Journal of Environmental Economics and Management 90 (2018) 249–268

Contents lists available at ScienceDirect

Journal of Environmental Economics and Management

journal homepage: www.elsevier.com/locate/jeem

Do networks matter after a natural disaster? A study of resource sharing within an informal network after Cyclone Aila[☆]

Asad Islam [a,*], Chau Nguyen [b]

[a] Department of Economics, Monash University, PO Box 197, Caulfield East, VIC 3145, Australia
[b] Australian Bureau of Statistics (ABS), 818 Bourke Street, Docklands VIC 3008, Australia

ARTICLE INFO

Article history:
Received 23 December 2016
Received in revised form 1 October 2017
Accepted 15 June 2018
Available online 27 June 2018

JEL classificaltion:
Q54
O13
D81

Keywords:
Disaster
Resource sharing
Resource pooling
Informal network
Risk sharing

ABSTRACT

Natural disasters frequently occur across both developed and developing countries. The vast majority of lives that are lost and affected by natural disasters are from poor areas in developing countries. We examine the post-disaster recovery of the households in rural Bangladesh that were affected by Cyclone Aila from 2009 to 2010. Exploiting exogenous variations in households' exposure to the disaster within the village, we provide empirical evidence of resource sharing within the households' informal network of neighbors and relatives to assist in recovery from the natural disaster. We find a household's own exposure to the disaster had no significant effect on its investment and income; however, exposure to a household's network had a significant effect on household investment and income two years and six months after the cyclone. We find that informal resource sharing within a household's network crowded out the household's need to purchase formal insurance against disasters.

1. Introduction

The poor in developing countries live under volatile conditions, as they are prone to various adverse shocks, ranging from disease to natural disasters. High-income risks are part of their lives. Climate change has exacerbated these risks and problems facing households in developing countries. These households lack access to either formal credit or formal insurance markets. This often intensifies the impacts of any long-term idiosyncratic or aggregate shocks. In response to shocks, households in developing countries have developed (ex-ante) risk-management and (ex-post) risk-coping strategies, including informal insurance through transfers, gifts, and credit among relatives and friends, diversification of labor between household members, and the sale of household assets (e.g., Islam and Maitra, 2012; Fafchamps et al., 1998; Dercon, 1996; Rosenzweig and Wolpin, 1993; Morduch, 1990). However, natural disasters affect entire communities at the same time,

☆ We thank Marcel Fafchamps, Paul Frijters, Amir Jina, Bereket Kebed, Lionel Page, Minhaj Mahmud, Paul Raschky, Russell Smyth, Benno Torgler, Yves Zenou, participants at the NEUDC 2014 conference, social network workshop and seminar participants at Monash, and the Economic Research Group in Dhaka. We are grateful for funding support from Monash University and the Australian Research Council. Kashem Khan, Zenarul Islam and Mujahid Islam provided excellent supports for field work, with a dedicated team of local enumerators.

* Corresponding author.
E-mail address: Asadul.Islam@monash.edu (A. Islam).

https://doi.org/10.1016/j.jeem.2018.06.007
0095-0696/

thereby rendering traditional community risk sharing arrangements ineffective. While informal risk-coping mechanisms could help cope with idiosyncratic shocks that affect one or a few households, they are ineffective when shocks are covariate and affect entire communities.

A large number of studies on developing countries have focused on idiosyncratic shocks and the role of informal insurance in smoothing of household consumption. Generally, these studies have suggested that while informal insurance has not been fully effective in smoothing household consumption at the local community level (for example, see Deaton, 1992, Townsend, 1994, Udry, 1994), informal risk-sharing networks have been shown to be effective in smoothing consumption for smaller sub-local community groups of individuals (De Weerdt and Dercon, 2006; Munshi and Rosenzweig, 2009). However, few researchers have conducted research beyond the examination of the effects of informal networks on household consumption smoothing. One exception is the study by Angelucci et al. (2017), who showed that resource pooling within an informal network can provide a household with the liquidity to invest in high-return but lumpy assets (such as large livestock).

This paper examines the risk-sharing behaviors of households in rural villages in Bangladesh following a community-wide natural disaster. Specifically, we examine the long-run effects of cyclone Aila, a cyclone that impacted Bangladesh in May 2009, along with the subsequent flooding in early 2010,[1] on household investment and income. We provide empirical evidence that household informal resource-sharing networks contribute to their recovery from natural disasters and long-run investment. In order to address the endogeneity of network formation, we exploit the within village variations in the intensity of the households' exposure to the cyclone as an exogenous shock to their resources and those of their networks. Unlike other coastal areas, the coastal area of Bangladesh that was affected by Aila is not often flooded, as it is usually largely protected from flooding by the Sundarbans, the largest single block of tidal halophytic mangrove forest in the world. Thus, Aila represented an unexpected shock to households living in the area; however, while Aila caused a community-wide disaster that affected all households in the area, the degree of exposure to the cyclone varied between households.

We follow the existing literature on informal network sharing to define the network as comprising the household's neighbors and relatives. We use two rounds of a panel data set on households living in the two districts, Satkhira and Khulna that were affected most by cyclone Aila in 2009–2010. The surveys included villages that were affected by Aila as well as those that were not. The dataset included information on the relationships between each pair of households in a given village. To determine whether resource pooling within a household's informal risk-sharing network was efficient, we examine the effects on a household's income and investments caused by its exposure and its informal network's exposure to Aila. We examine the effects both in the short-term, defined as a few months after the disaster occurred, and in the long-term, defined as three and a half years after the disaster started or two and a half years after it passed. We find that a household's own exposure to the disaster had no significant effect on its investment or income, but the exposure of the household's network did have a significant effect on household investment and income two and a half years after the cyclone. We also find that the informal sharing network had a crowding-out effect on the household's preference for formal insurance to protect it against disasters.

When considering the household's attitude toward risk, which has the potential to affect a household's investment choices, we examine the effects of resource pooling within the informal network from the effects of exposure to the disaster. We exploit experimental data from a risk-taking and risk-pooling game to examine whether the level of exposure of a household and its networks to Aila had any effect on the household's risk-taking and risk-sharing behaviors. The game was conducted with the participants from the follow-up survey at the same time that the follow-up survey was administered, which was from 2012 to 2013. The experimental data also support the conclusion that the effect of the network's exposure to Aila is solely a result of resource sharing within the network.

This study contributes to the literature in the following important ways. To the best of our knowledge, this is the first study to examine the role of resource sharing within informal networks regarding household investment and income in the context of a community-wide natural disaster. Previous studies have mostly investigated household-specific income shocks, such as health shocks, and little research has been conducted in the context of a community-wide shock, such as a natural disaster.[2] We provide important evidence as to whether, and how, households share resources when all members in the network are exposed to the same community-wide shock simultaneously. We also contribute to the literature on natural disasters by examining the long-term effects of a natural disaster as well as the relief distribution that follows the disaster on households' investments and incomes. Finally, we contribute to the studies concerning demands for formal insurance in response to natural disasters.

2. Related studies

This paper is related to recent studies on risk-taking behaviors of households in response to natural disasters. For example, Page et al. (2014) found that homeowners who were victims of the 2011 Australian flood were more risk-loving than those who were not affected by the flood. In a different context, Cameron and Shah (2015) found that individuals living in villages in Indonesia that had been affected by an earthquake or flood during the previous three years exhibited higher levels of risk

[1] In this paper, the two events are treated as one and are referred to hereafter as Aila. The reason is discussed in Section 3.

[2] The studies most similar to this one were conducted by Fafchamps et al. (1998) and Kazianga and Udry (2006), who studied consumption smoothing, though not investment and income, against community-wide shocks.

aversion than those in villages that had not experienced a disaster recently. In the context of the United States, Eckel et al. (2009) provided experimental evidence of increased risk-seeking behavior immediately after Hurricane Katrina. Other studies that examined the housing market also suggested that risk perceptions can be altered by hazardous events or notices (Bernknopf et al., 1990; and Bin and Landry, 2013). For example, if a household becomes more risk averse due to its own exposure and its network's exposure to a disaster, the household might invest less in high-return but lumpy investments.

This research contributes to the growing stream of literature in which the full insurance model is tested against the partial insurance model. Many studies have tested the full insurance model and found that informal insurance plays an important role in smoothing households' consumption, but is not fully effective at the local community level (Deaton, 1992; Gertler and Gruber, 2002; Ligon et al., 2002; Townsend, 1994; Udry, 1994; Islam and Maitra, 2012). The full-insurance model predicts Pareto-efficient full risk-pooling outcomes, where household consumption allocations are only affected by the community's aggregate consumption, not the household income. This implies that any idiosyncratic shock that affects a household's income will not affect the household's consumption.

This paper is closely related to studies of informal insurance arrangements that focused on risk sharing within networks, usually between friends and relatives, rather than at the community or village level. De Weerdt and Dercon (2006) found evidence of full risk-sharing at the village level for food consumption and of insurance at the network level for non-food consumption in Tanzania. On the other hand, Grimard (1997) found evidence of partial insurance among members of the same ethnic group in Côte d'Ivoire, particularly for those who lived in regions with limited access to formal financial markets. In the context of the Philippines, Fafchamps and Lund (2003) found that risk sharing takes place through networks as opposed to at the village level. Similarly, Munshi and Rosenzweig (2009) determined that risk sharing plays an important role among members of sub-caste networks. More recently, Angelucci et al. (2017) showed that extended family networks are important informal resource-sharing arrangements and that households that have relatives in the village allocate resources and invest differently than households that do not have relatives in the village.

We contribute empirically to the recent studies that have attempted to explain the reason that risk-sharing arrangements are more likely to take place among networks at the sub-village level instead of the village level. These studies identified a number of constraints that limit the extent and effectiveness of informal insurance. These include incentive constraints, information asymmetries, lack of enforcement and commitment (Barr and Genicot, 2008; Genicot and Ray, 2003), transaction costs of establishing links with insurance partners and implementing insurance transfers (Murgai et al., 2002), and repeated interactions among group members (Fafchamps, 1999). More recently, Ambrus et al. (2014) examined the degree and structure of risk-sharing networks and showed that the level of insurance is characterized by the expansiveness of the network, which is defined as the per-capita number of connections between a group and the rest of the community. These theories have also been tested in the growing literature of empirical and experimental evidence on the formation of risk-sharing networks (see, for example, Attanasio et al., 2012; Barr and Genicot, 2008; Barr et al., 2012; Fafchamps and Gubert, 2007; Foster and Rosenzweig, 2001). Our study contributes to this literature examining risk-sharing networks in the context of natural disaster in poor areas in a developing country.

