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Natural disaster and risk-sharing behavior: Evidence from rural Bangladesh

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Abstract

Using a unique field experiment in rural Bangladesh, this paper investigates how exposure to a natural disaster affects risk-sharing behavior. We conducted a risk-sharing experiment that randomly assigned different levels of risk-sharing commitments to individuals who were exposed and unexposed to a recent natural disaster and asked them to form risk-sharing groups. Our results show that disaster-affected individuals are less likely to defect from risk-sharing groups, regardless of the level of ex-ante commitment. Interestingly, individuals from disaster-affected villages chose riskier bets and realized higher average returns compared with individuals from non-disaster-affected areas. Our results have important implications for the design of financial risk-transfer mechanisms in developing countries.

Keywords Risk preference · Risk-sharing · Intrinsic motivation · Asymmetric information · Natural disaster · Field experiment

JEL Classification C90 · C93 · D03 · D71 · D81 · O12 · Q54

1 Introduction

The vast majority of households in developing countries have no access to formal types of insurance. Therefore more informal types of risk-sharing are often the only methods to insure against consumption shocks (Townsend 1994; Holzmann et al. 2000). There is a substantial amount of literature that documents the use of informal

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risk-sharing networks to counter the adverse income effects associated with sickness and unemployment (Ravallion and Dearden 1988; Fafchamps and Lund 2003), weather shocks (Morduch 1991), and natural disasters (Freeman and Kunreuther 2002; Zylberberg and Gröger 2016).

Considering that informal risk-sharing networks do not rely on formal contracts, an interesting question is whether commitment to informal risk-sharing is stable over time and, in particular, if individual risk-sharing behaviour is affected by exposure to large negative shocks, such as natural disasters or violent conflict. This question is important for various reasons. Informal mechanisms are often insufficient to cover the damages from large negative shocks because the individual risks are often highly correlated, resulting in very large cumulative damages. In addition, large negative shocks could potentially distort or fully eradicate the only available mechanism that allows households to smooth consumption in poor societies. Eventually, this might have longer lasting adverse effects on the individuals' livelihoods, even after the initial losses of that shock have been absorbed.

There are a number of studies that hint towards the idea that there could be a link between large negative shocks and risk-sharing behaviour. First, large losses affect individual risk preferences, which, in turn, can impact individual risk-sharing behaviour. A number of empirical studies have confirmed that risk attitudes tend to be systematically affected by large negative events (e.g., Eckel et al. 2009; Malmendier and Nagel 2011; Voors et al. 2012; Haushofer and Fehr 2014; Page et al. 2014; Cameron and Shah 2015; Hanaoka et al. 2018). So far, there is no clear consensus in the empirical literature about the effect of natural disasters on risk aversion. One group of studies (Cameron and Shah 2015; Cassar et al. 2017) has found increased risk aversion, while another set of studies (Eckel et al. 2009; Page et al. 2014; Hanaoka et al. 2018) finds that people tend to become more risk tolerant after experiencing a natural disaster and that this effect can even persist over multiple years (Hanaoka et al. 2018). Further, work by Ghatak (1999), Ahlin (2009), and Attanasio et al. (2012) provide evidence of the link between individual risk preferences and the formation of informal risk-sharing groups. Although Ahlin (2009) finds evidence of assertive matching based on risk preferences in risk-sharing groups in general, Attanasio et al. (2012) reveal that this is only the case for groups with strong social networks. Second, large negative shocks are believed to have a systematic impact on social networks and social capital (e.g., Fleming et al. 2014; Cassar et al. 2017; Toya and Skidmore 2014; Yamamura 2016). Fleming et al. (2014) find that reciprocity among rural villages decreased a year after the 2010 Chilean earthquake. In contrast, using a number of lab-in-the-field experiments, Cassar et al. (2017) show that trust and pro-social behavior increased among respondents in areas affected by the 2004 tsunami. Relying on cross-country data, Toya and Skidmore (2014) find that the frequency of major natural disasters has a positive effect on social capital accumulation. Our paper links this literature with existing studies showing that social capital is important for the formation and stability of informal risk-sharing networks (e.g., Weerdt and Dercon 2006; Fafchamps and Gubert 2007; Mazzocco and Saini 2012; Munshi and Rosenzweig 2016). A third link between large negative shocks and risk-sharing behavior is that exposure to a disaster can affect individuals' risk perceptions (e.g., Botzen et al. 2009; 2015), which, in turn, can increase the demand for private protective measures and risk-sharing mechanisms such as disaster insurance (e.g., Botzen and Van Den Bergh 2012b; Bubeck et al. 2012; Botzen et al. 2019; Thieken et al. 2006). What is, however, absent from the literature is an empirical analysis that directly investigates the relationship between large negative shocks and risk-sharing behaviour.

The purpose of the current paper is to fill this gap using data from a field experiment in Bangladesh. More specifically, we exploit the random cut-offs of inundation zones resulting from Cyclone Aila in 2009 in the districts of Khulna and Satkhira to identify the effect of disaster exposure on risk-sharing commitments. Villages that were hit by the cyclone-related flooding are the treatment villages, and the adjacent villages that were unaffected by the disaster serve as the control villages.

To aid in the interpretation of our findings, we also develop a theoretical model of risk-taking, risk-sharing, and defection. The model highlights the role of social costs in deterring defection. Precisely, in villages that exhibit a combination of (i) more risk-taking, (ii) smaller risk-sharing groups, and (iii) less defection, the within groups must face stronger social norms to prevent defection. As discussed below, this mix of behaviors is exactly what we observe among our treatment villages.

Our identifying assumption is that the individuals in the flood-affected villages are comparable to the individuals in the unaffected villages. A common concern among studies that use natural disasters as a natural experimental setting (e.g., Page et al. 2014; Cameron and Shah 2015; Hanaoka et al. 2018), however, is that the population in affected and unaffected villages might differ because of some unobservable factors, which simultaneously drive the selection into the treatment group and their risk-taking behaviour. For example, more affluent villages could afford better flood protection and also have a different demographic composition, which affects their members' risk-taking commitments (e.g., Kousky et al. 2006).

With respect to this concern, Cyclone Aila and the resulting inundation of Khulna and Satkhira provide a unique setting for a natural experiment. First, man-made protective measures are largely absent, and the few structural measures (i.e., elevated roads) were no match for Aila's storm surge. Second, the study area is located in a large delta on Bangladesh's coast on the gulf of Bengal, and the entire area is flat and lacks significant elevational changes. As such, the topography does not offer any elevated places for settlement to be more protected in the case of flooding. Therefore, the selection into the treatment group is solely driven by the physical magnitude of the cyclone and the resulting storm surge and is, as such, random. To provide further auxiliary support that our identification assumption is valid, we show evidence that the participants in the adjacent villages are similar regarding a set of observable characteristics.

To measure risk-sharing behaviour, we invited a random subset of households in both the treatment and control villages to participate in a series of lab-style experiments in makeshift laboratories set up in each village. The design of this lab-in-field type of experiment closely follows the design of Barr and Genicot (2008). In the first step, participants had to choose from different lotteries in a standard risk-taking game.[1] In the second step, they were asked to form a risk-sharing group that pools and shares the gains from the group members' gambles. Then, the participants were assigned into one of the three different information treatments. Treatments varied with respect to the level of exogenous commitments that allowed individuals to defect and whether such a defection was public or private information. The main findings are that the participants in disaster-affected areas are more risk loving, form smaller risk-sharing groups, and are less likely to defect in risk-sharing commitments, regardless of the level of exogenous commitment and information. Viewed through the lens of our theoretical model, this suggests a strengthening of the social norms supporting risk-sharing commitments in the wake of natural disasters.

Our study's major contribution is that it builds an empirical link between the literature on the impact of large negative shocks on risk preferences (e.g., Loewenstein and Angner 2003; Eckel et al. 2009; Malmendier and Nagel 2011; Page et al. 2014; Cameron and Shah 2015; Hanaoka et al. 2018) and the literature on the nexus between individual risk preferences and risk-sharing behavior (e.g., Ahlin 2009; Attanasio et al. 2012).

To the best of our knowledge, our paper is the first one that combines the use of disasters as a natural experiment from the former strand of literature with the methods for investigating risk-sharing behaviour in an incentivized manner from the latter strand.

Our findings are of particular importance for the literature that deals with decision making under uncertainty with respect to low-probability-high-loss (LPHL) events (e.g., Kunreuther 1996; Kunreuther et al. 2001; Kunreuther and Pauly 2002; Browne et al. 2015). In line with existing studies (e.g., Viscusi and Zeckhauser 2006; Page et al. 2014; Hanaoka et al. 2018), we confirm that the recent exposure to a natural disaster makes people less risk averse. This could be problematic if this adversely affects the individuals' willingness to prepare for such LPHL events, which are already prone to under-insurance. However, the result of our second experiment suggests that despite becoming more risk tolerant, individuals are also more likely to commit to risk-sharing institutions. This could be an indication that the affected individuals do not necessarily shirk risk-sharing responsibility despite becoming less risk-averse. As such, our results also provide new insights for economic research on the demand for disaster insurance. In particular, we offer an additional explanation why individuals tend to underinsure against LPHL events such as natural disasters (Botzen and Van den Bergh 2012a; Gallagher 2014; Kousky 2010; Kunreuther 1996; Kunreuther et al. 2009; Landry et al. 2016; Petrolia et al. 2013; Raschky et al. 2013).

