for controlled communication among co-players could further illuminate a potential normative

[7]There is little evidence that injunctive norms can include mixed strategies.

[8]This also provides an explanation why we find a larger share of participants taking action B in treatment CC. Choosing to be exposed to co-player risk does not have a norm-based negative connotation.

mechanism that causes the ESRF.

A second possible mechanism causing the ESRF could be that humans, and other social animals such as chimpanzees (Calcutt et al., 2019), are especially sensitive to mean-variance trade-offs with payoff externalities. For social groups to be successful, it is a decisive factor to ensure mutual insurance in face of moral hazard and natural risks. In situations in which both social and natural risks are present and the social risk could be influenced while the natural risk could not, it makes sense to condition insurance (redistribution in case of an averse event) on the cause of the event, both to discourage shirking and to encourage learning (avoiding situations that lead to averse outcomes in the future). Indeed, the expectation of cause-dependent insurance could reconcile the evidence that, on the one hand, humans accept inequality much more when it is caused by nature rather than other humans (Blount, 1995) while, on the other hand, third-party spectators redistribute to a greater extent when an unequal allocation has been caused by nature, rather than by the affected individuals themselves (Cappelen et al., 2013; Almås et al., 2020). While these studies focus on the causal attribution of the outcome, our study emphasizes the effect of experience on action in a repeated, identical situation. Our study highlights the decisive role of active involvement by the decision makers for the ESRF to be appear. Those participants in our study that could have avoided the outcome had they – all else equal – chosen differently are twice as likely to change their behavior than those participants who would have not avoided the outcome had they – all else equal – chosen differently. Such counterfactual thinking points to potentially important interaction effects between causal attribution and experience. In our design, attribution is perfect: decision makers are fully informed about what caused the outcome they experienced. In many real-world situations where outcomes are jointly determined by natural and social risks, attribution is imperfect. On the one hand, we would expect that the ESRF decreases the more uncertain it is whether a different action would have, ceteris paribus, led to a different outcome. On the other hand, it could be the case that decision makers overestimate their impact on the outcome, which could counteract this effect and maybe even increase the ESRF. Designing experiments that shed a light on this question is an important avenue for future work.

6 Conclusion

The experiment that we present here is to our knowledge the first detection of an 'experience of social risk' factor. This ESRF takes the shape of an intertemporal spill-over onto decision-making from experiencing the outcome of a previous round of the same simultaneous-move, anti-coordination game in which the decision-maker chose to expose himself to the action of a randomly matched co-player who happens to be a person rather than nature. Real-world examples that conform to the structure under which the ESRF arises can be found in a variety of settings. Internet outages can arise as a result of network component failure or an uncoordinated surge in demand. Traffic jams can be the result of inclement weather or of poorly coordinated commuting schedules. Fisheries collapse both due to climate extremes, but also due to excessive exploitation by too many users. In such settings, there is scope that risk experience differentially affects decision-making depending on the source of the adverse event.

The features under which the ESRF arises contrast with those employed to study the social risk premium. The SRP takes the shape of an anticipatory change in decision-making when the decision-maker in a sequential-move trust game chooses whether to expose himself to the action of a co-player who is a person. This means that the ESRF and the SRP differ not just in terms of timing (past vs. future), but also the order of moves (simultaneous vs. sequential), and the game form (anti-coordination vs. trust game). These differences lead us to postulate that the ESRF is a social risk effect that is distinct from the SRP. It shares with the SRP that only the source of the risk, nature versus another person, matters for an impact on decision-making. The economic situations that favor the presence of an ESRF and a SRP are otherwise quite different. This difference is important because it means that explanations for the SRP are likely to struggle for traction when being asked to explain the ESRF in particular and social risk effects in general. Explanations for the SRP involve betrayal aversion, loss of control aversion and depend on intent. These explanations neatly exploit the specifics of the trust game to provide a compelling narrative. To the extent that the ESRF does not rely on the structural features of the trust game, alternative explanations must be invoked.