3. Cyclone Aila and the context

In May 2009, Bangladesh experienced a catastrophic cyclone that affected various parts of the country. Although flooding is a common characteristic of Bangladesh's ecology, the 2009 cyclone, known as Aila, was particularly severe. The cyclone caused a storm surge that swept inland and brought heavy rains, high winds, and flash floods. The surge inundated large swathes of land, while the rain and high winds damaged or destroyed thousands of homes. The storm surge contaminated drinking wells and rice crops, shrimp farms, ponds, and trees were also severely damaged. According to the United Nations (2010) report on Aila, the immediate impact of the cyclone resulted in 190 deaths and approximately 7100 injuries, with over 3.9 million people affected, 100,000 livestock killed, and nearly 350,000 acres of crop land destroyed. The final statistics show that more than a million people were displaced and several hundred killed in Satkhira and Khulna, which were the most heavily affected districts.

In Satkhira and Khulna, several rivers broke through their embankments, causing widespread inland flooding. These embankments, built in the 1960s, had been a source of protection from river and tidal flooding for the coastal people (Sarawat, 2009). Over the past 20–30 years, these embankments had been cut at several points to allow the saline water to enter the land for shrimp cultivation; however, the embankments had not been maintained properly and collapsed easily during Aila due to high tides in the rivers with flood waters (Roy, 2011). The government's efforts to repair the damage were not timely, resulting in the collapse of the embankments during new moon tides due to water pressure (NNN-IRIN, 2010).[3] Consequently, thousands of Cyclone Aila survivors were affected by flooding again in February and March 2010 after the river embankments were breached by high tides.[4] This left hundreds of thousands of people homeless, forcing them to gather in municipal buildings and schools or to camp outside on higher ground (UN, 2010). Communities that had begun to recover from Aila

[3] After talking to local elected representatives and reading local media reports, we learned that the government was waiting for the arrival of donated money before repairing the damage caused by Aila. The family of one of the authors lives in this area. There are also reports that the embankments were left unrepaired to draw attention from donors in an effort to channel more money for the Aila-affected areas.

[4] See Appendix 1 for the timeline of Aila and associated events as well as the timeline for the survey.

again had their homes, crops, and infrastructures destroyed. It is generally believed that the reason for the flooding at the beginning of 2010 was that the embankments damaged by Aila either were not rebuilt at all or were not rebuilt properly (Mahmud and Prowse, 2012). Unlike other coastal areas, this type of flooding is uncommon in this coastal area of Bangladesh, as it is protected largely by the Sundarbans, the largest single block of tidal halophytic mangrove forest in the world. Thus, this flood can be considered a significant and unexpected shock to households living in the area.

Although the flood in 2010 is naturally a separate event from the 2009 Aila cyclone, most of the impact of the flood was due to the damage to infrastructure facilities caused by Aila. Households that were affected in 2009 had not yet recovered when they were hit again by the flood in early 2010. Thus, it is difficult for those affected to assess the impacts of the two events separately. Therefore, the two events are treated as a single incident when examining their impacts.

About 64% of the Bangladesh population live in rural areas, and 46.4% of this population depend on agriculture, fisheries, or forestry for sustenance (Bangladesh Bureau of Statistics (2010)). Thus, their incomes and livelihoods are extremely vulnerable to hydro-meteorological hazards, which have been shown to cause asset loss, crop damage, unemployment, disease, and fatalities around once every five to 10 years (Akter, 2012). This vulnerability is also exacerbated by the lack of access to social safety nets. While there are some microinsurance plan that cover life and health risks, there is currently no insurance plan for hedging natural disaster risks in Bangladesh (Akter, 2012).[5] There were targeted food distribution and cash-for-work programs initiated by government, local, and international NGOs. Most workers who participated in these programs were hired locally. The cash-for-work program was developed to repair roads, broken embankments, and public places (community infrastructures such as ponds for drinking water, canals, and plinth raising) both for short-term measures to help people return to their normal lives and long-term measures to reinstate transports and communication.

4. Model and econometric specification

To test for resource sharing within informal networks of neighbors and relatives following Aila, we examine how the household's exposure to Aila, and that of its network, affect households' incomes and investments. If resource pooling is efficient within networks, the household's exposure to Aila should have no effect on the outcome variables, but the exposure of its networks should have a significant effect.

4.1. Theoretical framework

We follow the theoretical framework for resource sharing and investment developed by Angelucci et al. (2017). This model is an extension of the framework that is usually employed in the literature for modelling the manner in which households insure consumption against income shocks (pioneer studies include those of Townsend (1994) and Udry (1994)). The model incorporates the household's investment decisions into the standard framework in which only the consumption decision is considered. Consider a pair of risk-averse households, $h=j$ and l, who exist for two periods, $t=1, 2$. In each period, each household receives an endowment y_h^t. In period $t=1$, households must determine how much to consume (c_h^1) and invest (I_h^1). There are two choices for investments: I^s and I^p, with rates of return of $r^s > r^p$. I^p is continuously divisible, while I^s is lumpy (e.g., large livestock, which are costly and relatively illiquid), so the return on I^s is zero for $I^s < I^s_{min}$ and $(1+r^s)$ for $I^s \geq I^s_{min}$. Thus, when endowments are high enough, households strictly prefer to invest in I^s rather than I^p. The two households are assumed to have identical Pareto weights, a constant relative risk aversion (CRRA) utility function, and a discount rate of one. If there is complete resource sharing between households, the maximization problem for the pair is as follows:

$$Max_{c_h^t} \sum_{h=j}^{l} \sum_{t=1}^{2} lnc_h^t$$

$$s.t. \sum_{h=j}^{l} \left(c_h^1 + I_h^s + I_h^p - y_h^1 \right) = 0$$

$$\sum_{h=j}^{l} \left(c_h^2 - (1+r^s)I_h^s - (1+r^p)I_h^p - y_h^2 \right) = 0$$

$$c_h^t > 0, I_h^p \geq 0, I_h^s \geq I^s_{min} \tag{1}$$

Case 1: When the total endowment in the first period is too low ($\sum_{h=j}^{l} y_h^1 < I^s_{min}$), the maximization solution is:

[5] One exception is the compulsory group-based insurance plan that is provided by the microfinance institution Proshika as part of their savings scheme. However, Proshika's insurance scheme does not cover loss of life and damage to property due to natural disasters. The main purpose of the Proshika's insurance contract is to protect itself against loan and savings defaults. Proshika's insurance scheme is not available in the study area and is only available to their clients.

$$I_h^p = \frac{\sum_{h=j}^{l} y_h^1}{2}$$

$$I_h^s = 0 \tag{2}$$

Case 2: When the total endowment in the first period is high enough ($\sum_{h=j}^{l} y_h^1 \geq I_{min}^s$), the maximization solution is:

$$I_h^s = \frac{\sum_{h=j}^{l} y_h^1}{2}$$

$$I_h^p = 0 \tag{3}$$

Therefore, each household's investment decision in the first period depends on the network's average endowment in the first period. When the network consists of more than two members $h = 1, 2, 3 \ldots, n$ and n is large enough:

$$\frac{1}{n}\sum_{h=1}^{n} y_h^1 = \frac{1}{n-1}\sum_{h=1}^{n-1} y_h^1 \tag{4}$$

Thus, if resource sharing is fully efficient within the network, each household's investment decision depends only on the average endowment of other members in the network rather than on its own endowment. When the average endowment of other members in the network experiences a negative shock, one of three scenarios could occur depending on whether the total pre-shock and post-shock endowments are at the level of Case 1 or Case 2.

Scenario 1: The total network's endowment is too low, as in Case 1, both before and after the shock. Thus, a negative shock to the network's endowment reduces investment I^p but does not change investment I^s.

Scenario 2: The total network's endowment is high, as in Case 2, before the shock, and low, as in Case 1, after the shock. Thus, a negative shock to the network's endowment reduces investment I^s and increases investment I^p.

Scenario 3: The total network's endowment is high, as in Case 2, both before and after the shock. Thus, a negative shock to the network's endowment reduces investment I^s but does not change investment I^p.

While the directions of change for investments I^s and I^p following the shock are theoretically ambiguous, the total value of investment and the household's income in the second period are expected to be negatively affected by the adverse shock of the disaster on the network. In other words, households that belong to a network that was affected more by the disaster are expected to have lower investments and lower incomes following the disaster.

4.2. Empirical strategy

To test for resource sharing within the network, we use the following empirical specification:

$$\Delta Y_{ijv} = \alpha Expose_i + \beta Expose_j + \gamma X_i + \delta \Delta X_i + \sigma_v + \varepsilon_{ijv}, \tag{1}$$

where ΔY_{ijv} is the change in household i's outcome variables between two periods: pre-Aila and post-Aila. For post-Aila outcome variables, we consider two time frames: the short-term, which is three months after Aila passed in 2010, and the long-term, which is more than two and half years later, in 2012–13. Due to data availability limitations, we only have household monthly income and household monthly self-employment income as the outcome variables for the short-term. Household income comprises both wage and self-employment incomes, while self-employment income excludes wage income. For the long-term, we have additional variables for livestock values and households' self-reported changes in overall conditions (e.g., whether the household's condition was worse than before Aila). We also look at two kinds of livestock separately: large livestock (cows, goats) and small livestock (poultry). As argued by Angelucci et al. (2017) and modelled in the theoretical framework, resource pooling within a network can relax liquidity constraints, channelling aggregate resources towards high-return and lumpy goods. $Expose_i$ and $Expose_j$ are the exposure of household i and its network j to Aila. X_i and ΔX_i are a household's pre-Aila characteristics and the change in the household's characteristics.[6] σ_v is a village fixed effect. Because no households experienced a disaster in the pre-Aila period, equation (1) functions as a difference-in-difference equation in which household and network fixed effects are controlled.

We are mainly interested in long-term outcomes. Our main identification strategy is to exploit variations in the intensity of shocks among affected households, as there was a wide variation in the level of flooding and related damage within and across villages. Within the villages, there were several instances in which households on one side of a road were affected

[6] The pre-Aila household characteristic variables are household per-capita income, household head's age, gender, and education, number of adult members, and number of children. The change variables are changes in the numbers of adult members and children.

severely by flood water, whereas those living on the other side of the road were not affected because the flood water did not reach them (although both sides of the road experienced the cyclone). Therefore, the variations in damage due to the cyclone both between villages and within a given village provided a potential instrument that could be used to identify the causal effects of the cyclone on household outcomes.