More broadly, our paper also contributes to the broader theoretical and empirical literature about individual decisions to join risk-sharing groups (e.g., Pratt and Zeckhauser 1989; Tausch et al. 2014; Cettolin and Tausch 2015). We extend this strand of literature by looking specifically at the effect of experiencing a LPHL event on one's decision to join a risk-sharing group. In addition, our field experiment

[1]The design in the first stage is also used by other related studies such as Carvalhoa et al. (2016) and Cameron and Shah (2015).

builds on existing evidence in this area, which is predominately based on laboratory experiments.

Our study can inform economists and policy-makers trying to explain why the level of disaster insurance is below an optimal social level (Kunreuther 1996; Kriesel and Landry 2004; Kunreuther et al. 2009; Raschky and Weck-Hannemann 2007; Kousky et al. 2018) and can help those want to design more efficient financial risk-transfer mechanisms against natural disasters, in particular in developing countries.

The remainder of the current paper is organized as follows: In Section 2, we provide a brief description of the disaster in question and the physical impact it had on the community. In Section 3, we discuss the experimental design that we adopt, which closely follows Barr and Genicot's (2013) design. Section 4 summarizes the theoretical model. Section 5 presents the field experiment and data. Section 6 discusses the results, and Section 7 concludes.

2 Cyclone Aila

Cyclone Aila struck the southwestern coastal region of Bangladesh (and the eastern coast of the neighboring West Bengal province of India) on the 25th of May 2009. The Satkhira and Khulna districts were the worst hit, with nine other districts in Bangladesh also badly affected. Hitting during high tide, the cyclone brought tidal surges of up to 6.5 meters (United Nations 2010). In the Khulna and Satkhira districts, several rivers broke through embankments, causing widespread inland flooding. This surge of water damaged and washed away embankments, removing the only protection available to many people along the coast. According to the United Nations (2010), the immediate impact of Aila resulted in 190 deaths and approximately 7,100 injuries, with over 3.9 million people being affected, along with the death of 100,000 livestock and the destruction of 350,000 acres of cropland. It also caused considerable infrastructure losses. Thousands of kilometers of road were damaged or totally destroyed, and hundreds of kilometers of flood protection embankments were washed away.

The main damage was caused by flood water breaching the already weakened embankments throughout the affected districts. Activities associated with shrimp farming, such as the frequent practice of opening the embankments to move saline water into shrimp ponds, made the half-century-old earthen embankments weak, causing them to break during the tidal surge. Silting up of the river beds, along with rapid coastal subsidence, also contributed to higher tidal surges and increased the strain on the embankments. The area remained waterlogged for a prolonged period, salinizing the soil and inland water. As a result, agriculture in the region was badly affected, and the people in the region suffered from an acute scarcity of drinking water.

Eight months later, the repair of the embankments was far from complete. Because of the lack of land and funds, there were far fewer reconstruction support programs, and thousands of families remained more vulnerable to future flooding. Aila survivors were again affected in February and March of 2010 from flooding resulting from breached river embankments because of high tides. Communities that were starting to recover from Aila again had their homes, crops, and infrastructure destroyed. The government's efforts to repair the damage were not timely, which caused the embankments to collapse because of water pressure during new moon tides. Embankments that were damaged by Aila were either not rebuilt at all or not rebuilt properly. In many areas, the damage to the network of embankments in the 2010 flood resulted in a prolonged continuation of negative effects on communities. Breaches in the embankments, which become severe during daily high tides and particularly during full moon periods, prevented high levels of self-recovery. The damage to the coastal embankment network was severe and directly contributed to the continuation of the post-cyclone 2010 flood (widespread flooding and tidal inundation).[2]

The government of Bangladesh, in coordination with non-government organizations (NGOs), international organizations, and bilateral donors, rapidly responded to the flood emergency and assisted the affected population. The government provided the bulk of the relief assistance, including food, cash, drinking water, emergency medicine, and other non-food materials to Aila-affected communities. Although a formal appeal was absent, the international community provided assistance to many national and international organizations and government agencies working in the most affected areas.

Although flooding is a natural and common phenomenon in Bangladesh, Aila had a large impact on local households. The Aila-hit area is characterized by low-lying lands protected by embankments and surrounded by water. It is home to households that primarily make a living from agriculture, forestry, fishing, and shrimp farming. Unlike in other coastal areas, such flooding is very uncommon in this coastal area of Bangladesh because it is protected largely by the Sundarban, the largest single block of tidal halophytic mangrove forest in the world. Thus, such largely unanticipated shocks could have significant impacts on the economic and social lives of the people in the area.

3 Experimental design

The purpose of our experiment was to investigate how disaster exposure affects risk-taking and risk-sharing. Using information from a previous survey conducted in 2010, we outlined the treatment and control set up, whereby we identified villages affected by the 2009 Aila disaster to serve as treatment villages and the nearby unaffected villages to serve as controls.

Figure 1 shows the locations of the treatment and control villages with respect to the flooded areas. An important topographical feature of the area is that it is very

[2] We conducted the survey immediately after flood in 2010 event, and conducted the experiment two and half years after this flood from December 2012 to January 2013. Although the flood in 2010 was after 2009 Aila cyclone, it is hard for the affected people to assess the impacts of the two events separately since the same communities were affected by both events in 2009 and 2010.

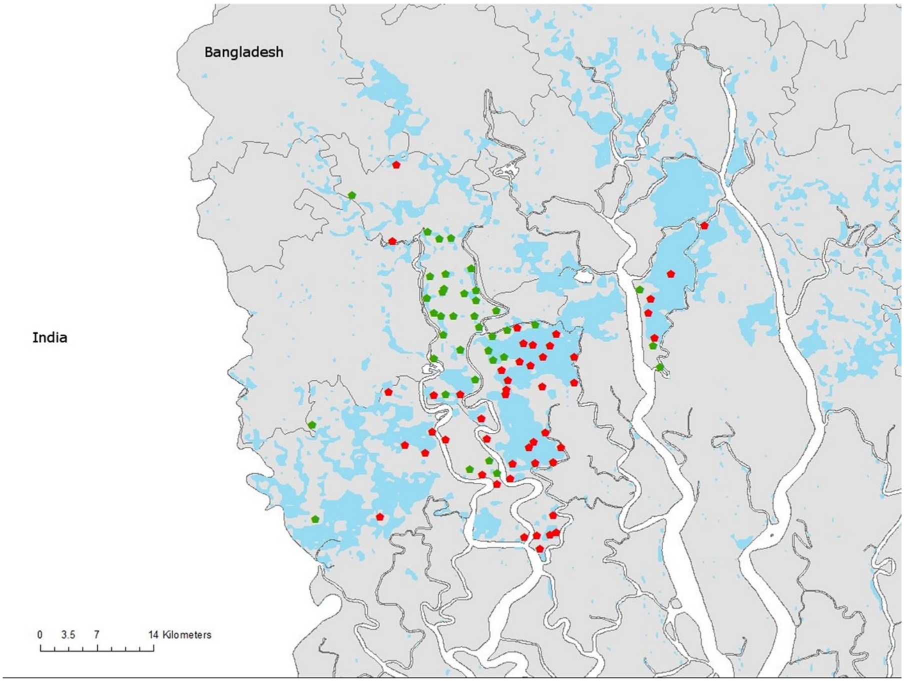

Fig. 1 Sample Villages and Inundated Area. *Note:* This figure depicts the study area in southwest Bangladesh. The pentagonal polytopes show the location of the treatment (red) and control (green) villages. The areas inundated by Aila are the darker gray areas, while the areas that were unaffected are coloured in lighter gray. The white lines indicate waterways, while the solid gray lines are administrative boundaries

flat, with hardly any natural or man-made undulations. The mean elevation of the treatment villages is 9.04 meters, whereas the mean elevation of the control villages is 9.25 meters.[3]

Elevation, however, is only one factor that determines hazard probability. Ideally, we would like to have information on the villages' expected inundation levels from official flood hazard maps. Unfortunately, to the best of our knowledge, there is no comprehensive flood risk mapping done for Bangladesh. Instead, we conducted our own flood simulation exercise for the area using information about the elevation, the location of the waterways, and the location of the villages. Assuming an increase in the water level of 2 metres, we then compared the fraction of the (simulated) inundated areas between the control and treatment villages. The results in Table 1 (variable *Sim. Flood Area*) show that there is no systematic difference in the (simulated) potential inundation areas between the control and treatment villages.[4]

[3]For a graphical illustration, refer to Figure B1 in the Online Appendix that overlays the location of the treatment and control villages with a digital elevation model.

[4]Figure B2 in the Online Appendix presents a visualisation of the results from this simulation exercise.

Households were randomly selected from both types of villages: disaster-affected (treatment) and non-affected (control) villages. We have comprehensive information about these households at baseline and at a follow-up conducted in 2012–13.