In light of the evidence that a social risk effect can be generated under radically different conditions from those that generate the SRP, it is interesting to speculate under which conditions we should expect social risk effects to be uncovered in future research. Clearly, the SRP and the ESRF do not exhaust the structural possibilities of situations in which decision-makers are exposed to both natural and social risks. A social risk effect might also be found in pure cooperation games where there is no risk of gainful exploitation by a co-player. Both the ESRF and the SRP consider decision-making by a single individual for itself. It is a matter of future research to examine whether a social risk effect also arises when groups, rather than individuals, jointly take a decision or when a decision-maker takes a risky choice on someone else's behalf.

Bohnet et al. (2008) conclude that their results imply that "shareholders would prefer a 1 percent chance of losing half their value due to a natural catastrophe than a somewhat smaller chance of the same loss due to the malfeasance of corporate leaders". Our results imply that those same shareholders would take greater precaution after experiencing the malfeasance of a corporate leader than after experiencing a natural catastrophe. In both cases, the consequences of non-consequentialist decision-making under risk are real and require sustained attention in our understanding of decision-making.

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Appendix

Table A-1: Participant characteristics.

variable	HC	CC	AA	AA/CC
age	36.98	37.01	36.88	37.59
female	0.46	0.5	0.49	0.5
education	0.44	0.42	0.45	0.41
risk	5.11	5.33	5.1	5.26

Note: Education is a dummy that equals one if a participant is in the modal category (bachelor degree). Risk tolerance is measured following (Dohmen et al., 2011) (scale from 0 (lowest willingness to take risk) to 10 (highest willingness to take risks). Out of our 3982 participants, 1931 identify with being female, 2032 with male, 12 preferred not to reveal their gender and 5 chose "other".

Table A-2: Probit regressions

	HC treatment		CC treatment		AA treatment	
	(1)	(2)	(3)	(4)	(5)	(6)
human_cause	0.520*	0.590**	0.015	0.084	0.995**	1.085***
	(0.210)	(0.220)	(0.209)	(0.215)	(0.317)	(0.329)
dual_cause	0.381	0.401	0.273	0.353	0.821*	0.885*
	(0.250)	(0.258)	(0.294)	(0.302)	(0.377)	(0.390)
risk		−0.124***		−0.032		−0.099*
		(0.036)		(0.037)		(0.041)
age		0.003		−0.005		0.003
		(0.008)		(0.007)		(0.010)
female		−0.047		0.464*		0.116
		(0.182)		(0.190)		(0.200)
education		0.049		−0.004		0.090
		(0.068)		(0.069)		(0.082)
Constant	−0.863***	−0.448	−0.852***	−0.795	−1.426***	−1.442*
	(0.176)	(0.459)	(0.176)	(0.456)	(0.296)	(0.571)
Observations	244	244	262	262	201	201
Log Likelihood	−147.377	−140.752	−134.102	−129.722	−112.023	−108.129
Akaike Inf. Crit.	300.754	295.503	274.204	273.445	230.046	230.257

Note: Probit regression models. Dependent variable is switching action between rounds 1 and 2. For Treatment 2, this is based on action preference. The sample consists of participants who have experienced histories BBg, BAr, or BBr. Risk is self reported risk tolerance, Education is the highest level of school or college completed. *p<0.05; **p<0.01; ***p<0.001.

Table A-3: Ordinary Least Squares regressions

	HC treatment		CC treatment		AA treatment	
	(1)	(2)	(3)	(4)	(5)	(6)
human_cause	0.172*	0.186**	0.004	0.025	0.256**	0.268***
	(0.070)	(0.070)	(0.060)	(0.060)	(0.080)	(0.080)
dual_cause	0.121	0.131	0.084	0.108	0.196	0.201
	(0.084)	(0.083)	(0.088)	(0.088)	(0.104)	(0.104)
risk		−0.041***		−0.009		−0.028*
		(0.012)		(0.010)		(0.012)
age		0.001		−0.002		0.002
		(0.003)		(0.002)		(0.003)
female		−0.012		0.130*		0.046
		(0.061)		(0.053)		(0.062)
education		0.015		−0.002		0.025
		(0.023)		(0.019)		(0.025)
Constant	0.194***	0.349*	0.197***	0.231	0.077	0.057
	(0.056)	(0.153)	(0.050)	(0.128)	(0.070)	(0.167)
Observations	244	244	262	262	201	201
Adjusted R^2	0.017	0.053	−0.003	0.015	0.040	0.057