We exploit the fact that a household's exposure to Aila was idiosyncratic and unpredictable. We can therefore treat the exposure as an exogenous shock to a household's resources. According to Morduch (1995), if an income shock is expected beforehand, households may engage in costly ex-ante smoothing strategies, such as the diversification of crops and activities, meaning that we would not find any effect on a household's ex-post coping mechanisms. This is not the case with Aila because natural disasters of this kind are not common in the area of study, as has been explained. To measure a household's exposure to Aila, the household's relief rate,[7] which is the value of a household's relief amount as a share of the total value of damaged assets, was used. The value of a household's relief amount is the total value of all relief (both in kind and cash) that the household received from the government and other organizations during Aila and in the three-month period after Aila. The measure accounts for both the value of damaged assets and the relief amount, so it can be considered a suitable proxy for the net exposure of the household to the disaster. Thus, the main equation of interest is:

$$\Delta Y_{ijv} = \alpha Relief_i + \beta Relief_j + \gamma X_i + \delta \Delta X_i + \sigma_v + \vartheta_{ijv}, \tag{2}$$

where $Relief_i$ and $Relief_j$ are the relief rate of household i and the average relief rate of network j, to which household i belongs, respectively. To account for the fact that wealthier households owned more valuable assets and therefore suffered higher losses, we also controlled for pre-Aila per-capita income.

We are concerned about potential endogeneity in the relief rate variable, which could arise if it is correlated with unobservables that could affect the outcome variables as well. For example, if households had more assets damaged during Aila, it may have been because they were better endowed, meaning they would be in a better position to recover from Aila. On the other hand, better endowed households might be protected well against disasters; for example, their houses could contain more concrete or could be more stable in another way. Moreover, the households that received more relief could be those with better connections with the village leaders and government officers who were responsible for distributing relief. Thus, these households were likely to be better placed for recovering from the disaster due to better resource endowments and better network connections. Similarly, households whose informal risk-sharing networks received more relief were also likely to recover faster for the same reason. If this is the case, the coefficients of the relief rate for a household and its network could also reflect the effects of the household's resource endowment and social connections, thus overestimating the effects of its exposure to Aila. On the other hand, the households that received more relief could also be those that were less endowed and/or less connected but more motivated to seek relief. In this case, the effects of the exposure of a household and its network to Aila would be underestimated.

Another channel through which an endogeneity bias could arise is if network formation is endogenous. De Weerdt and Dercon (2006) argued that households may choose either network partners with positively correlated income streams due to concerns regarding trust and information flows or networks with negatively correlated income streams for a better diversification of idiosyncratic income. In either case, the factors that determine a household's network partners could have a direct effect on its investments and income. While Aila was unpredictable, endogeneity is present if a household chooses its network partners based on its knowledge about the partners' ability to cope with risk in general. For this study, this issue is partly resolved by the fact that a household's network is defined based on its existing kinship rather than its self-reported risk-sharing network, as defined by De Weerdt and Dercon (2006). In a self-reported risk-sharing network, the network partners are likely to be selected based on the household's preferences, including trust and intentional income smoothing. This would thus be likely to bias the estimates of network risk-sharing effects either ambiguously downwards or upwards; however, it is less likely in this context when choosing relatives and neighbors to form part of a network that households would take into account their ability to cope with disasters. Moreover, in rural Bangladesh, the location of a household's residence is determined mostly by family inheritance rather than choice, as the son's family usually lives with his parents. Even when households choose the location of their residence, such as when a son's family moves away from his parent's house, their choices are probably not affected by any consideration for disasters, as the area studied is geographically flat and homogeneous.

We address both sources of endogeneity bias using the instrumental variable method.[8] We instrument the relief rates of households and their networks by the number of days and average number of days, respectively, required for the roads to their homes to become operational after Aila. A number of Aila aid reports have indicated that roadblocks due to damage caused by Aila prevented relief distribution from reaching affected villages and households (for example, International Federation of Red Cross and Red Crescent Societies, 2009). Studies on the logistics management of relief distribution

[7] In the previous version, the actual value of the damage incurred by the household, which is calculated as the household's total value of damaged assets after deducting the relief amount; however, a suitable instrument variable for the actual damage variable could not be identified. Thus, the focus shifted to analyzing the findings using the relief rate variable.

[8] This method can also deal with the issue of measurement error in the relief rate due to households' misreporting of the total relief and total damage amounts. This type of measurement error introduces an attenuation bias that biases the coefficient towards zero.

following natural disasters have also discussed the importance of road networks for effective disaster relief distribution (for example, Kovács and Spens, 2007, Yan and Shih, 2009).

We expect that the longer the period required for the road network to a household to recover, the lower the relief rate that the household would have received due to the difficulty to access relief. While roadblocks are correlated with the endogenous variable, the relief rate, they do not have any direct effect on the outcome variables, nor are they correlated with any of a household's unobservables that could affect the outcome variables. Because floods are uncommon in the area, it is unlikely that households would have selected the location within the village based on areas in which the road networks were built better to cope with disasters.[9] These villages contain mostly clay roads, which are similarly constructed, and the location within a village is largely determined by the location of ancestral property. People of the same ancestral link, clan, or family history (e.g., same surname) tend to live in the same neighborhood ("para").[10] A village is segregated into several clusters, or *paras*. As has been discussed, some households, or *paras*, within affected villages were lucky enough to escape the flood simply because they were on the other side of the road, which is used mainly for movement within and across villages. Some of these roads were inundated with flood waters due to breaches in the river embankment.[11] The data indicated that all roads had been restored and were operational again within two to three months after Aila in 2010, as the flood waters receded. Thus, roadblocks were not expected to have any direct long-term effect on a household's investment and income. Moreover, the variations within a given village, where some areas were fortunate because roads within the village prevented the water from reaching them, were examined. Thus, the potential endogeneity problem with between-village variation is avoided, such as where villages with more effective or better-connected local leaders might have regained road access sooner. This endogeneity hardly applies to the within village variations because the restoration of the road networks and river embankments were planned and implemented mostly by the government rather than the local leaders due to the need for considerable funding and heavy machinery.

Therefore, the first-stage regressions were run as follows:

$$Relief_{ijv} = \alpha Road_i + \beta Road_j + \gamma X_i + \delta \Delta X_i + \sigma_v + \mu_{ijv} \tag{3}$$

and

$$Relief_{jv} = \alpha Road_i + \beta Road_j + \gamma X_i + \delta \Delta X_i + \sigma_v + \pi_{jv}, \tag{4}$$

where $Road_i$ is the time (number of days) required for the road networks to household i to become operational again, and $Road_j$ is the average time for the road networks j to become operational.[12] The second-stage regression is as follows:

$$\Delta Y_{ijv} = \alpha \widehat{Relief}_i + \beta \widehat{Relief}_j + \gamma X_i + \delta \Delta X_i + \sigma_v + \rho_{ijv}, \tag{5}$$

where $\widehat{Relief}_i$ and $\widehat{Relief}_j$ are the predicted relief rates, which are estimated from the first-stage regressions in equations (3) and (4). The standard errors were corrected to take the estimated value of the relief rate into account. The standard errors at the village level were also clustered. As we use village fixed effects, the identification strategy relies on the variations in damage within the village. Moreover, we use a difference specification, which addresses the concern regarding endogeneity that could arise at the household or network level, as discussed. In Table 3, we also provide evidence that supports the claim that the higher the amount of relief received, the greater the damage.

We also run the regressions in equations (3)–(5) without including the variables on household characteristics that might have changed after Aila, taking into account the concern that these changes may have been induced by the disaster. In particular, household members could migrate or remain away from home for work as a response to the disaster. Moreover, the decision to have more children, and therefore the number of children in a household, could also be affected by the disaster. These results are not reported, as they are similar to those from the regressions that include these controls.

We also test whether resource pooling within an informal network of neighbors and relatives reduces a household's need for formal insurance against disasters. We run regressions similar to the specifications in equations (3)–(5), and use three outcome variables that are based on survey questions related to the annual premium that the respondent was willing to pay

[9] In rural Bangladesh, most families live on their ancestral land, and moving out within the village is less common. 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) showed that the movement out of villages in response to disasters such as floods is quite limited in Bangladesh. Instead, they found that crop damage that is unrelated to disasters is the major cause of migration.

[10] Road networks could differ across villages; however, within a given village, that is not the case because there is no such thing as "wealthier" neighborhoods/*paras* in a village setting for reasons mentioned. Thus, it is not likely the case that there are poorer parts of the village that would have poorer-quality roads.

[11] These villages, which are small and densely populated, are on low-lying, flat land that is traditionally used for cultivation, and the homestead land is no different from that used for cultivation. This low-lying land was submerged with flood water almost everywhere, destroying the standing crops, other vegetation, and in many cases, houses, which were mostly built using clay soil.

[12] We explain in Section 5.1, under the definition of networks, the reason household *i*'s road networks and its network *j*'s road networks were not affected the same by Aila.

to insure against disaster. In particular, the questions ask how much he/she was willing to pay for an insurance company to (1) compensate for the full value of any damaged assets, (2) compensate for half of the value of any damaged assets, or (3) meet their basic needs during and shortly after the disaster. The survey questions were asked both in 2010, just after Aila, and in 2012–2013 survey. Since we are interested in the long-term effects of network sharing, we use the same specification as in the first-stage equations (3) and (4) and the second-stage equation (5). Thus, the dependent variable is the change in the annual premium that the respondent was willing to pay between 2010 and 2012. Because they were obtained post-disaster, the responses in 2010 were likely to have already been influenced by the network risk-pooling effect. Thus, it was expected that the estimated effects from using the change in the annual premium would be the lower bound of the actual effects.

A crucial assumption made in the model is that the household's CRRA utility function is fixed. Thus, it was assumed that there was no change in risk behavior after the disaster, an assumption that may not hold in this context. Among others, Eckel et al. (2009), Page et al. (2014), and Cameron and Shah (2015) showed that risk attitudes could be affected by experiencing disasters. To examine post-disaster risk-taking behaviors, we exploit experimental data from a risk-taking and risk-pooling game conducted with participants from the households that completed the follow-up survey as well as at the same time as the survey. As the game was played two and half year after Aila, any change in a risk-taking behavior is interpreted as the long-term effect of disaster exposure, which could be different from the short-term effect. This is thus relevant to the research purpose due to the focus on examining the long-term outcomes. We follow the standard risk game based on the work of Binswanger (1980), as applied by Barr and Genicot (2008), which was easier for the subjects to understand. The instructions for the risk game are provided in Appendix 2. Whether the exposure of a household and its network to Aila had any effect on household risk-taking and risk-sharing behaviors was investigated. Therefore, we also run the regression in equation (5) for two additional dependent variables that were measured by the game: whether the household is risk-loving and whether the household chooses to join a risk-sharing group.