In 2010, we surveyed the disaster-affected villages for a different purpose: to understand the magnitude of the loss due to a disaster and the coping mechanisms used by disaster-affected people. At the same time, we had another survey ongoing in the nearby non-disaster villages (and some disaster-affected villages) as part of the baseline survey of a randomized field experiment on education. Hence, the disaster and non-disaster areas in this survey were not planned and were initially chosen for different purposes. As a result, we do not have a balance in the characteristics among households between the disaster and non-disaster villages when we consider the full sample from these villages. Thus, the subjects in the experiment in the disaster and non-disaster areas differ across numerous observable characteristics. To allay concerns about confounding variables, we used covariate matching and selected a subsample from both the treatment and control villages, this subsample was composed of participants who were similar in terms of age, education, gender, and income. We report the results using this matched sample in the Online Appendix D. In addition, because the level of disaster exposure also varies across communities/villages within the affected villages (treatment villages), we created a disaster affectedness index using information related to various levels of exposure to a disaster.[5] This index was then used as a level of exposure to a disaster that we could utilize to check the robustness of our principal findings. In the latter case, we considered only villages affected by flooding that were affected disproportionately because of the natural disaster; hence the level of exposure to a disaster is exogenous.

For the experiment, a total of 45 villages were selected randomly from our survey villages. Of these, 24 are from disaster-affected areas and 21 from non-disaster areas. The number of individuals in different versions of the risk-sharing game is shown in Online Appendix A, Table 8. We invited the adult members of the same households that responded to our survey in 2010 to participate in our risk-taking game or gamble choice game in two different rounds.

One potential concern is that migration because of a disaster could cause the sample to be biased. If, for example, risk-averse individuals leave their villages in anticipation of or in response to a disaster, our results will be biased because of sample selection. In rural Bangladesh, most families live on their ancestral land, and moving away from one's village is uncommon. Most of the households in these areas live below the poverty line and live on a plain (there are no hill tracts). A study by Gray and Mueller (2012) find that movement out of villages in response to disasters such as floods is very limited in Bangladesh. Instead, crop damage unrelated to a disasters is the major cause of migration. Moreover, we conducted the experiment

[5]The exposure index of a village is a weighted index (with value from 0 to 1) created based on how much that village is affected in 12 different aspects. The four most important aspects (agro-crops, domestic animals, road, house) account for 80% of the total weight. The remaining 20% of the weight is made up by the eight less important aspects (dam, educational institutions, government offices, electricity, water, fish gar, tree plantation, water height). The exposure in each aspect is indicated in either one of three levels: low, average, and high. We give these numerical values of 1, 2, and 3, respectively.

almost two and half years after the disaster was over; hence, many people who had migrated from the region had returned to the area. Hence, migration is not a major issue in our case.

The people who attended the experiments were the adults who made financial decisions in their families. In the first round, each participant chose their preferred gamble from a series of six gambles presented to them. The gambles differed in terms of riskiness and expected payoff,[6] with higher risks associated with larger expected payoffs. Once the choice was made, depending on the outcome of a coin toss for the chosen gamble, the payoff was recorded and given to the respondents after all experiments were completed. The choice of gamble by the participants allowed us to understand their risk preferences. We followed this simple experiment to elicit risk preferences because simple methods have been found to be useful in trying to capture treatment effects and differences in individuals' risk preferences (Charness et al. 2013).

In the second round, we conducted a risk game similar to the one described above, except the participants were invited to form risk-sharing groups (described to them as "income-sharing" groups), in which they played a similar gamble choice game but pooled their individual earnings from the gamble (if any) and agreed to share the pooled income equally with their group members. However, individuals were not forced to form groups, meaning that they could play alone. Once a group had been formed, the group members were required to abide by the sharing rules described to them beforehand. This second round allowed us to measure the risk-sharing preferences of individuals, whereby we were able to understand whether people tend to form risk-sharing groups and, if so, to determine the typical size of a risk-sharing group. Finally, we investigated the relationship between risk attitude and the formation of risk-sharing groups (in terms of group size).

Following the experimental design of Barr and Genicot (2008), we introduced a control and three additional information treatments to be randomly assigned to our original treatment (disaster-affected) and control (non-affected) households. First, we introduced a control group without any risk-sharing option. This no-risk-sharing group played the same gamble choice game as in the first round. Three risk-sharing treatment groups were then created related to different risk-sharing commitments, such as full exogenous commitment, limited commitment with the possibility of secretly leaving the group (private defection) after learning one's personal payoff from the gamble, and limited commitment with the possibility of leaving the group and letting others know (public defection) after learning one's personal payoff from the gamble. We explain the three information treatments regarding the risk-sharing rules that we adapted from Barr and Genicot (2008) as follows:

1) Full information and full exogenous commitment: Individuals are allowed to form risk (income)-sharing groups before choosing a gamble for a lottery payout. Each member of the group will share the realized group earnings from the gamble equally, irrespective of their individual gamble payoffs. After learning

[6] Table C1 in the Online Appendix presents the payoffs associated with each lottery game.

the outcome of their personal gamble payoff, the members will not be allowed to withdraw from the group. Thus, the risk-sharing decision is binding.

2) Limited exogenous commitment (with private defection): Individuals are allowed to form income-sharing groups, but the commitment to income sharing is limited in that they are allowed to withdraw, in private, from their group after learning of their individual payoff from the chosen gamble. This means that other group members will not know if someone has defected (private defection). It is assumed that the possibility of social sanctions may not encourage individuals to stay in their groups because the identities of the defecting individuals will not be disclosed. Knowing this ahead of their decision-making, individuals are assumed to form groups within trustworthy networks of individuals who are not expected to defect. It is likely that fear of defection results in lower rates of group formation or risk-sharing. Instead, if we observe more risk pooling and less defection under this treatment, then it would imply that intrinsic motivation is stronger in inducing risk-sharing commitments.
3) Limited exogenous commitment (with public defection): Individuals are allowed to form income-sharing groups and subsequently withdraw from them after discovering their own income from the gamble if such a defection is made publicly. This means that if an individual prefers to quit their group and take their own gambling income, other group members will be informed of their defection. However, the defector's earnings from their gamble will not be known to others. This treatment allows the possibility of social sanctions in response to defections, and, knowing this ahead of group formation, individuals might choose to join groups where the chance of implementing such sanctions is less likely (such as groups of friends or close family members).[7]

Therefore, we elicit the risk-sharing and risk-taking behavior of our households in our treatment and control villages under each of these risk-sharing rules. For improved comparability of our findings, we will primarily focus on the following measures of risk-sharing: 1) decision to join the risk-sharing group, 2) size of the risk-sharing group, and 3) riskiness of the choices made under the risk-sharing arrangement. In our context, the larger the group size is, the lower the risk associated with the payoffs from lottery will be. Thus, the larger risk-sharing group in a treatment would imply more risk-sharing among members. Note, however, that risk-taking behaviour could be different following the formation of a group or being in a group with a larger number of individuals. In our analysis, therefore, we focus on different measures of risk-sharing and also control for previous (round 1) risk-taking behaviour.

It is hypothesized that if members joining a group choose riskier gambles, this would suggest that they are pooling more risk to maximize their expected returns.

[7]Because Aila could have affected the social network structure in the affected villages, we examine if there are differences in the social networks between participants in the affected and non-affected villages. In our survey, we collected information on 10 different measures of social networks among all participants. Table E2 in the Online Appendix compares the average responses to these social network questions between affected and non-affected villages. The results show no sysmtematic differences in the social networks in disaster and non-disaster villages.

Following our hypotheses above, we will compare this risk-sharing measure across treatments to see how limited commitment and asymmetric information about defection induces risk pooling among disaster-affected households in comparison to non-affected households.

4 Theoretical framework and predictions

In this section, we summarize the theoretical model and results provided within the Appendix. Our model casts a risk averse agent i choosing both a private risky lottery, and whether or not to defect when she pools her private lottery with others' private lotteries. The agent carries a concave utility function $u_i(x|\gamma_i)$ over ex-post earnings x, where the parameter γ_i measures the agent's aversion to risk.[8]

In the control group, the agent i maximizes his expectation of $u_i(\tilde{x}_i^*|\gamma_i)$ when selecting an optimal lottery $\tilde{x}_i^*$ from the set of available lotteries. In each treatment group, taking as given a chosen lottery $\tilde{x}_i$, agent i chooses whether or not to defect upon observing the outcome of his private lottery by taking an expectation of $u_i(\tilde{y}|\gamma_i)$, where the lottery $\tilde{y}$ gives i's share of the aggregation of the pool members' contributions and $\tilde{x}_i$. Indeed, if $u_i(\tilde{x}_i|\gamma_i) > \mathbb{E}_{\tilde{y}}[u_i(\tilde{y}|\gamma_i)]$ for the largest value of $\tilde{x}_i$, then agent i can experience a utility gain from defection.

What prevents agents from defecting may be the resulting implicit or explicit sanctions due to prevailing social norms.[9] These norms may depend on whether a natural disaster previously occurred in the region or the visibility of defection. We capture this by modeling a common utility cost $c > 0$ incurred by defecting agents. Moreover, we derive a threshold Δ^{D*} such that defection can be deterred precisely when the defection cost $c \geq \Delta^{D*}$. The value Δ^{D*} depends on preferences for risk as captured by $u_i(x|\gamma_i)$, the optimal lottery $\tilde{x}_i^*$, and the size of the risk-sharing pool.

With this framework, we can establish the following comparative statics on the threshold Δ^{D*} when agents share a common γ and play a symmetric Bayesian Nash Equilibrium.