Note: Linear (OLS) regression models. Dependent variable is switching action between rounds 1 and 2. For Treatment 2, this is based on action preference. The sample consists of participants who have experienced histories BBg, BAr, or BBr. Risk is self reported risk tolerance, Education is the highest level of school or college completed. *p<0.05; **p<0.01; ***p<0.001

Table A-4: Difference in Difference Estimates, OLS regressions

	AA treatment		AA/CC treatment	
	(1)	(2)	(3)	(4)
human_cause	0.003	-0.008	0.173**	0.173**
	(0.059)	(0.059)	(0.063)	(0.064)
prefers_b	-0.720***	-0.719***	-0.455***	-0.441***
	(0.084)	(0.084)	(0.078)	(0.079)
human_cause × :prefers_b	0.253**	0.271**	-0.076	-0.082
	(0.096)	(0.096)	(0.092)	(0.093)
risk		-0.024**		-0.010
		(0.008)		(0.008)
age		-0.0002		0.001
		(0.002)		(0.002)
female		0.004		-0.010
		(0.040)		(0.042)
education		0.008		0.007
		(0.016)		(0.016)
Constant	0.797***	0.900***	0.590***	0.585***
	(0.052)	(0.108)	(0.055)	(0.111)
Observations	447	447	435	430
Adjusted R^2	0.284	0.293	0.274	0.265

Note: Dependent variable is switching action between rounds 1 and 2. The sample consists of participants who have experienced histories BBg, BAr, or BBr. Risk is self reported risk tolerance, Education is the highest level of school or college completed. *p<0.05; **p<0.01; ***p<0.001

Table A-5: Difference in Difference Estimates, Probit regressions

	AA treatment		AA/CC treatment	
	(1)	(2)	(3)	(4)
human_cause	0.011	−0.040	0.488*	0.496*
	(0.203)	(0.206)	(0.193)	(0.194)
prefers_b	−2.257***	−2.345***	−1.328***	−1.291***
	(0.345)	(0.356)	(0.261)	(0.264)
human_cause × prefers_b	0.984**	1.115**	−0.119	−0.136
	(0.376)	(0.387)	(0.304)	(0.307)
risk		−0.086**		−0.033
		(0.027)		(0.026)
age		−0.002		0.004
		(0.006)		(0.006)
female		−0.004		−0.027
		(0.137)		(0.135)
education		0.029		0.023
		(0.056)		(0.051)
Constant	0.831***	1.269***	0.228	0.193
	(0.178)	(0.378)	(0.162)	(0.350)
Observations	447	447	435	430
Log Likelihood	−232.574	−227.448	−236.420	−233.975

Note: Dependent variable is switching action between rounds 1 and 2. The sample consists of participants who have experienced histories BBg, BAr, or BBr. Risk is self reported risk tolerance, Education is the highest level of school or college completed. *p<0.05; **p<0.01; ***p<0.001

Table A-6: Additional Analysis: Interactions of social risk experience and demographics

	OLS	*Probit*
	(1)	(2)
human_cause	0.685**	2.361**
	(0.252)	(0.824)
dual_cause	0.133	0.439
	(0.083)	(0.267)
risk	−0.042***	−0.133***
	(0.012)	(0.037)
age	0.005	0.019
	(0.004)	(0.012)
female	−0.096	−0.362
	(0.086)	(0.282)
education	0.059	0.215
	(0.034)	(0.114)
human_cause × age	−0.008	−0.029
	(0.005)	(0.016)
human_cause × female	0.158	0.525
	(0.118)	(0.368)
human_cause × education	−0.083	−0.281*
	(0.045)	(0.143)
Constant	0.094	−1.456*
	(0.194)	(0.660)
Observations	244	244
Adjusted R^2	0.068	
Log Likelihood		−136.864