5. Data and descriptive statistics

5.1. Survey data

The survey dataset forms a panel of two rounds, carried out in 2010 and December 2012 to February 2013. The 2010 survey was conducted in June 2010, about three months after Aila. A total of 1526 households in 50 affected villages in the two districts of Khulna and Satkhira was surveyed. The survey included questions regarding the household's main characteristics both pre- and post-Aila as well as specific questions regarding the household's situation during and after Aila. At the same time, a separate survey was administered to 2000 households in the same districts but in neighboring villages that (fortunately) were not affected by Aila.[13]

During the second round 2012–13, the same affected households as in the 2010 survey were revisited and surveyed. The follow-up survey focused more on post-Aila coping mechanisms, migration, and employment. The total number of affected households that could be followed was 1,447, yielding an attrition rate between the two rounds of 5.2%, which is relatively low. In addition, 1024 random households in the unaffected areas were followed. Thus, a total panel dataset of 2471 households was obtained; however, for the purposes of this paper, information on the relationships between households within each village was also required. This information was only available for a much smaller sample, which consisted of the households that participated in the experiment (as discussed in the next section). These participants were from a subset of 34 villages, 18 of which were affected by Aila. In these villages, all households that were surveyed using the baseline survey were also surveyed in 2012 and participated in the game. Therefore, the final dataset consisted of a two-year panel spanning 505 households in affected villages and 461 households in unaffected villages across the two districts; however, the primary analysis focused only on households in the affected villages.

A person's informal network is defined as comprising those whom participants reported as being relatives or neighbors. Due to the relatively small sample size within each village, only direct ties were considered, and indirect ties were excluded (for example, relatives of relatives). In the context of rural villages in Bangladesh, people define “neighbor” quite loosely: they usually consider all people in a given neighborhood (*para*/village) to be neighbors and have close relationships with them; thus, it is not necessarily limited to next-door neighbors. The average travel time between households that reported being neighbors is 7 min, which is a relatively long distance for the traditional definition of neighbors.[14] Of the neighbor pairs, 30% reported that it took 5 min or less to travel between houses, while 23% reported that it took 10 min or more. Therefore, people in a given network would not necessarily have been affected the same way by the disaster (in terms of level of damages, road networks, etc.). An alternative network definition was also used in which relatives and neighbors who lived more than 15 min away from the household were excluded.[15] These definitions are in line with other studies in the risk-sharing network

[13] The survey in the unaffected areas was conducted just before Aila. Pre-Aila data was collected from affected areas within three months after Aila using the recall method. The potential concern regarding recall bias is addressed in the robustness section.

[14] The villagers live in a dense network, and therefore such a distance is quite high for any typical definition of neighbors. Among non-neighbor pairs, the average travel time between those in a pair was 20 min.

[15] The results using the alternative definition are similar but with a lower significance level due to the smaller sample size. Because a large number of households did not belong to any network, these were excluded from the regression.

Table 1
Main household descriptive statistics.

No. of observations = 448						
Variable	mean/%					s.d.
Disaster and household demographic variables						
relief amount (taka)	13,514					12,981
damage value (taka)	101,068					94,508
relief rate (%)	19.87					22.45
damage rate (%)	59.46					29.40
roadblock time (no. of days)	50.50					40.81
water height (ft)	6.57					1.32
water stay (no. of days)	6.52					0.87
head's age	46.42					13.07
head's schooling (no. of years)	3.49					3.99
female head	0.03					0.17
no. of adult members	3.21					1.30
no. of child members	1.51					1.10
Household outcome variables	Before Aila		After Aila (2010)		After Aila (2012)	
monthly household income (taka)	5677	2993	3667	2400	7072	5559
monthly self-employment income (taka)	2891	3279	1643	1988	2226	3384
monthly per-capita (adult equiv.) income (taka)	1451	622	926	472	1808	1312
monthly per-capita (adult equiv.) self-employment income (taka)	767	868	436	518	602	939
total livestock value (taka)	6258	8334			2962	5485
big livestock value (taka)	4790	7998			1935	4962
small livestock value (taka)	1467	1588			864	1092
subjects who are risk-loving					44%	
subjects who joined risk-sharing groups					91%	
willingness to pay for full insurance (taka)	6153	4484			1066	1092
willingness to pay for half insurance (taka)	4393	3003			686	698
willingness to pay for facility insurance (taka)	2824	1856			457	423

Note: Before-Aila data are based on survey questions that were asked after Aila in 2010.

literature that emphasize the importance of social and geographical proximity for risk sharing (for example, Angelucci et al., 2017, Attanasio et al., 2012, Fafchamps and Gubert, 2007). In particular, Fafchamps and Gubert (2007) showed that intra-village mutual insurance is determined mostly by geographical proximity, which may be correlated with kinship, but is determined only weakly by a purposeful diversification of income risk.

5.2. Experimental data

At the same time as the follow-up survey was administered from December 2012 to February 2013, a risk-taking and risk-pooling game was played for a subset of the survey sample. The experiment is based on the work of Attanasio et al. (2012) and Barr et al. (2012) in examining the effects of pre-existing social networks and enforcement mechanisms on risk-sharing group formation. The risk game (following Binswanger (1980)) includes two rounds. In the first round, subjects were asked to choose one of six gamble options, ranked from the least to the riskiest. The instructions for the risk game are given in Appendix 2. In the second round, subjects played the gamble choice game again but had the option of forming risk-sharing groups with other subjects.[16] In the same session, data on the pre-existing relationships between each pair of subjects were collected. This means that within a given village, we were able to examine who shared risks with whom and whether their risk preferences affected their decisions regarding who to form a risk sharing group with.

5.3. Descriptive statistics

The descriptive statistics of the main dependent and independent variables are reported in Table 1. We observe a wide variation in households' exposure to the cyclone in terms of relief amounts, values of damaged assets, relief rates, and damage rates. For example, the mean relief rate is 19.9%, with a standard deviation of 22.5%. The damage rate of 59.5% seems quite high. In part, this may reflect the fact that the calculation was based on a proxy for total asset holdings rather than actual asset holdings. Because data on the households' total value of assets were not available, the damage rate was calculated using

[16] Before playing the game, each subject was allocated randomly to one of three treatment groups, which differed in terms of whether or not and in what way (privately/publicly) subjects could choose to leave the sharing group after they learned the outcome of their own gamble (as per Barr and Genicot, 2008; Attanasio et al., 2012). The main results showed that under all enforcement mechanisms, subjects were most likely to group with relatives, followed by neighbors; however, when the possibility of a social sanction was present, the propensity to form groups with relatives was reduced. Only data on the subject's levels of risk-taking and risk-sharing, which were measured in the first and second rounds of the game, respectively, were used. We did not account for different enforcement mechanisms that subjects were allocated to in the second round. As the treatments were allocated randomly, it is unlikely that the results were affected.

answers to the survey question that includes a list of household assets and their values and asks respondents to report which assets they owned, which assets were damaged, and the value of the damage incurred. The damage rate was calculated as the total listed damage value divided by the total listed asset value; however, the relief rate was calculated using the total damage amount, which was reported separately, because this also includes the value of the damaged assets that were not listed in the survey question. The spreads of the relief rate and the period for which the roads were blocked, which was used as the instrumental variable, are also relatively high. These statistics are consistent with the expectation that households in the affected area were affected differently, mostly due to variations in the locations of their residences.

The descriptive statistics for the outcome variables are reported in the bottom panel of Table 1. In general, the mean household income from self-employment and livestock holdings was lower in 2012–2013 than before Aila, with the only increase being for total household income; however, this decrease in income from self-employment and livestock holdings may not be attributable to the effects of Aila, as a similar trend among households living in the unaffected villages was observed. Still, the household income in 2012–13 was higher than in 2010 post-Aila. This suggests that households were hit severely shortly after the disaster but had recovered at least partly by about two and half years later. There was also a significant reduction in the amount of annual premium that a household was willing to pay for formal insurance against disasters in 2012–2013 relative to the 2010 survey. This could be explained by their recovery from the disaster over the two-and-a-half year period, which might have decreased their perceived need for insurance. Other possible explanations could be the reduced salience of the disaster or the reduced recall of household damages over time.

We also report the mean and standard deviation for risk attitude variables. “Risk-love” is a dummy variable and was constructed from the first stage of the risk-pooling game. The variable takes the value of one if the subject chose the two riskiest options in the game and the value of zero otherwise. The “risk-share” variable is also a dummy variable and was based on the subject's decision of whether or not to join a risk-pooling group in the second stage of the game. We found that 44% of the subjects were risk-loving and that 91% of the subjects chose to share the risk.

Table 2A shows the statistics regarding households’ mechanisms for coping with Aila and general health shocks. In general, there are four main coping mechanisms: drawing on household funds, borrowing from financial institutions and/or moneylenders, receiving help from neighbors or/and relatives, and selling assets. In the specific case of Aila, another mechanism was to receive relief from the government or/and NGOs. For general shocks, only health shocks were considered, as these are the most frequently reported shock, and the existing literature on the effects of health shocks on household outcomes is well-established (for example, see Asfaw and Von Braun, 2004, Dercon and Krishnan, 2000, De Weerdt and Dercon, 2006, Gertler and Gruber, 2002, Wagstaff, 2007, and Islam and Maitra, 2012). In coping with Aila, we examine how households financed house repair expenses and the way they recovered damaged assets. We observe a few differences between the coping mechanisms for dealing with health shocks and those designed to assist in recovering from Aila. The most frequently reported mechanism for health shocks, apart from drawing on household funds, was receiving help from neighbors and relatives, while the main coping mechanism for dealing with Aila was receiving relief. This indicates the crucial role of receiving relief in helping households recover from a disaster. Only 10%–12% of households reported receiving help from neighbors and relatives to repair houses and recover damaged assets, while the corresponding figure for health shocks was 25%. This indicates the important role that network resource sharing plays in insuring households against shocks. When all households in the network are affected by a common shock (as in the case of Aila), the extent to which a household can seek help from other network members is limited. In this case, households must resort to other coping mechanisms, such as drawing on their own funds (including savings with interest) or selling valuable assets, which might be costlier in the long

Table 2
Household's mechanisms for insuring against shocks.