(i) Holding fixed the size of the pool and the riskiness in each agent's private lottery, Δ^{D*} is decreasing in the agents' coefficient of risk aversion γ.
(ii) Holding fixed the size of the pool, if γ is sufficiently low and riskier, private lotteries correspond to mild increases to expected return, so then Δ^{D*} is increasing in the riskiness in the pools' private lotteries.
(iii) Holding fixed the riskiness in each agent's private lottery and γ, Δ^{D*} is decreasing in the size of the pool.

Prediction (i) establishes that more aversion to risk among pool members curbs defection. Prediction (ii) establishes that riskier private lotteries beget defection among

[8] The properties of $u_i(x|\gamma_i)$ satisfy the standard conditions shared by constant relative risk aversion (CRRA) and constant absolute risk aversion (CARA) utility functions.

[9] As the Appendix shows, these costs are necessary to prevent defection for all $\tilde{x}_i$ realizations under any symmetric risk-pooling equilibrium.

risk tolerant pool members. Prediction (iii) establishes that larger risk-sharing pools curb defection.

Importantly, all of these comparative statics are independent of the cost c. As stated above, the costs of defection may vary depending on village characteristics, including whether or not a natural disaster occurred in the region. Moreover, natural disasters may affect preferences for risk along with incentives to share risk among community members. Below, we turn to our experimental data, which will inform of the various features of the model.

5 Subjects and the field experiment

Our sample consists of villagers exposed to the Aila disaster (in 2009) in the Satkhira and Khulna districts of Bangladesh. Using the information from a previous baseline survey, we identified the villages affected by this disaster to serve as the treatment villages in our experiment, and we identified nearby non-affected villages as the control villages. Our final sample included 24 treatment and 21 control villages. About 25–35 households from each village that were interviewed for the survey were invited to participate in the experiment. The experiment was preceded by a short survey to verify the household identities and basic demographic and socio-economic characteristics of the participants. All individuals took part in two rounds of the risk game, as discussed above. The first round consisted of a simple lottery choice game. In the second round, a sub-sample (defined as the control group for risk-sharing) only participated in the same risk game, while three other sub-samples of villagers within both the treatment and control villages were assigned to three different risk-sharing rules, characterized by different levels of exogenous commitment and information.

The households participated in two rounds of experiments in the morning and in the afternoon/evening of the same day. Trained enumerators conducted the experiments face to face with the respondents in a one-to-one setting. In the risk game, the subjects were presented with six gambles, which were ordered from least risky to most risky, keeping the probability of winning and losing, in each gamble, equally likely. The first gamble offered a guaranteed payout; an individual who chose the first gamble, regardless of the lottery results, received 100 Taka. After recording the subject's choice of gamble, the enumerator then conducted the coin toss and recorded the result; at the end of the round, each person received their earnings from the gamble. If the coin turned up heads, the participant received the high payoff, and if the coin turned up tails, the participant received the lower guaranteed payoff of 100 Taka. The gambles were described using pictures of paper bill notes next to the payoff amount and pictures of coin sides attached to each outcome[10] to facilitate the participants' comprehension of the exercise. Before the actual choice, the context was presented, and the subjects were provided with examples and training on the coin toss experiment to facilitate their understanding of the probabilities.

[10]Refer to Online Appendix C.

After the first round, the participants' income from the lottery was recorded, they were told about the second round of experiments, and they were informed that payouts from both rounds would be distributed in private once everything was over. In the risk-sharing treatment groups, the participants were privately informed that in the second round, they would be playing the same game but would have the opportunity to form their own groups to pool their members' incomes. Each individual from the first round was told that they were free to form a group with anyone (including strangers). Once individuals submitted the group members' names, they were asked several questions about the group members' identities and their relationships with the individuals being questioned. After all the information was carefully recorded, the subjects were privately interviewed and made decisions in the risk games.

The rules and financial implications of (income-sharing) group formation in each case were explained using examples until everything was clear. The subjects were told that groups could consist of as many individuals as they wanted and that the group members would be friends, family, neighbors, or any other villagers, even strangers. The researchers explained that by forming a group, all group members were, by default, agreeing to share the total group income from the gamble choice lottery equally, regardless of what an individual member actually earned from their own choices in the gamble. They were also informed that if the total earnings were zero, no one in the group would receive any money. Similarly, if all but one participant received zero earnings in the individual lotteries, then the single earner's income would be divided equally among all the group members. The individuals were told that this rule ensured that losers would be compensated with the gainers' income, which is the essence of income sharing. It was also explained that individuals would not be allowed to change their minds after declaring a group; that is, they could not refuse to share earnings with others in the group. Regardless of their individual outcomes, group members' earnings would be pooled and shared equally.

In cases of limited commitment treatments (private and public defection), subjects were given the opportunity to leave the group, and take with them their personal income. Such defection decisions were recorded immediately, and the defecting individual's earnings were not added to the respective group's total. However, all earnings were paid at the end. The enumerators recorded the defection decisions and subsequent earnings first. After calculating everyone's earnings, the enumerators informed each subject of their private earnings. They then recorded whether the subject would like to leave the group with their personal earnings or stay in the group to pool everyone's income. The summary statistics show that the disaster and non-disaster groups are not balanced across a number of demographic characteristics. We address this in two ways. First, we include the demographic variables as additional control variables in our specifications. Second, in Online Appendix D, Table D2 we present our main results using a balanced sample. The results stay qualitatively the same.

Table 1 reports the respondents' characteristics.

The protocol and instructions used in the experiment are presented in Online Appendix C.

Table 1 Descriptive statistics

	Non-Disaster			Disaster				
Variable	Obs.	Mean	Std. Dev.	Obs.	Mean	Std. Dev.	Diff.	Std. Error
Head Age	578	40.79	7.10	654	46.52	12.94	5.73***	(0.59)
Head Sex	578	0.01	0.11	654	0.02	0.15	0.01	(0.01)
Head Edu.	578	4.51	4.02	653	3.39	3.98	–1.11***	(0.23)
HH Size	578	4.82	1.29	654	5.00	1.44	0.18**	(0.08)
Housewife	575	0.02	0.12	653	0.01	0.12	–0.00	(0.01)
HH Income	578	7287	2980	654	5894	3185	–1392***	(175)
Elevation	578	9.25	1.31	654	9.04	1.21	–0.21	(0.20)
Sim. Flood Area	578	0.62	0.21	654	0.66	0.03	0.04	(0.04)

6 Estimation strategy and results

6.1 Estimation strategy

This section estimates the effect of being exposed to the disaster event on risk-taking and the likelihood of joining and defecting from a risk-sharing group. Considering that the inundation cut-offs as a result of Aila are random, we can identify the average treatment effect by simply comparing the mean outcomes of the treatment and control villages. We estimate the overall average effect of being in a treatment village on a given outcome by using the following specification:

$$Y_{ij} = \alpha_{ij} + \beta disaster_j + \mathbf{X}'_{ij}\theta + \mathbf{D} + \varepsilon_{ij} \tag{1}$$

Subscript i stands for individual i in village j. Y denotes one of four, binary outcome variables: 1) *Risk-taking* switches to one if the participant chose a risky bet and zero otherwise. 2) *Risk-sharing* is a dummy variable that is one if the individual decided to join a risk-sharing group and zero otherwise. 3) *Group formation* is one if the individuals in the game decided to form a risk-sharing group and zero otherwise. 4) *Defecting* is a dummy that switches to one if the individual defects from a risk-sharing group and zero otherwise. $disaster$ is the main variable of interest, which is an indicator variable that is one if individual i is in a treatment (disaster-affected) village and zero if the individual is located in a control (non-affected) village. $\mathbf{X}$ is a vector of individual-level covariates such as their level of education, income before disaster, age, household size, and gender. $\mathbf{D}$ is a vector of district dummies to control for any geographic differences at the district level.

We also interacted a village-level disaster dummy with an indicator variable if the flood water level in a village was above the median to account for the high level of flooding within the flood-affected villages. Finally, instead of using a dummy variable for $disaster$, we also use a continuous variable for $disaster$ that varies across disaster-affected villages. Specifically, we construct a disaster-affectedness index using village-level information related to various levels of exposure to a disaster.[11] Considering the binary nature of the outcome variables, we estimate equation 1 with a probit estimator.

6.2 Results: risk-taking

We commence the presentation of our results, by discussing the results of the risk-taking experiment. We found that 35.2% of the participants (standard deviation 0.47) chose risky bets (gamble 5 or gamble 6). In Table 2, we present the distribution of the gambles along with the subjects' (disaster-affected and non-affected households) choices and differences in choices between the two groups, here focusing on the first round. We found significant differences in the context of risk-taking between these two groups: Among the disaster-affected villagers, 40% chose risky bets, and among the non-disaster-affected villages, 29% chose risky bets. This significant difference in risk-taking behavior suggests that individuals directly exposed to a disaster may become more risk tolerant than those not directly affected by the disaster. This result is consistent with the findings of Eckel et al. (2009), which also provide experimental evidence of increased risk seeking behavior immediately after a disaster (hurricane) in the USA. In addition, Li et al. (2011) provide survey evidence from China that people become risk seeking to secure increased gains.