Note: Linear and nonlinear regressions with interaction terms. Dependent variable is switching action between rounds 1 and 2. The sample consists of participants who have experienced histories BBg, BAr, or BBr. Risk is self reported risk tolerance, Education is the highest level of school or college completed. *p<0.05; **p<0.01; ***p<0.001

Table A-7: OLS regressions on Changes in beliefs

	HC treatment		CC treatment		HC & CC treatment	
	(1)	(2)	(3)	(4)	(5)	(6)
action_b_r1	3.551	3.177	2.373	2.130	2.373	1.976
	(2.211)	(2.274)	(2.346)	(2.380)	(2.245)	(2.260)
other_b_r1	2.603	2.463	2.170	2.155	2.170	2.183
	(2.213)	(2.215)	(2.418)	(2.423)	(2.314)	(2.315)
ball_red_r1	1.294	1.397	−0.238	−0.074	−0.238	−0.144
	(2.378)	(2.377)	(2.949)	(2.957)	(2.823)	(2.825)
age		−0.041		−0.010		−0.025
		(0.095)		(0.105)		(0.071)
risk		0.018		0.412		0.223
		(0.418)		(0.448)		(0.307)
education		−1.828**		−1.106		−1.456**
		(0.853)		(0.932)		(0.632)
HC treatment					−2.458	−2.481
					(2.715)	(2.733)
action_b_r1 × HC					1.178	1.035
					(3.232)	(3.261)
other_b_r1 × HC					0.433	0.250
					(3.281)	(3.283)
ball_red_r1 × HC					1.532	1.512
					(3.770)	(3.772)
Constant	−2.055	5.433	0.403	2.356	0.403	5.150
	(1.823)	(5.252)	(2.009)	(5.839)	(1.923)	(4.223)
Observations	986	986	1,025	1,024	2,011	2,010
Adjusted R^2	0.001	0.003	−0.001	−0.002	−0.0001	0.001

Note: Dependent variable is within participant change in beliefs about co-player action between round 1 and round 2. Risk is self reported risk tolerance, Education is the highest level of school or college completed. *p<0.05; **p<0.01; ***p<0.001

Table A-8: OLS regressions on Changes in beliefs

	HC treatment		CC treatment		HC & CC treatment	
	(1)	(2)	(3)	(4)	(5)	(6)
action_b_r1	3.800*	3.616	3.413	3.587	3.413	3.049
	(2.182)	(2.291)	(2.582)	(2.634)	(2.406)	(2.425)
other_b_r1	37.880***	37.801***	45.921***	45.858***	45.921***	45.900***
	(2.177)	(2.167)	(2.645)	(2.662)	(2.464)	(2.468)
ball_red_r1	0.819	0.815	5.212	5.128	5.212*	5.163*
	(2.358)	(2.350)	(3.172)	(3.195)	(2.955)	(2.960)
age		0.010		−0.072		−0.031
		(0.097)		(0.116)		(0.075)
risk		−0.317		−0.108		−0.190
		(0.418)		(0.485)		(0.319)
education		−2.467***		−0.176		−1.388**
		(0.832)		(1.042)		(0.660)
HC treatment					5.386*	5.042*
					(2.860)	(2.887)
action_b_r1 × HC					0.388	0.697
					(3.367)	(3.413)
other_b_r1 × HC					−8.041**	−8.096**
					(3.406)	(3.406)
ball_red_r1 × HC					−4.393	−4.409
					(3.901)	(3.902)
Constant	−18.761***	−9.556*	−24.147***	−20.416***	−24.147***	−17.216***
	(1.838)	(5.101)	(2.209)	(6.381)	(2.059)	(4.395)
Observations	581	581	546	545	1,127	1,126
Adjusted R^2	0.346	0.354	0.355	0.353	0.352	0.353

Note: Dependent variable is within participant change in beliefs about co-player action between round 1 and round 2. Sample is participants that are consistent with Bayesian updating. Risk is self reported risk tolerance, Education is the highest level of school or college completed. $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$