Panel A: Coping mechanisms			
% households	health shock (N = 225)	repairing house after Aila (N = 454)	recovering damaged assets after Aila (N = 474)
drawing from own money	35	49	73
borrowing from banks/NGOs/ moneylenders	20	20	24
seeking help from relatives/neighbors	25	10	12
selling assets	3		13
getting relief		56	62

Panel B: Borrowing/lending activities among relatives and neighbors	
% households receiving help from relatives/neighbors (N = 505)	
from relatives for money	54
from relatives for food	16
from neighbors for money	52
from neighbors food	35
% households borrowing from/lending to relatives/neighbors in the sample	
borrow from neighbors (***N*** = 497)	53
borrow from relatives (***N*** = 173)	47
lend to neighbors (***N*** = 497)	52
lend to relatives (***N*** = 173)	49

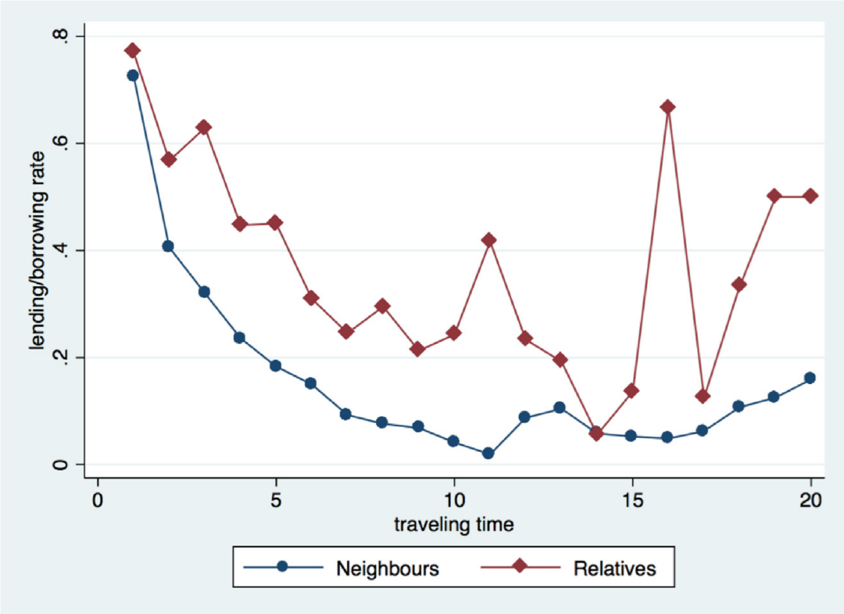


Fig. 1. Geographical distance and borrowing/lending rates among relatives and neighbors.

run. For example, 13% of households sold assets to assist in recovering from Aila, while only 3% did so to cope with a health shock.

Table 2B shows how frequently households seek help from neighbors and relatives, which indicates whether the construction of the sharing network is appropriate. In the survey, a question asked whether a household generally received help from their neighbors or relatives when they are in need. The percentages of households that reported seeking help from relatives and neighbors are 54% and 52%, respectively, for money, and 16% and 35%, respectively, for food. We also look at whether during the month preceding the survey date households borrowed from or lent to their relatives and neighbors in the sample. Among households that had at least one neighbor in the sample, 53% reported borrowing from their neighbor(s), and 42% reported lending to their neighbor(s). Of those who had at least one relative in the sample, 47% reported borrowing from their relative(s), and 49% reported lending to their relative(s). These statistics suggest that neighbors and relatives are an important source of resource sharing for households in the area surveyed.

We also examined whether geographical proximity affects risk sharing among neighbors and relatives. The roles of geographical and social distances have been discussed by Fafchamps and Lund (2003), Fafchamps and Gubert (2007), and Attanasio et al. (2012). Zenou (2015) also developed a social interaction model in which workers can find jobs through either strong or weak ties and showed that increasing the time spent with weak ties increases workers' employment rates. Figures (1) and (2) show the relationship between the travel time between two households and the propensity for those two households to share risks. The risk-sharing propensity was measured as either the percentage of pairs of households that reported having borrowed from or lent to each other (Fig. 1) or the percentage of pairs of households that were in a same risk-pooling group in the experiment (Fig. 2). Both figures show that geographical distance is an important determinant of risk sharing among neighbors who have no kinship with each other, while it is less so among relatives. This suggests that the geographical and social distances could be substitutes for determining intra-village risk sharing. In order to conduct a rigorous examination of the role of geographical proximity in post-Aila risk-sharing, we would need to compare the effects of risk sharing within "close" and "distant" networks. However, both the sample of households that belong to "close" networks and the sample that belong to "distant" networks were relatively small. The small sample size when the networks are separated out like this leads to a weak identification in the first stage regression. Thus, the focus was the entire sample of households that belong to any network, whether they be strong ties (relatives and near neighbors) or weak ties (distant neighbors).

6. Results

6.1. What determines a household's relief rate?

Before presenting the main results, we analyze the factors that determined a household's relief rate but that might affect the outcome variables at the same time. While we cannot look at a household's unobservable characteristics, there are some observable measures that could offer insights into the direction in which we expect the OLS estimates to be biased. We look at three main factors: the damage rate, the social capital index, and per-capita income. The damage rate is defined as the value of

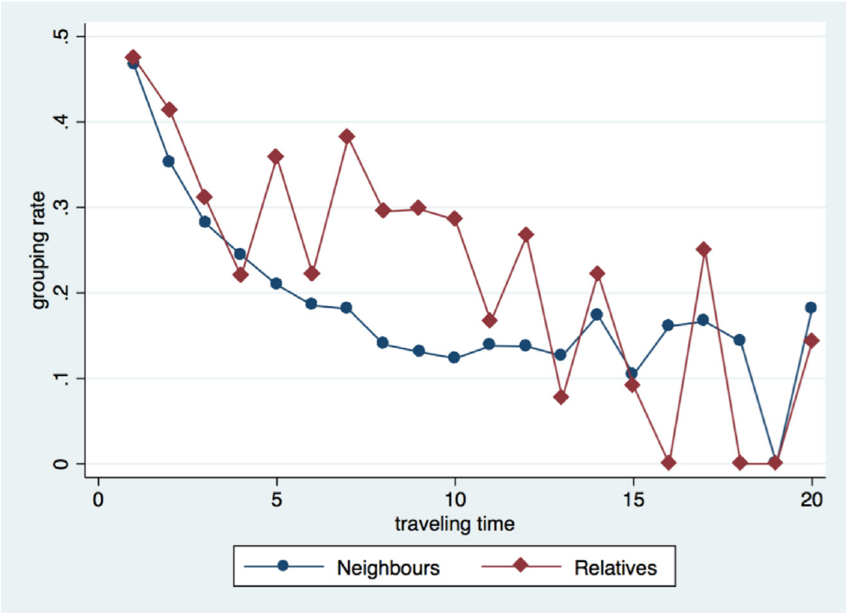


Fig. 2. Geographical distance and risk-sharing rate (in the experiment) among relatives and neighbors.

Table 3
Determinants of the relief rate.

	(1)	(2)	(3)	(4)
damage rate (%)	0.086*** (0.023)			0.088*** (0.024)
social capital index (%)		−0.35*** (0.095)		−0.37*** (0.098)
log (income per capita)			−3.86** (1.64)	−3.94** (1.56)
No. obs	479	479	479	479
R−sq	0.086	0.077	0.073	0.108

Notes: All specifications include the covariates: household head's age, gender and education, number of adult members, and number of children. All specifications control for a village fixed effect and correct the standard errors for village clusters. The corrected standard errors are in parentheses. * significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level.

a household's damaged assets as a percentage of its total asset value. The social capital index is a proxy for a household's connection with the local government and the political parties or leaders, and it was calculated based on eight questions on social capital in the 2010 survey.[17] The literature on corruption in the distribution of post-disaster relief suggests that households with better political connections receive a higher proportion of relief distribution (see e.g., Garrettt and Sobel, 2003). For the household's per-capita income, we use the pre-Aila level.

The results are presented in Table 3. We found that all three variables have significant effects on a household's relief rate, whether used separately or together in one regression. The damage rate is positively correlated with the relief rate, while the social capital index and per-capita income are negatively correlated. Thus, the correlations suggest that poorer households, those with fewer connections with the government, and those that incurred the most damage from Aila were targeted by relief distribution policies and/or were more motivated to seek relief and thus more likely to receive relief. In addition, the values of the assets damaged during Aila for less well-endowed households were lower because they possessed fewer assets before the disaster.

We also ran similar regressions to test the relationship between a network's average relief rate and its damage rate, social capital index, and per-capita income. The results were similar to the household-level results. The findings suggest that any effect of a household's relief rate and that of its network, if it exists, would be biased downwards (in absolute value) because it is expected that households that were better off and incurred less damage would be in a better position to recover from Aila and to invest post-Aila.

We also check whether the relief rate of a household and its network are correlated with each other. After controlling for the village fixed effect, we found that a household's relief rate is not correlated significantly with its network's relief rate, respectively (Table A1, Appendix 5). This therefore alleviates the concern that network formation is endogenous in the expectation of future disasters.

[17] These questions are detailed in Appendix 3. The social capital index ranges from 0.125 to 0.625, with a mean of 0.27 and standard deviation of 0.057.

Table 4
IV first-stage: effects of household and network relief rates on short- and long-term outcomes.

	Aila villages only		Aila and non-Aila villages	
	(1)	(2)	(3)	(4)
	household's relief rate	network's relief rate	household's relief rate	network's relief rate
household's roadblock time	−0.088*** (0.017)	−0.020*** (0.0048)	−0.093*** (0.017)	−0.020*** (0.0046)
network's roadblock time	−0.032 (0.049)	−0.13*** (0.035)	−0.029 (0.047)	−0.13*** (0.034)
N	445	445	873	873
$\boldsymbol{R}^2$	0.141	0.193	0.114	0.189
F-test	19.63	13.66	25.75	14.50
Weak identification test:				
Angrist-Pischke F-statistics	16.67	71.67	20.02	79.70
Kleibergen-Paap Wald rk ***F***-statistics	7.08		7.92	
Stock-Yogo weak ID test critical values:		10% maximal IV size	7.03	
		15% maximal IV size	4.58	
		20% maximal IV size	3.95	
		25% maximal IV size	3.63	

6.2. Main results

6.2.1. First-state estimates

Before reporting the main results for the IV estimates of the effects of the relief rates for a household and its network, we report the first-stage results in Table 4. Both of the instrumental variables, namely the periods of time for which the roads were blocked for a household and for its network, are correlated significantly (at less than the 1% level) with the household's and network's relief rates, respectively. The longer the roads were blocked, the lower the household's relief rate. In particular, a one standard deviation increase in the period of time that the roads were blocked could lower the household's relief rate by 3.5 percentage points and the network's relief rate by 3.97 percentage points. The Angrist-Pischke F-statistics for both IVs are high. At the same time, the joint *F*-tests of excluded variables for both regressions are above 10 (columns 1 and 2). The Kleibergen-Paap Wald *F*-statistics[18] are also high at 7.08, so we can reject the null hypothesis of weak identification at the 10% maximal IV size. The results are similar when the sample includes villages that were not affected by Aila (columns 3 and 4), but the *F*-statistics are higher.[19] In order to address the issue of weak identification that could arise if the correlations between the endogenous regressors and the excluded instruments, the household's and network's roadblock periods, are weak, we report the results between each endogenous variable and the instrument used to address its endogeneity. Specifically, we test the relationships between the household's relief rate and its roadblock period and between the network's relief rate and its roadblock period separately. Table 5 shows that a household's relief rate is determined strongly by its roadblock period when the network's roadblock period does not enter the regression, and the same applies for a network's relief rate and roadblock period when the household's roadblock period is not used.