Table 3 presents the results from probit estimates of the probability of risk-taking. Individuals from disaster-affected villages were more likely to take risks. The results were robust to the inclusion of other individual characteristics, such as age, income, and education, as well as village-fixed effects. Interestingly, we also found that, controlling for disaster exposure, women and poorer households exhibited more risk aversion, whereas people with more education exhibited less risk aversion (or a higher risk appetite). However, we also observed that within the disaster-affected villages, the households that were more inundated with water were less likely to take risks.

6.3 Results: risk-sharing

We focused primarily on the three measures of risk-sharing: 1) group formation (whether the individuals decided to join the risk-sharing group or decided to play alone in the second round of the experiment), 2) group size (conditioned on group formation, the size of the group an individual chose to form), and 3) the riskiness of the chosen gamble (conditional on group formation for risk-sharing, for example, if the members joined a group choosing riskier gambles, this would suggest that they are

[11] Refer to footnote 5 for details of the construction of the index. The results, reported in the Online Appendix, are qualitatively very similar.

Table 2 Choice of gamble by treatment and control group

Lottery Gamble/choice	Expected payoff	Standard deviation	Non-Disaster Group (I) N=578	Disaster Group (II) N=656	Difference (II-I)
			0.123	0.122	–0.001
1) 100 for sure	100	0	(0.329)	(0.327)	(0.019)
			0.137	0.136	–0.001
2) 200 vs. 80	140	84.85	(0.344)	(0.343)	(0.020)
			0.185	0.123	–0.061***
3) 250 vs. 70	160	127.28	(0.389)	(0.329)	(0.020)
			0.263	0.215	–0.049**
4) 300 vs. 60	180	169.71	(0.441)	(0.411)	(0.024)
			0.237	0.305	0.067***
5) 350 vs 50	200	212.13	(0.426)	(0.461)	(0.025)
			0.055	0.101	0.044***
6) 400 vs. 0	200	282.84	(0.229)	(0.299)	(0.015)
Risk loving					
(=1 if chooses			0.292	0.404	0.11***
gamble 5 or 6)			(0.455)	(0.491)	(0.027)

Probit regressions, marginal effects reported. District Dummies included. Standard errors are clustered at the village level. ***, **, * indicate significance at the 1, 5 and 10%-level

pooling more risk to maximize the expected return). Then, we compared these behaviors between disaster and non-disaster samples and also under different information treatments. That is, we compared how limited commitments and asymmetric information about defection affected risk-sharing behavior. For example, as suggested by Barr and Genicot (2008), if under limited information conditions and under the possibility of private defection we observed more risk-sharing and less defection, this would suggest that intrinsic motivation primarily induces risk-sharing commitments. Following Solnit (2009), we would then expect this to happen among the disaster-affected group. Indeed, we found higher risk-sharing attitudes, in terms of likelihood of group formation and the size of the groups, among the non-disaster-affected group. However, defection was less likely among disaster-affected groups, regardless of information treatment. Again, among non-disaster groups, larger groups formed under full information than under limited information conditions, whereas among the disaster-affected sample, group sizes were larger under limited information conditions. In the disaster-affected population, we also observed a higher tendency to choose risky gambles under private defection treatment by the disaster group. These observations suggest that lower levels of defection among more risk-pooling groups imply that intrinsic motivation primarily induces risk-sharing commitment.

Table 3 Probability of risk-taking

	(1)	(2)	(3)	(4)
Disaster Village	0.110***	0.086**	0.076*	0.130**
	(0.038)	(0.038)	(0.044)	(0.053)
Age of Respondent		–0.000	-0.000	–0.000
		(0.001)	(0.001)	(0.001)
Female		–0.069**	–0.069**	–0.071**
		(0.034)	(0.034)	(0.034)
Education		0.012***	0.012***	0.012***
		(0.004)	(0.004)	(0.004)
Household Size		0.0012	0.001	0.001
		(0.011)	(0.011)	(0.011)
Log(HH Income)		–0.067**	–0.067**	–0.060*
		(0.034)	(0.034)	(0.034)
District Dummy			–0.022	–0.022
			(0.042)	(0.042)
Disaster village × Inundation above median				–0.090**
				(0.044)
N	1232	1221	1221	1221

Probit regressions, marginal effects reported. District Dummies included. Standard errors are clustered at the village level. ***, **, * indicate significance at the 1, 5 and 10%-level

6.4 Results: group formation

We observed that about 94% (out of 1,234) subjects formed groups in order to share income from the risk-taking in round 2. The proportion of individuals forming risk-sharing groups was 6% higher (97% versus 91%) among the non-disaster-affected group. Interestingly, the proportion of individuals willing to form risk-sharing groups was significantly higher among the non-disaster group under all three treatments; the differences between these two groups regarding group formation were 5%, 7%, and 6% under defection, private defection, and public defection treatments, respectively. The extremely high percentage of individuals (over 90%) who chose to form risk-sharing groups and the higher percentage of individuals who chose risky bets in round 2 compared with round 1 suggest that the participants understood the benefit of risk-sharing.

As reported in Table 4, the likelihood of joining a group was higher in the non-disaster sample. However, we did not find any differences across information treatments in terms of the likelihood of group formation. Interestingly, winning in a

Table 4 Probability of joining a risk-sharing group

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Disaster Village	–0.065****	–0.049*	–0.056**	–0.054*	–0.059**	–0.059*	–0.059*
	(0.024)	(0.026)	(0.027)	(0.028)	(0.026)	(0.029)	(0.029)
Age		–0.001	–0.001	–0.001	–0.001	–0.001	–0.001
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Female		0.022	0.023	0.022	0.023	0.021	0.021
		(0.017)	(0.016)	(0.016)	(0.015)	(0.016)	(0.016)
Education (Years of Schooling)		0.003	0.003	0.003	0.003	0.003	0.003
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Household Size		0.002	0.002	0.002	0.002	0.002	0.002
		(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Log(HH Income)		0.013	0.014	0.013	0.008	0.009	0.009
		(0.024)	(0.024)	(0.023)	(0.023)	(0.023)	(0.023)
Risk Loving in Round 1				–0.021	–0.023	–0.020	–0.026
				(0.017)	(0.017)	(0.016)	(0.039)
Winner in Round 1 Gamble					–0.078***	–0.079***	–0.083
					(0.021)	(0.022)	(0.034)
Private Defection						0.019	0.018
						(0.026)	(0.026)
Public Defection						0.012	0.012
						(0.0280)	(0.028)
Risk loving × Winner in round 1	0.007						
							(0.040)
N	966	956	956	956	956	956	956

Probit regressions, marginal effects reported. District Dummies included. Standard errors are clustered at at the village level. . ***, **, * indicate significance at the 1, 5 and 10%-level

round 1 gamble negatively predicted the likelihood of joining a group. In addition, the winners in round 1 formed significantly smaller groups during the risk-sharing game in round 2.

The average group sizes were 4.44 and 4.88 among the disaster and non-disaster groups, respectively. The group sizes were significantly higher under full information and private defection conditions for the non-disaster-affected sample than for the disaster sample. Group sizes were higher among non-disaster individuals than among disaster individuals under both the full information and private defection treatments. Within the non-disaster group, group sizes were higher under the full information treatment (5.03) than under asymmetric information treatment (4.88). Conversely, within the disaster group, group sizes were higher under the asymmetric information treatment (4.61) compared with the full information treatment (4.00). This essentially distinguishes the motivations for risk-sharing between the treatment and control group. Conditional on the likelihood of joining a group, we regressed group size on the main treatment (disaster affectedness) and information treatments, as well as on other relevant variables (see Table 5). The standard errors were clustered at the village level to account for the fact that group formation might represent a social process within the villages. Although we did not find any significant effects of information treatments on group size, we found that group size was significantly smaller among the disaster-affected participants.

6.5 Results: defection

We now look at defection under two treatments: private and public. As reported in Table 6, generally (pooled sample), less defection is observed under public defection (21%) than under the private defection (26%) treatment, suggesting that, generally, people opt out more when exogenous extrinsic commitment is limited. In other words, group members may be more hesitant to leave the group when social sanctions are likely. Subjects who are more likely to defect are less likely to be selected under public defection treatment due to the fear of social sanctions. We observed significantly more defection among non-disaster groups under public defection and private defection; however, we observed less defection among disaster people. The difference between these groups is higher in the case of private defection (0.34 persons in the non-disaster area versus 0.08 person in disaster area) than public defection (0.24 persons in the non-disaster area versus 0.03 persons in the disaster area), suggesting that the non-disaster group defected less under the public defection treatment than under the private defection treatment.

However, as reported in Table 6, overall defection was much lower among disaster-affected people; only 5% left the group, as opposed to 28% of the non-disaster-affected group. It is quite interesting to note that, although the non-disaster-affected sample formed risk-sharing groups at a higher percentage under each treatment (p-value 0.024, 0.027, and 0.029 under no defection, private defection, and public defection, respectively), they also tended to defect at higher percentages under each information treatment (26% and 21% higher defection rates for non-disaster-affected villagers compared with disaster-affected villages under both treatments: private defection and public defection).