6.2.2. IV estimates

The IV results are reported in Table 6. We found that the household's relief rate consistently failed to have any significant effect on any of the outcome variables for both the short- and long-term, suggesting that households share resources efficiently within their villages or informal networks. We also found that the network's relief rate had no effect on household incomes in the short-term. Thus, in the short-term, when households were affected largely by the general situation of the village as a whole and with common facilities such as water and electricity still in poor condition, the exposure of the household and its network to the disaster might not matter; however, the informal network seems to have a more significant effect in the long-term. The network's relief rate has a significant positive effect on the household's long-term changes in income from self-employment (columns 5 and 6) but not on the change in total income (columns 3 and 4). In particular, a 10% increase in a network's relief rate could lead to a 1890 taka increase in monthly self-employment income or a 555 taka increase in monthly per-capita self-employment income for a household in the network. This suggests households were fully insured (fully unaffected by their own exposure) within their informal network for self-employment income; however, long-term, a household's total income was not affected by either its or its network's exposure to Aila. The standard errors for the variables, the household's relief rate and the network's relief rate, are large. The point estimates are also relatively large but too imprecise to reach a conclusion.

To obtain an understanding of the way in which the household's income from self-employment is insured within its network, we look at the long-term changes in its livestock holdings as a proxy for a household's investment.[20] The network's relief rate has a significant positive effect on the long-term changes in a household's total value of livestock and value of large

[18] We use the Kleibergen-Paap Wald rk *F*-statistic instead of the usual Cragg-Donald Wald *F*-statistic because our standard errors are corrected for village clusters.

[19] For households in non-Aila villages, the relief rate is taken to be one, and the roadblock time is zero.

[20] Data was not available for households' other asset holdings (e.g., crop holdings, non-livestock).

Table 5
IV first-stage: testing the effect of roadblocks on household and network relief rates separately.

	Aila villages only		Aila and non-Aila villages	
	(1)	(2)	(3)	(4)
	household's relief rate	network's relief rate	household's relief rate	network's relief rate
household's roadblock time	−0.095*** (0.017)		−0.100*** (0.015)	
network's roadblock time		−0.15*** (0.039)		−0.15*** (0.038)
N	445	445	873	873
R^2	0.140	0.185	0.113	0.181

Notes: All specifications include the covariates: household head's age, gender and education, number of adult members, number of children, water height, length of water stay, logarithm of pre-Aila per-capita (adult equiv.) income, change in the number of adult members, and change in the number of children. All specifications control for a village fixed effect and correct the standard errors for village clusters. The corrected standard errors are in parentheses. * significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level.

Table 6
IV second-stage (Aila villages only): effects of household and network relief rates on short- and long-term outcomes.

	(1)	(2)	(3)	(4)	(5)
	SR income	SR self-employment income	LR income	LR per-capita income	LR self-employment income
household's relief rate	58.6 (35.7)	31.9 (30.6)	−520.9 (518.0)	−128.2 (126.3)	−75.3 (102.1)
network's relief rate	32.7 (65.3)	13.4 (45.6)	464.9 (384.3)	132.9 (95.2)	189.0* (98.9)
N	445	445	445	445	445
	(6)	(7)	(8)	(9)	(10)
	LR per-capita self-employment income	LR total livestock	LR big livestock	LR small livestock	Reporting worse condition
household's relief rate	−11.5 (26.4)	−114.8 (157.9)	−128.3 (127.3)	41.1 (48.0)	0.0038 (0.012)
network's relief rate	55.5** (28.2)	416.0* (232.6)	464.0** (184.5)	−49.8 (63.4)	−0.025** (0.012)
N	445	445	445	445	445

Notes: All specifications include the covariates household head's age, gender and education, number of adult members, number of children, water height, length of water stay, logarithm of pre-Aila per-capita (adult equiv.) income, change in the number of adult members, and change in the number of children. All specifications control for a village fixed effect and correct the standard errors for village clusters. The corrected standard errors are in parentheses. * significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level.

livestock but not on the value of small livestock (columns 7–9). This result is consistent with the hypothetical Scenario 3 (section 4.1) in which the aggregate network resource level is high enough for households to invest in lumpy assets both before and after Aila. In particular, a 10% increase in a network's relief rate led to 4160 taka and 4640 taka increases in households' total livestock value and value of large livestock, respectively. This finding suggests that resource pooling within a household's informal network allowed the household to make more profitable investments, thus improving its income from self-employment. This also means that households belonging to networks that were more exposed to Aila would have been more limited in their investment options and their opportunities for increases in self-employment income.

We also look at the households' self-reported assessments of their post-Aila household situations. The results are consistent with those for income and investment. We find full resource pooling within informal networks, as households were less likely to report their situation to be worse when the network to which they belonged received a higher relief rate (column 10). In particular, a 10% increase in its network's relief rate lowered a household's propensity to report their household situation as being worse by 0.25.

In Table 7, we report the same set of long-term results as in Table 6 but for the combined sample of all Aila and non-Aila villages, except three outcome variables: total livestock holdings, small livestock holdings, and a propensity to report the situation to be worse due to the lack of data for the non-Aila villages. All the results are similar to those using only the sample of Aila villages, though the magnitudes of the effects are slightly smaller.

6.3. Did informal insurance crowd out formal insurance?

Table 8 reports the results of a test to determine whether resource pooling within an informal network of neighbors and relatives reduces a household's need for formal insurance against disasters. The survey questions for the insurance policy are shown in Appendix 4. The results reported in Section 6.2 (using the same specifications of the IV regressions in equations (3)–(5) suggest that resource pooling within informal networks was an efficient mechanism in the long-term for enabling households to recover from Aila through investment and self-employment income. Therefore, if the informal network crowded out formal insurance, it would be expected that households that belong to a network that was exposed less to Aila would have less need for formal insurance during the period from 2010 to 2012 than households that belong to a more

Table 7
IV second-stage (Aila and non-Aila villages): effects of household and network relief rates on short- and long-term outcomes.

	(1)	(2)	(3)	(4)	(5)
	LR income	LR per-capita income	LR self-employment income	LR per-capita self-employment income	LR big livestock
household's relief rate	−493.4 (490.1)	−120.4 (118.8)	−61.8 (91.8)	−8.03 (23.4)	−47.3 (116.3)
network's relief rate	452.0 (366.9)	128.0 (90.6)	174.3* (90.5)	51.8** (25.7)	398.1** (170.1)
N	873	873	873	873	873

Notes: All specifications include the covariates: household head's age, gender and education, number of adult members, number of children, water height, length of water stay, logarithm of pre-Aila per-capita (adult equiv.) income, change in the number of adult members, and change in the number of children. All specifications control for a village fixed effect and correct the standard errors for village clusters. The corrected standard errors are in parentheses. * significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level.

Table 8
IV second-stage (Aila villages only): does informal insurance crowd out formal insurance?.

	(1)	(2)	(3)
	full insurance	half insurance	facility insurance
household's relief rate	158.8 (120.7)	96.8 (76.7)	65.4 (49.4)
network's relief rate	−169.5*** (63.7)	−106.7** (45.6)	−56.4* (30.9)
N	445	445	445

Notes: All specifications include the covariates household head's age, gender and education, number of adult members, number of children, water height, length of water stay, logarithm of pre-Aila per-capita (adult equiv.) income, change in the number of adult members, and change in the number of children. All specifications were controlled for a village fixed effect, and the standard errors for village clusters were corrected. The corrected standard errors are in parentheses. * significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level.

exposed network. The results in Table 8 support this hypothesis, as households that belonged to a network with a higher relief rate were not willing to pay as much for insurance against disasters. For example, a 10% increase in the network's relief rate lowered a household's willingness to pay the premium by 1695 taka for full insurance and by 1067 taka for partial (half) insurance against asset loss. The crowding-out effect on insurance that provides basic needs during and after a disaster is relatively smaller. This finding could reflect the fact that the effect of network resource sharing, which was channeled through the network's relief rate, was mostly present in the long-term when most of the recovery from the disaster took place, rather than during or shortly after the disaster.

6.4. Did exposure to Aila change risk attitudes?

Table 9 reports the results from the question of whether the household and its network's exposure to Aila had any effect on the household's risk-taking behavior. Here, we use the same IV specifications from equations (3)–(5). If the household's risk-taking behavior changed due to its exposure, or that of its network, to Aila, it may be impossible to disentangle this effect from the effect of network resource pooling, meaning that changes in a household's long-term investment and income might be due to either or both of these effects. We use two outcome variables obtained from the risk game to measure a household's risk-taking behavior: whether the household is risk-loving and whether the household chooses to join a risk-sharing group. We find no evidence that the relief rate of a household, or its network, changed the household's risk-taking or risk-sharing behaviors. While the risk attitudes of those who experienced a disaster and those who did not could differ, as was suggested by the findings of Eckel et al. (2009), Page et al. (2014), and Cameron and Shah (2015), the results of this study show that there are no significant differences among those with different levels of exposure to Aila. Therefore, it is most likely that the effect of the network's relief rate on a household's investment and income is operated by efficient resource pooling within the network. This suggests that network resource sharing plays an important role in insuring households against shocks. When all households in the network are affected by a common shock (as in the case of Aila), the extent to which a household can seek help from another network member is limited.

Table 9
IV second-stage (Aila villages only): risk attitudes.

	Aila villages only		Aila and non-Aila villages	
	(1)	(2)	(3)	(4)
	risk loving	join risk-sharing group	risk loving	join risk-sharing group
household's relief rate	−0.0070 (0.011)	0.0041 (0.0054)	−0.0072 (0.010)	0.0032 (0.0055)
network's relief rate	0.0047 (0.010)	0.0033 (0.0064)	0.0045 (0.0099)	0.0040 (0.0060)
N	445	445	873	873

Notes: All specifications include the covariates: household head's age, gender and education, number of adult members, number of children, water height, length of water stay, logarithm of pre-Aila per-capita (adult equiv.) income, change in the number of adult members, and change in the number of children. All specifications control for a village fixed effect and correct the standard errors for village clusters. The corrected standard errors are in parentheses. * significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level.

6.5. Further robustness checks

Although the village fixed effect should account for all village-level factors that could influence a household's recovery from a disaster, concerns remain regarding the spillover effects from other households in the same village but that are not within the household's network. These effects could be channelled through local economic activities, including wage labor and the local market. To alleviate the potential issue, we added a control for the relief rate that the other households received in regressions (3), (4), and (5). The results are similar to the original results and are presented in Appendix 5, Table A2.