Finally, we analyzed the probability of defection (see Table 7) and found that disaster-affected groups were less likely to defect, after controlling for winning the gamble, risk-taking, and other variables such as gender, education, and age. Overall, winners were more likely to defect, but we did not find evidence that risk preference (risk loving) has any significant effect on defection. The fact that disaster-affected

Table 5 Group size conditional on group formation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Disaster Village	–0.650** (0.240)	–0.600** (0.250)	–0.550** (0.260)	–0.540** (0.260)	–0.540** (0.250)	–0.600** (0.250)	–0.530** (0.260)	–0.530** (0.260)
Age		0.005 (0.005)	0.005 (0.005)	0.005 (0.005)	0.005 (0.005)	0.006 (0.005)	0.006 (0.005)	0.006 (0.005)
Female		0.140 (0.140)	0.140 (0.140)	0.140 (0.140)	0.140 (0.140)	0.140 (0.130)	0.110 (0.120)	0.110 (0.120)
Education		0.014 (0.017)	0.013 (0.016)	0.0140 (0.016)	0.014 (0.016)	0.0140 (0.015)	0.013 (0.014)	0.0140 (0.014)
Household size		–0.016 (0.043)	–0.018 (0.044)	–0.018 (0.044)	–0.018 (0.044)	–0.020 (0.044)	–0.025 (0.042)	–0.025 (0.042)
Log (HH income)		0.081 (0.160)	0.079 (0.160)	0.074 (0.160)	0.074 (0.160)	0.036 (0.140)	0.051 (0.140)	0.050 (0.140)
Risk Love				–0.098 (0.110)	–0.098 (0.110)	–0.11 (0.120)	–0.051 (0.120)	0.071 (0.240)
Winner R1						–0.580*** (0.140)	–0.600*** (0.140)	–0.580*** (0.160)
Private Defection							0.370 (0.330)	0.380 (0.340)
Public Defection							0.400 (0.340)	0.410 (0.340)
Risk love × Winner R1								–0.190 (0.300)
District Dummy	*No*	*No*	*No*	*No*	*Yes*	*Yes*	*Yes*	*Yes*
N	948	939	939	939	939	939	939	939
Adj. R^2	0.041	0.038	0.037	0.037	0.037	0.067	0.076	0.076

OLS. Standard errors are clustered at the village level. ***, **, * indicate significance at the 1, 5 and 10%-level

people form smaller groups and are less likely to defect from risk-sharing may suggest that they select themselves into groups based of general trust and solidarity. This is also confirmed by the observation that disaster-affected people are less likely to choose from near neighbors (significantly over 10% less under each treatment) but more from distant neighbors (11% more under private defection treatment, see

Table 6 Differences in risk-sharing and risk-taking behaviour between disaster and non-disaster group

Variable	Treatments		
	No Defection	Private Defection	Public Defection
	Difference estimates		
	Disaster - No Disaster	Disaster - No Disaster	Disaster - No Disaster
Group Formation	–0.054** (0.024) N=424	–0.072** (0.027) N=262	–0.064** (0.029) N=282
Group Size	–1.040*** (0.140) N=387	–0.270* (0.160) N=245	0.190 (0.160) N=260
Choose Risky Bet	0.076** (0.038) N=424	0.015*** (0.042) N=262	0.088* (0.046) N=282
Defection		–0.230*** (0.048) N=249	–0.210*** (0.038) N=264
Have Near Neighbour in Group	–0.110*** (0.041) N=387	-0.100* (0.054) N=245	–0.120** (0.049) N=260
Have Distant Neighbour in Group	0.041 (0.046) N=387	0.110** (0.047) N=245	0.012 (0.025) N=260
Difference in Average Individual Payoff Before Pooling Income	14.3 (13.9) N=424	7.67 (17.1) N=262	0.074 (16.9) N=282
Differences in Average Payoff on Risk-Sharing	8.66 (7.83) N=393	49.6*** (11.6) N=198	9.74 (9.57) N=231

Probit regressions, marginal effects reported. Standard errors are clustered at the village level. ***, **, * indicate significance at the 1, 5 and 10%-level

Table 6). This suggests that individuals are much more driven by intrinsic motivation and pro-social behavior in the ex-post disaster environment. This is also consistent with the hypothesis that individuals are less likely to be selected into a group if they are expected to defect. Although the disaster-affected group members were less likely to form risk-sharing groups, once they formed these groups, they were less

Table 7 Probability of defection in risk-sharing commitments

	(1)	(2)	(3)	(4)	(5) Round 2 Winners only
Disaster	–0.210***	–0.220***	–0.210***	–0.210***	–0.280***
	(0.050)	(0.053)	(0.054)	(0.054)	(0.056)
Age		–0.001	–0.001	–0.001	–0.003**
		(0.001)	(0.001)	(0.001)	(0.001)
Female		–0.004	–0.005	–0.008	–0.001
		(0.029)	(0.030)	(0.029)	(0.045)
Education		0.003	0.003	0.002	0.003
		(0.003)	(0.003)	(0.003)	(0.006)
Household Size		0.022	0.021	0.021	0.027
		(0.014)	(0.015)	(0.015)	(0.023)
Log (HH income)		–0.082**	–0.082**	–0.084**	–0.130*
		(0.034)	(0.034)	(0.033)	(0.073)
Risk Loving	0.021	0.018	0.020	0.100	0.098
	(0.027)	(0.024)	(0.026)	(0.071)	(0.091)
Risk Loving × Winner R1				–0.110	0.030
				(0.095)	(0.120)
Winner R2	0.150***	0.150***	0.150***	0.150***	
	(0.030)	(0.030)	(0.030)	(0.030)	
Private Defection	0.083	0.078	0.061	0.056	0.054
	(0.053)	(0.053)	(0.064)	(0.061)	(0.065)
District Dummy	*No*	*No*	*Yes*	*Yes*	*Yes*
N	513	509	509	509	283

Probit regressions, marginal effects reported. Standard errors are clustered at the village level. ***, **, * indicate significance at the 1, 5 and 10%-level

likely to defect, suggesting that risk-sharing (group formation) follows from feelings of cohesiveness, trust, and inequality aversion.

As a robustness check to our main findings, we conducted a similar analysis focusing on only the disaster villages by defining the level of exposure to a disaster. The results reported above are similar (see Appendix) when focusing on disaster-affected villages, implying that our conclusions on risk-sharing and risk-taking behaviors are robust to the identification of disaster exposure. The overall results suggest that the more an individual is exposed to a disaster, the more likely that person will be to take risks and the less likely they will be to share risks. The results are also similar when we examine the different risk-sharing commitments.

In a second robustness check, we address the issue that the full sample is not balanced across a number of demographic characteristics. We therefore created a balanced sub-sample from the full sample data and reran the models from our main results in Tables 5 and 7. The results stay qualitatively and quantitatively the same and are presented in Online Appendix D.

6.6 Consolidating theoretical and experimental results

We now return to the theory discussion of Section 4, which puts forward three predictions concerning how defection incentives depend on (i) risk aversion, (ii) riskiness in private lotteries, and (iii) the size of the risk-sharing pool. We now position these predictions against the main experimental results:

(a) Compared with the control regions, subjects in disaster regions exhibit significantly less aversion to risk, choosing significantly riskier private lotteries.
(b) Risk-sharing pools in disaster regions are significantly smaller than controls.
(c) Compared with the control regions, subjects in disaster regions partake in significantly less defection.

We can now support the conclusion that defection costs increase among villages who experienced natural disasters. When holding defection costs fixed, results (a) and (b) support *more* defection, as predicted by (i) through (iii) in Section 4. Thus, within the constraints of our model, the observation (c), that defection is significantly *less* frequent amongst villages that witnessed natural disasters, must be rationalized by an increase in defection costs.[12]

7 Conclusion

We investigated how disaster exposure affects risk-sharing behavior by using a unique field experiment in rural Bangladesh. Generally, we observed substantial risk-sharing and risk-taking behaviors among both disaster-affected and non-disaster-affected individuals in our sample. We observed less defection under public information than under private information of defection. Our results suggest that

[12] The one exception that could prevent this conclusion is for subjects in disaster regions to be so risk averse (while also being less risk averse than controls) that the predication (ii) of Section 3.1 is reversed. The Appendix shows that predication (ii) indeed holds over a plausible range of γ_i under CRRA preferences and under the lottery choice set of the experimental design. We focus on CRRA, which has the attractive feature of a decreasing coefficient of absolute risk aversion.

disaster-affected individuals are less likely to defect from risk-sharing commitments, regardless of the level of ex-ante exogenous commitment. More interestingly, this group significantly chose riskier bets and also realized a higher average return than the non-disaster-affected group. These results suggest that enhanced risk-sharing ex-post disaster exposure is driven by intrinsic motivation and pro-social preferences, such as trust, reciprocity, and altruism, rather than external incentives, such as social sanction. This result is consistent with the assertion made by Solnit (2009), that disasters are often catalysts for increasing social capital. Solnit (2009) reports various examples of mutual support, generosity, and greater degrees of participation in disaster-affected communities, suggesting that such effects may persist in the aftermath of a disaster. Although the probability of joining a risk-sharing group might be affected by the degree of disaster affectedness (weak evidence in terms of statistical significance), which also affected the sizes of the risk-sharing groups, we found strong evidence that disaster-affected people are less likely to defect once they enter into a risk-sharing commitment.