We also did another robustness check to address the issue of the small number of clusters (34 villages in total and 18 affected villages). Because the asymptotic justification for cluster-robust errors assumes that the number of clusters goes to infinity, when the number of clusters is too few, the cluster-robust standard errors are biased downwards (Cameron, Gelbach, and Miller, 2008). We thus applied the wild-cluster bootstrap method proposed by Cameron, Gelbach, and Miller (2008) to account for the small number of villages. Because the method is not directly applied to IV regressions, we ran the first-stage regressions using the wild-cluster bootstrap method, and then ran the second-stage regression using the predicted relief rates from the first stage and applying the wild-cluster bootstrap method. We present the results, which are consistent with the original results, in Appendix 5, Table A3.

Finally, we address the potential concern regarding recall bias, which could arise because the outcome variables for the pre-disaster level were collected immediately after the disaster. The pre-Aila data were collected within three months after Aila passed; however, data from non-affected areas were collected just before Aila. Households in an affected area are more likely to accurately remember details about their income and assets given the damage they experienced. Thus, while recall bias could be an important concern in many settings, it is of less concern in this context. However, to the extent the pre-Aila data from Aila affected people suffer from recall bias, our estimates could be subject to bias. In order to address the concern, we run an ANCOVA model for each variable of interest in which we controlled for the baseline values of the outcome (following the approach suggested by McKenzie, 2012) using the post-disaster level as outcomes of interest, rather than using changes in the outcome variable between pre-and-post-Aila. McKenzie (2012) argued that this model is expected to minimize the bias of estimates relative to simple differences in endline means or a diff-in-diff. The results of using the ANCOVA model, which are reported in Appendix 5, in Table A4, show similar results[21]; however, it should be noted that our preferred approach is to consider the change in outcomes between pre-Aila and post-Aila levels. Our preferred approach can control for unobservables that are time-invariant and could potentially bias the estimates due to the endogeneity of the network. This method is akin to the fixed effects regression method used to control for unobserved characteristics.

7. Conclusion

This paper provides evidence regarding the way in which resource sharing within an informal network of neighbors and relatives assists rural households in recovering from a natural disaster. The findings show that borrowing and lending among neighbors and relatives are prevalent among the subjects and that while geographical distance matters for risk sharing, social distance could be a substitute. Risk sharing is affected by geographical distance among people who do not have any kinship with each other, though less so among relatives. In the context of a natural disaster, when all households in the network are affected by a common shock, the extent to which a household can seek help from another network member is limited. Indeed, we find evidence that, in the short-term, Aila-affected households were not able to mitigate shocks by sharing resources with their network members.

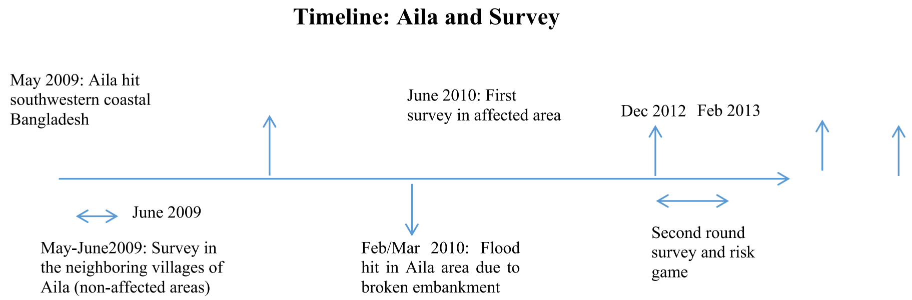
While the findings show that the disaster still had an effect on the household's investment and income two and half years after cyclone Aila, the effect is shared within the household's informal network. We find that the household's own exposure to the disaster had no significant effect on the household's investment and income, but that its network's exposure to the disaster did have a significant effect on the household's investment and income. Households belonging to a network in which member households were affected less by the disaster on average invested more in lumpy assets such as large livestock. These households had higher incomes from self-employment two and half years after the disaster than those belonging to networks that were affected more by the disaster. We find that informal sharing within the network crowds out formal insurance against disasters. Households belonging to a network that was affected less by the disaster were not willing to pay as much for formal insurance against disasters. We show that the household's risk attitude was not affected by either its or its network's exposure to the disaster. Therefore, we can exclude the potential effects of changes in risk attitude, and attribute the effect of the network's exposure to Aila solely to the sharing of resources within the informal network.

The findings confirm the important role played by the informal resource-sharing network in providing insurance against income shocks. Informal networks affect not only the household's consumption smoothing but also the household's investment and income. Even when households are faced with a community-wide disaster, such as Cyclone Aila, to which all network members are exposed, resource sharing within the network still has a significant effect on the long-term process of recovering from the disaster. Moreover, the findings also have important policy implications for formal insurance against disaster and post-disaster policies, such as those regarding relief distribution. To cope with the increasing risks due to the

[21] In another case, we also ran the same regressions (equations (3)–(5)) but adding baseline ('Pre-Aila') value of the outcome variable as an additional regressor. The results are almost identical, and not reported for brevity.

impact of climate change, the National Adaptation Programme of Action and Bangladesh Climate Change Strategy and Action Plan (BCCSAP) recommends the exploration of options for a micro-flood-insurance market in Bangladesh (Ministry of Environment and Forest, 2005; Ministry of Environment and Forest, 2009); however, research has shown that "the market for a standard, stand-alone weather microinsurance in Bangladesh is characterized by low demand, poor governance, and lack of prospects for commercial viability" (Akter, 2012). The findings on the efficiency of informal insurance networks and the crowding-out effect of such networks on formal insurance support these results and suggest that group-based insurance should be offered or that insurance could be packaged in microcredit or savings plan as alternatives to traditional insurance. In terms of impact evaluation, the paper shows the necessity of taking the interactions among affected households within the community into account as part of the externality of policies targeting disaster-affected households.

Appendix 1



Appendix 2

Instructions for the risk game

Now, suppose you are given the following six options. ***[Interviewer: show pictures of money notes as in the next page.]*** Which option would you choose? ***you will actually be paid the final earning from your choice.*** Circle ONE option:

1) You get 100 taka for sure.
2) A coin is tossed, and if it is heads, you get 200 taka. If it is tails, you get 80 taka.
3) A coin is tossed, and if it is heads, you get 250 taka. If it is tails, you get 70 taka.
4) A coin is tossed, and if it is heads, you get 300 taka. If it is tails, you get 60 taka.
5) A coin is tossed, and if it is heads, you get 350 taka. If it is tails, you get 50 taka.
6) A coin is tossed, and if it is heads, you get 400 taka. If it is tails, you get zero taka.

Before you make your actual choice, for your understanding, let us practice each of the options above by tossing coins. [Enumerator ensures that respondents clearly understand what it means by a 50/50 chance of landing on heads or tails when tossing a coin.]

Appendix 3

Survey questions on social capital

1. Is anyone in your family a member of Union Parishad?
2. Are you a member of any social/cultural organization?
3. Are you a member of a Hat committee?
4. Do you have any connection with political party officers?
5. Do you have any connection with your urban political leader?
6. Do you have any communication with Union Parishad members?
7. Do you have any communication with your member of parliament?
8. Do you receive invitations to attend social functions?

Appendix 4

Insurance policy survey questions

Insurance is a way to recover from disasters. An insurance policy helps during a financial crisis. After becoming a member of an insurance company, if the defined premium is paid, then compensation is available at the defined moment; however, it depends on the yearly premium and losses due to the disaster. It is important to note that if a disaster occurs during a defined period, then compensation is available. Otherwise, no benefits are available from the insurance premium.

5.1 Are you informed about a risk remedial insurance policy? 1=Yes; 2=No

5.2 Have you/your family member ever had an insurance policy? 1=Yes; 2=No

If yes:

1) Type of insurance ____________________

2) Name of insurance company ____________________

5.3 Do you think it is necessary for everyone to have an insurance policy for an uncertain future? 1=Yes; 2=No

5.4 Do you think it is necessary to have a disaster remedial insurance policy? 1=Yes; 2=No

5.5 If Insurance is available for a natural disaster, what types of facilities will be available? (Multiple answer)

1= compensation will be available after the disaster;

2= compensation will be available on death or body part losses;

3= compensation will be available on crop losses;

4= compensation will be available on death of domestic animals;

5= education allowance will be available;

6= treatment allowance will be available.

5.6 If an insurance company provides for your needs during a disaster and after a disaster, how much of an annual subscription/premium are you willing to pay? (Taka)

5.7 If an insurance company will provide half of the value of the assets destroyed by a disaster, how much of an annual subscription/premium are you willing to pay? (Taka)

5.8 If an insurance company will provide the full price of assets destroyed by a disaster, how much of an annual subscription/premium are you willing to pay? (Taka)

Appendix 5

Table A1
is the own relief rate correlated with the network relief rate?

	Own relief rate	
Network relief rate	0.81*** (0.068)	−0.066 (0.21)
Controlling for village fixed effect	No	Yes
N	455	455

All specifications include the covariates: household head's age, gender and education, number of adult members, and number of children. All specifications correct the standard errors for village clusters. The corrected standard errors are in parentheses. * significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level.

Table A2
IV second-stage (Aila villages only): effects of household and network relief rates on long-term outcomes − adding out-network's relief rate

	(1)	(2)	(3)	(4)
	LR income	LR per-capita income	LR self-employment income	LR per-capita self-employment income
household's relief rate	−489.2 (511.4)	−117.8 (124.4)	−47.0 (99.3)	−2.88 (24.9)
network's relief rate	627.0 (486.4)	185.1 (122.1)	325.7** (165.9)	97.0* (49.6)
out-network's relief rate	419.0 (524.5)	135.0 (132.2)	355.0 (224.0)	107.8* (62.3)
N	445	445	445	445
	(5)	(6)	(7)	(8)
	LR total livestock	LR big livestock	LR small livestock	Reporting worse condition
household's relief rate	−33.8 (149.1)	−37.6 (113.7)	37.8 (42.1)	0.00050 (0.013)
network's relief rate	805.7** (363.9)	901.5*** (283.4)	−66.7 (110.5)	−0.042* (0.023)
out-network's relief rate	1012.5** (477.3)	1136.6*** (386.7)	−43.7 (125.9)	−0.044 (0.037)
N	445	445	445	445

Notes: All specifications include the covariates: household head's age, gender and education, number of adult members, number of children, water height, length of water stay, logarithm of pre-Aila per-capita (adult equiv.) income, change in the number of adult members, and change in the number of children. All specifications control for a village fixed effect and correct the standard errors for village clusters. The corrected standard errors are in parentheses. * significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level.

Table A3
IV second-stage (Aila villages only): effects of household and network relief rates on long-term outcomes − wild-cluster bootstrap method.

	(1)	(2)	(3)	(4)
	LR income	LR per-capita income	LR self-employment income	LR per-capita self-employment income
household's relief rate	−519.4 (669.1)	−125.9 (154.7)	−101.4 (119.8)	−15.2 (32.3)
network's relief rate	456.8 (443.8)	129.7 (107.4)	205.3** (81.4)	57.9*** (18.6)
N	445	445	445	445
	(5)	(6)	(7)	(8)
	LR total livestock	LR big livestock	LR small livestock	Reporting worse condition
household's relief rate	−149.2 (167.0)	−157.0 (130.6)	46.2 (54.4)	0.0018 (0.011)
network's relief rate	436.3 (330.9)	480.8 (301.9)	−52.2 (81.1)	−0.023*** (0.0080)
N	445	445	445	445

Notes: All specifications include the covariates: household head's age, gender and education, number of adult members, number of children, water height, length of water stay, logarithm of pre-Aila per-capita (adult equiv.) income, change in the number of adult members, and change in the number of children. All specifications control for a village fixed effect and correct the standard errors for village clusters. The corrected standard errors are in parentheses. * significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level.

Table A4
IV second-stage (Aila villages only): effects of household and network relief rates on long-term outcomes − ANCOVA method

	(1)	(2)	(3)	(4)
	LR income	LR per-capita income	LR self-employment income	LR per-capita self-employment income
household's relief rate	−591.1 (564.7)	−137.7 (134.9)	−121.8 (107.2)	−22.0 (28.3)
network's relief rate	524.8 (436.3)	142.2 (106.0)	202.5** (93.1)	63.5** (28.3)
N	445	445	445	445
	(5)	(6)	(7)	
	LR total livestock	LR big livestock	LR small livestock	
household's relief rate	−186.4* (89.6)	−186.1* (98.8)	25.8 (25.6)	
network's relief rate	94.0 (161.7)	159.3 (127.7)	−77.7 (59.5)	
N	445	445	445	

Notes: All specifications include the covariates: household head's age, gender and education, number of adult members, number of children, water height, length of water stay, baseline of the outcome variables. All specifications control for a village fixed effect and correct the standard errors for village clusters. The corrected standard errors are in parentheses. * significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level.

References

Akter, S., 2012. The role of microinsurance as a safety net against environmental risks in Bangladesh. J. Environ. Dev. 21 (2), 263–280.
Ambrus, A., Mobius, M., Szeidl, A., 2014. Consumption risk-sharing in social networks. Am. Econ. Rev. 104 (1), 149–182.
Angelucci, M., De Giorgi, G., Rasul, I., 2017. Consumption and Investment in Resource Pooling Family Networks. Econom. J. Forthcoming.
Asfaw, A., Von Braun, J., 2004. Is consumption insured against illness? Evidence on vulnerability of households to health shocks in rural Ethiopia. Econ. Dev. Cult. Change 53 (1), 115–129.
Attanasio, O., Barr, A., Cardenas, J.C., Genicot, G., Meghir, C., 2012. Risk pooling, risk preferences, and social networks. Am. Econ. J. Appl. Econ. 4 (2), 134–167.
Bangladesh Bureau of Statistics, 2010. Report of the Household Income and Expenditure Survey. Ministry of Planning, Dhaka, Bangladesh.
Barr, A., Dekker, M., Fafchamps, M., 2012. Who shares risk with whom under different enforcement mechanisms? Econ. Dev. Cult. Change 60 (4), 677–706.
Barr, A., Genicot, G., 2008. Risk sharing, commitment, and information: an experimental analysis. J. Eur. Econ. Assoc. 6 (6), 1151–1185.
Bernknopf, R.L., Brookshire, D.S., Thayer, M.A., 1990. Earthquake and volcano hazard notices: an economic evaluation of changes in risk perceptions. J. Environ. Econ. Manag. 18 (1), 35–49.
Bin, O., Landry, C.E., 2013. Changes in implicit flood risk premiums: empirical evidence from the housing market. J. Environ. Econ. Manag. 65 (3), 361–376.
Binswanger, H.P., 1980. Attitudes toward risk: experimental measurement in rural India. Am. J. Agric. Econ. 62, 395–407.
Cameron, L., Shah, M., 2015. Risk-taking behavior in the wake of natural disasters. J. Hum. Resour. 50 (2), 484–515.
Cameron, A., Gelbach, J., Miller, D., 2008. Bootstrap-based improvements for inference with clustered errors. Rev. Econo. Stat. 90, 414–427.
De Weerdt, J., Dercon, S., 2006. Risk-sharing networks and insurance against illness. J. Dev. Econ. 81 (2), 337–356.
Deaton, A., 1992. Saving and income smoothing in Cote d'Ivoire. J. Afr. Econ. 1 (1), 1–24.
Dercon, S., 1996. Risk, crop choice and savings: evidence from Tanzania. Econ. Dev. Cult. Change 44 (3), 385–514.
Dercon, S., Krishnan, P., 2000. In sickness and in health: risk sharing within households in rural Ethiopia. J. Polit. Econ. 108 (4), 688–727.
Eckel, C.C., El-Gamal, M.A., Wilson, R.K., 2009. Risk loving after the storm: a Bayesian-network study of Hurricane Katrina evacuees. J. Econ. Behav. Organ. 69 (2), 110–124.
Fafchamps, M., 1999. Risk sharing and quasi-credit. J. Int. Trade Econ. Dev. 8 (3), 257–278.
Fafchamps, M., Gubert, F., 2007. The formation of risk sharing networks. J. Dev. Econ. 83 (2), 326–350.
Fafchamps, M., Lund, S., 2003. Risk-sharing networks in rural Philippines. J. Dev. Econ. 71 (2), 261–287.
Fafchamps, M., Udry, C., Czukas, K., 1998. Drought and saving in West Africa: are livestock a buffer stock? J. Dev. Econ. 55 (2), 273–305.
Foster, A.D., Rosenzweig, M.R., 2001. Imperfect commitment, altruism, and the family: evidence from transfer behavior in low-income rural areas. Rev. Econ. Stat. 83 (3), 389–407.
Garrett, T.A., Sobel, R.S., 2003. The political economy of FEMA disaster payments. Econ. Inq. 41 (3), 496–509.
Genicot, G., Ray, D., 2003. Group formation in risk-sharing arrangements. Rev. Econ. Stud. 70 (1), 87–113.
Gertler, P., Gruber, J., 2002. Insuring consumption against illness. Am. Econ. Rev. 92 (1), 51–70.
Gray, C.L., Mueller, V., 2012. Natural disasters and population mobility in Bangladesh. Proc. Natl. Acad. Sci. Unit. States Am. 109 (16), 6000–6005.
Grimard, F., 1997. Household consumption smoothing through ethnic ties: evidence from Cote d'Ivoire. J. Dev. Econ. 53 (2), 391–422.
Islam, A., Maitra, P., 2012. Health shocks and consumption smoothing in rural households: does microcredit have a role to play? J. Dev. Econ. 97 (2), 232–243.
International Federation of Red Cross and Red Crescent Societies, 2009. Emergency Appeal No. MDRBD004. Glide no. TC-2009-000105-BGD.
Kazianga, H., Udry, C., 2006. Consumption smoothing? Livestock, insurance and drought in rural Burkina Faso. J. Dev. Econ. 79 (2), 413–446.
Kovács, G., Spens, K.M., 2007. Humanitarian logistics in disaster relief operations. Int. J. Phys. Distrib. Logist. Manag. 37 (2), 99–114.
Ligon, E., Thomas, J.P., Worrall, T., 2002. Informal insurance arrangements with limited commitment: theory and evidence from village economies. Rev. Econ. Stud. 69 (1), 209–244.
Mahmud, T., Prowse, M., 2012. Corruption in cyclone preparedness and relief efforts in coastal Bangladesh: lessons for climate adaptation? Global Environ. Change 22, 933–943.
McKenzie, D., 2012. Beyond baseline and follow-up: the case for more T in experiments. J. Dev. Econ. 99 (2), 210–221.
Ministry of Environment and Forest, 2005. National Adaptation Program of Action (NAPA) (Dhaka, Bangladesh).
Ministry of Environment and Forest, 2009. Bangladesh climate Change Strategy and Action Plan 2009 (Dhaka, Bangladesh).
Morduch, J., 1990. Risk, Production and Saving: Theory and Evidence from Indian Households. Harvard University. Manuscript).
Morduch, J., 1995. Income smoothing and consumption smoothing. J. Econ. Perspect. 9 (3), 103–114.
Munshi, K., Rosenzweig, M., 2009. Why is mobility in India so low? Social insurance, inequality, and growth. National Bureau of Economic Research. Working paper No. 14850.
Murgai, R., Winters, P., Sadoulet, E., Janvry, A.D., 2002. Localized and incomplete mutual insurance. J. Dev. Econ. 67 (2), 245–274.
NNN-IRIN, 2010. Bangladesh: Cyclone Aila Survivors Take Another Hit, 3 May 2010. http://news.brunei.fm/2010/04/08/bangladesh-cycloneaila-survivors-take-another-hit/.
Page, L., Savage, D.A., Torgler, B., 2014. Variation in risk seeking behaviour following large losses: a natural experiment. Eur. Econ. Rev. 71, 121–131.
Rosenzweig, M., Wolpin, K., 1993. Credit market constraints, consumption smoothing, and the accumulation of durable production assets in low-income countries: investment in Bullocks in India. J. Polit. Econ. 101 (2), 223–244.
Roy, D., 2011. Vulnerability and Population Displacements Due to Climate-induced Disasters in Coastal Bangladesh. Publication Series of UNU-EHS, No. 15/2011. United Nations University.
Sarawat, F., 2009. Lessons from Aila. In: Forum: the Daily Star, vol. 3 no. 10, October 2009. http://www.thedailystar.net/forum/2009/october/Aila.htm, 14 April 2010.
Townsend, R.M., 1994. Risk and insurance in village India. Econometrica 62 (3), 539–591.
Udry, C., 1994. Risk and insurance in a rural credit market: an empirical investigation in northern Nigeria. Rev. Econ. Stud. 61 (3), 495–526.
United Nations, 2010. Aila Cyclone Aila: Joint UN Multisector Assessment & Response Framework. Dhaka, June. Available at. http://www.lcgbangladesh.org/derweb/Needs%20Assessment/Reports/Aila_UN_AssessmentFramework_FINAL.pdf.
Wagstaff, A., 2007. The economic consequences of health shocks: evidence from Vietnam. J. Health Econ. 26 (1), 82–100.
Yan, S., Shih, Y.L., 2009. Optimal scheduling of emergency roadway repair and subsequent relief distribution. Comput. Oper. Res. 36 (6), 2049–2065.
Zenou, Y., 2015. A dynamic model of weak and strong ties in the labor market. J. Labor Econ. 33, 891–932.