Our results have important applications for policy-makers who are concerned about improving the financial risk-transfer mechanisms against natural disasters in developing countries. Informal risk-sharing arrangements are important forms of insurance in areas where market insurance is missing. A number of scholars have indicated that these risk-sharing institutions are not necessarily stable and have been slowly eroding over time (e.g., Lybbert et al. 2004). Our results suggest that the shared experience of enduring a natural disaster could possibly strengthen existing, informal risk-sharing networks.

However, informal insurance arrangements are mainly suited to mitigate the adverse effects of idiosyncratic shocks that affect individual households rather than covering damages from cumulative events such as natural disasters. As such, innovative products such as index insurance can be a helpful addition to fill the compensation gap in the absence of private primary insurers and effective governmental relief. A recent paper by Takahashi et al. (2018) has investigated whether there is a crowding-out effect of index insurance instruments on informal risk transfer among pastoralist communities in Ethiopia. Interestingly, they find some weak evidence that households who take up index insurance are also more likely to make informal transfers to members in their network who have also taken up index insurance. This complementary relationship between informal risk-transfer in social networks and index insurance could present a starting point for a future research agenda. In particular, one could investigate if peers who are members of informal risk-sharing groups are more likely to take up index insurance or other types of micro-insurance.

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Appendix

A model of risk-sharing and defection

Here, we develop a model of risk-sharing and defection. For simplicity, we assume a common defection cost $c \geq 0$, which may depend on whether a natural disaster previously occurred in the region, the public visibility of defection, and prevailing social norms. We let $u_i(x|\gamma_i)$ denote agent i's vNM utility function over certain monetary payments $x > 0$, for $\gamma_i > 0$ agent i's risk aversion parameter. $u_i(x|\gamma_i)$is assumed to be increasing and strictly concave in x, and:

$$\frac{\partial}{\partial\gamma_i}\frac{\frac{\partial^2}{\partial x^2}u_i(x|\gamma_i)}{\frac{\partial}{\partial x}u_i(x|\gamma_i)} < 0.$$

We also assume that $\frac{\partial}{\partial\gamma_i}u_i(x|\gamma_i) \leq 0$, $\frac{\partial}{\partial\gamma_i}\frac{\partial}{\partial x}u_i(x|\gamma_i) \leq 0$ and $\frac{\partial}{\partial\gamma_i}\frac{\partial^2}{\partial x^2}u_i(x|\gamma_i) \leq 0$ when x is non-negative. That is, the utility agents receive from cash payments is decreasing as they become more risk-averse. These properties are satisfied for both constant relative risk aversion (CRRA):

$$u_i(x|\gamma_i) = \begin{cases} \frac{x^{1-\gamma_i}-1}{1-\gamma_i} & if\gamma_i \neq 1 \\ ln(x) & if\gamma_i = 1 \end{cases}$$

and constant absolute risk aversion (CARA):

$$u_i(x|\gamma_i) = \frac{1-e^{-\gamma_i x}}{\gamma_i}$$

Players choose (i) whether to share risk by joining a pool, (ii) a lottery $\tilde{x}_i$, and when joining a pool (iii), a defection strategy d_i , which we describe as follows: if player i joins a pool P (a set of pool members), their expected payoff is:

$$V_i^P(\tilde{x}, d) = E_{\tilde{x}}\left[u_i\left(d_i(\tilde{x}_i)\tilde{x}_i + (1-d_i(\tilde{x}_i))\tilde{y}|\gamma_i\right)\right] - E_{\tilde{x}_i}\left[d_i(\tilde{x}_i)\right]c$$

where $\tilde{x} \equiv \left(\tilde{x}_j\right)_{j\in P}$ denotes the profile of lotteries that players in P choose, we denote:

$$y = \frac{\sum_{j\in P} d_j\left(x_j\right)x_j}{\sum_{j\in P} d_j\left(x_j\right)},$$

equal to the total payment to i when in the pool, $d_i(x_i) \in \{0, 1\}$ gives i's lottery-outcome-contingent defection strategy (i.e., $d_i(x_i) = 1$ iff defect), and we denote the profile of defection strategies by $d \equiv \left(d_j\right)_{j\in P}$. Each player's action is the choice $\tilde{x}_i \in X$, where X gives the set of lotteries to choose from and the defection strategy $d_i(x)$, which is either "no defection" or "defection" depending on the outcome of $\tilde{x}_i$ (i.e. x_i). We assume that X is ordered, with a "greater" $\tilde{x}_i$ yielding a greater expected return and greater variance (riskiness). To simplify the environment, we focus on the experimental design where lotteries are determined via a fair coin toss. That is, $\tilde{x}_i$ is $x_{i,HIGH}$ and $x_{i,LOW}$ with probability 1/2 each.[13] When convenient, we assume that

[13] All results maintain in a neighbourhood of the class of 50/50 lotteries by continuity of expected utility.

the set X is smooth, with $x_{i,HIGH}(\tilde{x}_i)$ and $x_{i,LOW}(\tilde{x}_i)$ continuous and differentiable in the chosen lottery $\tilde{x}_i$ (note that the implemented design takes finite $|X| = 6$).

If player i does not join a pool, their expected payoff is simply:

$$V_i^{NP}(\tilde{x}_i) = E_{\tilde{x}_i}\left[u_i(\tilde{x}_i|\gamma_i)\right].$$

Thus, i will choose between the optimal strategy d maximizing $V_i^P\left(\tilde{x}^P, d\right)$ versus not joining the pool which yields $V_i^{NP}\left(\tilde{x}_i^{NP}\right)$, where $\tilde{x}^P$ gives the profile of optimal lotteries when entering the pool and $\tilde{x}_i^{NP}$ gives i's optimal lottery when not entering the pool.

Whether agent i joins a pool or not, their choice of $\tilde{x}_i$ will determine the expected return and riskiness associated with the lottery. If this agent does not join a pool, this lottery is simply $\tilde{x}_i = \tilde{x}_i^{NP}$. If the agent does join a pool, this lottery is $\tilde{y}$ under $\tilde{x}_i = \tilde{x}_i^P$. In either case, the expected return and riskiness of the lottery that i faces is increasing in the expected return and riskiness of $\tilde{x}_i$. Under our assumptions on $u_i(x|\gamma_i)$ and X, the following can be shown:

Proposition 1 *The expected return and riskiness of optimal $\tilde{x}_i$ in X is decreasing in γ_i.*

Proof Online Appendix A. □

Observation 1 *Proposition 1 is consistent with the conclusion that individuals directly exposed to a disaster become more risk tolerant in order to secure increased gains.*

We turn to defection incentives when agents join a risk-sharing pool. If i enters the pool and takes a defection strategy $d_i(x_i) = 1$ if $x_i = x_{i,HIGH}$ and $d_i(x_i) = 0$ if $x_i = x_{iLOW}$, then $V_i(\tilde{x}, d)$ can be written as follows:

$$V_i(\tilde{x}, d) = V_i^{P-D}(\tilde{x}, d_{-i}) \equiv \frac{1}{2}\left(u_i\left(x_{i,HIGH}|\gamma_i\right) - c\right) + \frac{1}{2}E_{\tilde{x}_{-i}}\left[u_i\left(y_{i,LOW}|\gamma_i\right)\right],$$

where:

$$y_{i,LOW} = \frac{x_{i,LOW} + \sum_{j\in P} d_j\left(x_j\right)x_j}{1 + \sum_{j\in P d_j}\left(x_j\right)}.$$

If i takes a no-defection strategy ($d_i(x_i) = 0$ always), then:

$$V_i(\tilde{x}, d) = V_i^{P-ND}(\tilde{x}, d_{-i}) \equiv \frac{1}{2}E_{x_{-i}}\left[u_i\left(y_{i,HIGH}|\gamma_i\right)\right] + \frac{1}{2}E_{x_{-i}}\left[u_i\left(y_{i,LOW}|\gamma_i\right)\right],$$

where:

$$y_{i,HIGH} = \frac{x_{i,HIGH} + \sum_{j\in P} d_j\left(x_j\right)x_j}{1 + \sum_{j\in P} d_j\left(x_j\right)}.$$

Clearly, defection is preferred to no defection iff $V_i^{P-D}(\tilde{x}, d_{-i}) > V_i^{P-ND}(\tilde{x}, d_{-i})$, equivalently:

$$u_i\left(\tilde{x}_{i,HIGH}|\gamma_i\right) - E_{\tilde{x}_{-i}}\left[u_i\left(y_{i,HIGH}|\gamma_i\right)\right] > c.$$

This provides our next result.

Proposition 2 *The incentives to defect in a pool depend on the pool size, the lotteries and defection strategies of others in the pool, the cost of defection c, and on the size of the high outcome of the lottery chosen by the defecting individual; incentives to defect are independent of the low outcome of the lottery chosen by the defecting individual.*

Now, further assume that $u_i = u$ and $\gamma_i = \gamma$ for all i (γ may still depend on the treatment). Then, by the symmetry of the setting, a *symmetric-pool equilibrium* can be obtained where each member of the pool takes a similar strategy, both in their chosen lottery and defection strategies. Indeed, when a symmetric-pool equilibrium is obtained all pool members choose a lottery $\tilde{x}^{P*}$, and the value to defection upon realizing $x^{P*}_{i,HIGH}$, equal to $u\left(x^{P*}_{i,HIGH}|\gamma\right) - E_{\tilde{x}_{-i}}\left[u\left(\tilde{y}^{P*}_{i,HIGH}|\gamma\right)\right]$, is always positive. When all others do not defect, then $\tilde{y}^{P*}_{i,HIGH} = \tilde{y}^{ND*}_{i,HIGH} \equiv \left(x^{P*}_{i,HIGH} + \sum_{j\in P}\tilde{x}^{P*}_{j}\right)/n$, for $n = |P|$ giving the size of the pool. Alternatively, when all others choose to defect, the incentives to enter and contribute to the pool (by not defecting) dissolve. Therefore, the value to defection $\Delta^{D*} \equiv u\left(x^{P*}_{i,HIGH}|\gamma\right) - E_{x_{-i}}\left[u\left(y^{ND*}_{i,HIGH}|\gamma\right)\right]$ when all others do not defect pins the threshold such that no members defect in equilibrium if $c \geq \Delta^{D*}$, and the pool disbands if $c < \Delta^{D*}$. Indeed, Δ^{D*} defines the equilibrium propensity to defect, which we describe next.

A.1 Comparative statics

Given that many variables are changing upon moving between the control and treatment (the risk aversion parameter γ, the optimal x_i^{NP} and x^{P*}, the defection cost c, and the size of the pool n), here we will assess the comparative statics of a symmetric-pool equilibrium with respect to each variable, *ceteris paribus*(i.e., we provide a partial-equilibrium analysis). The broad takeaway will be that an increase in the defection cost c is necessary to rationalize an observed decrease in defection in disaster regions.

A.1.1 Risk-sharing and defection

For our first set of comparative statics results, we focus on defection behaviour under risk-sharing (i.e., joining a pool), and set aside the endogenous $\tilde{x}_i^{NP}$ and the corresponding choice between joining and not joining a pool. We then consider the incentives to join the pool as risk preferences change in the following subsection.

First, we hold the endogenous $\tilde{x}^{P*}$ and n fixed and marginally increasing γ (note that the former will hold for local changes to γ).

Proposition 3 *In the symmetric-pool equilibrium, the cut-off Δ^{D*} is decreasing in the coefficient of risk aversion γ.*

Proof Online Appendix A. □

In words, holding all else equal, the incidence of defection (i.e., the range of $c < \Delta^{D*}$) decreases as the agents become more risk-averse. The reason is as follows: as agents become more risk averse, the gain to absconding with the high payment $x_{i,HIGH}^{P*}$ decreases. Conversely, the opportunity cost of remaining in the pool decreases less abruptly, and approaches the value to defection. In total, the defection gain Δ^{D*} decreases.

Observation 2 *With subjects exhibiting significantly less risk aversion in the disaster treatment (revealed in the first task), the finding that less defection is observed in the disaster treatment is inconsistent with Proposition 3.*

Second, we hold γ and n fixed and increase the risk of endogenous $\tilde{x}^{P*}$ chosen from X. With an increase to the mean and standard deviation of $\tilde{x}^{P*}$, the effect on $E_{\tilde{x}_{-i}}\left[u_i\left(\tilde{y}_{i,HIGH}^{ND*}|\gamma\right)\right]$ is ambiguous. Therefore, for the following result, we impose an additional structure to the form of $u(x|\gamma)$ and to the ordering of X . First, we assume that $u(x|0) = a + bx$ for some $b > 0$ (as with CRRA utility). Second, we take lotteries $\tilde{x}$ and $\tilde{x}'$ such that $\tilde{x} - \delta$ gives a mean-preserving spread of $\tilde{x}'$ for some $\delta \geq 0$. In the experimental design, $\delta = 40$ Taka between lottery options 1 through 5 ($\delta = 0$ between options 5 and 6). We say that $\tilde{x}$ and $\tilde{x}'$ are ordered "simply" if $\tilde{x}$ can be obtained from $\tilde{x}'$ via such homogenous upward shifts coupled with mean-preserving spreads. For the next result, which establishes sufficient conditions for Δ^{D*} to be increasing in the riskiness of $\tilde{x}^{P*}$, we assume the lotteries $\tilde{x}^{P*} \in X$ are ordered "simply".

Proposition 4 *In the symmetric-pool equilibrium, there is some $\gamma > 0$ and $\delta > 0$ such that for all $\gamma < \gamma$ and $\delta < \delta$, the cut-off Δ^{D*} is increasing in the riskiness of $\tilde{x}^{P*}$.*

Holding all else equal, the incidence of defection (i.e., the range of $c < \Delta^{D*}$) increases as the agents bring greater risk to the risk-sharing pool, provided that the agents are not too risk averse and the additional expected value of each lottery is not too large. The intuition is as follows: as agents bring more risk to the pool, the gain from absconding with the high payment $x_{i,HIGH}^{P*}$ increases. Conversely, the opportunity cost of remaining in the pool increases more slowly, provided the agents are not too risk-averse and the additional expected return is not too large. Consequently, greater x^{P*} under small γ and δ yields an increasing value to defection.

We exhibit the bounds of the result numerically, as follows: Table 8 provides Δ^{D*} values for various γ values under CRRA utlity. For γ values of 0.5 and 1, Δ^{D*} increases monotonically across the lottery choices of the experimental design; note that $\Delta^{D*} = 0$ for lottery 1. For $\gamma = 2$, this trend reverses between lottery 4 and 5, and for $\gamma = 4$, the trend reverses across lotteries 1 to 5. For lottery 6, which gives a mean-preserving spread of lottery 5, Δ^{D*} always increases.

In Table 9 , 1000 Taka is added to all payoffs, capturing a non-zero initial level of wealth. Now, the Δ^{D*} increases monotonically across all lottery choices. We see

Table 8 Lottery Table 1

γ	Lottery 2	Lottery 3	Lottery 4	Lottery 5	Lottery 6
0.5	3.47	4.76	5.89	6.9	8.9
1	0.27	0.34	0.39	0.43	0.54
2	0.0016	0.0018	0.0018	0.0017	0.0022
4	0.66×10^{-7}	0.54×10^{-7}	0.44×10^{-7}	0.36×10^{-7}	0.57×10^{-7}

that the domain of Proposition 4 is quite broad, particularly when including non-zero initial wealth.

Observation 3 *With subjects taking significantly greater risk to the pool in the disaster treatment, the findings that agents are less risk-averse and less defection in the disaster treatment are inconsistent with Proposition 4.*

Next, we hold γ and x^{P*} fixed and increase the size of the pool n. Now, the risk associated with staying in the pool decreases (because of the diversification in $y_{i,HIGH}^{ND*}$), while the expected return remains fixed. It is straight forward to show the following:

Proposition 5 *In the symmetric-pool equilibrium, the cut-off Δ^{D*} is decreasing in n.*

Proof Online Appendix A. □

Observation 4 *With the average size of the pools in the disaster treatment significantly smaller than those of the control, the finding that less defection is observed in the disaster treatment is inconsistent with Proposition 5.*

Main Observation Given that Propositions 3, 4 and, 5 are each inconsistent with the experimental findings, a significant increase in the defection cost c is necessary to rationalize the observation that defection decreases significantly in the disaster treatment.

A.1.2 Risk-sharing choice

The comparative statics for the values of agents choosing not to pool are straightforward. Precisely, given that the expected return and variance options from lottery choices in set X remain the same, facing less aversion to risk implies that agent i enjoys greater expected utility, both directly through a decrease in γ and indirectly through the chosen riskier $\tilde{x}_i^{NP}$ (under our assumptions on $u_i\,(x|\gamma)$). That is, each i faces less cost when it comes to bearing risk and reaps more gains when it comes to greater expected return. The comparative statics on values to agents choosing to share risk, however, are less straight-forward given that the expected utilities depend on the risk choices of other pool members. For simplicity, we consider the comparative

Table 9 Lottery Table 2

γ	Lottery 2	Lottery 3	Lottery 4	Lottery 5	Lottery 6
0.5	1.32	1.94	2.56	3.15	4.17
1	0.04	0.06	0.07	0.09	0.12
2	0.33×10^{-4}	0.47×10^{-4}	0.59×10^{-4}	0.70×10^{-4}	0.90×10^{-4}
4	0.24×10^{-10}	0.32×10^{-10}	0.39×10^{-10}	0.43×10^{-10}	0.54×10^{-10}

static holding fixed $\tilde{x} = \tilde{x}^{NP} = \tilde{x}^{P*}$. Moreover, we consider the case of $c > \Delta^{D*}$, where the pool can exist. The following is immediate:

Proposition 6 *In the symmetric-pool equilibrium, the gain to sharing risk via joining the pool without defection, $V_i^{P-ND}\left(\tilde{x}, d_{-i}^{ND}\right) - V_i^{NP}(\tilde{x})$, is non-decreasing in both γ and n.*

Intuitively, incentives to share risk are increasing with risk aversion and the size of the pool.

Observation 5 *With subjects exhibiting significantly less risk aversion in the disaster treatment (revealed in the first task), the finding that the frequency of subjects joining a pool is significantly lower in the disaster treatment is consistent with Prediction 5.*

Note that the observed lower frequency of joining pools and the significantly lower pool size in the disaster treatment group are complementary observations.

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