Does network matter after a natural disaster? A study on resource sharing within informal network after cyclone AILA

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Abstract:

The paper looks at post-disaster recovering process of households in the 2009-2010 cyclone AILA-affected area in rural Bangladesh. Exploiting the exogenous variations of household's exposure to the disaster, we provide empirical evidence on efficient resource sharing within the informal network of neighbours and relatives for the households to recover from a natural disaster. We find no significant effect of household's own exposure to the disaster but only significant effect of its network's exposure on household's investment and income two years after the cyclone was over. This led to a crowding-out effect on the household's need for formal insurance against disaster. Using experiment data on risk-taking and risk-sharing behaviour, we also find evidence that household's risk attitude was not affected by household's and its network's exposure to the disaster. Therefore, we can attribute the effect of the network's exposure to AILA solely to the sharing of resource within the informal network.

Key words: resource sharing, resource pooling, informal network, risk sharing, Bangladesh, AILA

1. Introduction

The poor in the developing countries are living under volatile conditions, being prone to various adverse shocks ranging from human diseases to natural disasters. At the same time they lack access to formal credit and formal insurance markets, thus any impact of shocks might be exacerbated and sustain in the long run. Therefore, the poor households have to resort to different risk-coping strategies, including informal insurance through transfers, gifts, and credit among relatives and friends, diversification of household members' labour supply, or selling of assets (Deaton (1997); Morduch (1990)). While the latter two mechanisms might be costly in terms of long-term investment, the arrangement of informal insurance could be at no cost if full or almost full insurance is achieved within the local community.

It has been widely shown in the literature that informal insurance plays an important role in smoothing household's consumption but is not fully effective at the local community level (for example, Deaton (1992), Townsend (1994), Udry (1994)) but mostly at a lower level of informal risk-sharing network (for example, De Weerdt and Dercon (2006), Munshi and Rosenzweig (2009)). However, most studies have focused on the aspect of consumption smoothing while little has been studied on the effect on investment. An exception is Angelucci et. al. (2012), who show resource pooling within an informal network can provide a household with liquidity to invest in high-return but lumpy investment.

Our paper aims to examine the risk-sharing behaviour of households in rural villages in Bangladesh following a community-wide natural disaster, particularly its long-run effect on household's investment and income. Our paper closely follows the theoretical framework developed in the Angelucci et. al. (2012) paper, which models the relationship between a household's investment and its network's aggregate resources. We thus provide empirical evidence that households are fully insured by their informal resource-sharing networks to recover from natural disasters and to invest efficiently in the long run. This is to our best knowledge the first study to examine the resource sharing within informal network in the context of a community-wide natural disaster. While previous studies mostly exploited household-specific income shocks like health shocks, little has been done in the context of a community-wide shock. Thus, it remains unknown whether households share resources when all members in the networks are exposed to the shock. Our main identification strategy is to exploit the variations of the intensity of exposure to the cyclone among the households as exogenous shocks to their resources and their network's resources. Unlike other coastal areas, such flood is uncommon in this coastal area of Bangladesh as it is usually protected largely by Sundarban, the largest single block of tidal halophytic mangrove forest in the world. Thus AILA is an unexpected shock to the households living in the area. On the other hand, although this is a community-wide disaster that affected all households in the area, the degree of exposure varied across households. We are guided by the existing literature on informal sharing network to define the network in our study to comprise of household's close neighbours and relatives. We use a two-round household panel data set of households living in the two districts of Satkhira and Khulna, the areas that were most affected by the cyclone AILA in 2009-2010. The data set includes information on relationships between every pair of households that reside in a same village. To examine whether resource pooling is efficient within a household's informal risk-sharing network, we particularly look at the effect of the household's and its informal network's exposure to AILA on its investment and income change in the short run - a few months after the disaster and in the long run - two years after the disaster passed. Our main measure for the exposure to AILA is defined as the household's relief rate, which is the total amount of relief a household received as a proportion of its total damage values. This measure takes into account the value of damaged assets that were recovered through household's receipt of relief following AILA, which we find to be a significant source of assistance for affected households to recover from the cyclone. Thus, another contribution of our paper is to examine the long-run effect of a natural disaster and the relief distribution that follows the disaster on household's investment and income. After accounting for the endogeneity of the relief rate using an instrument variable, we find that resource sharing is fully efficient within the household's network of neighbours and relatives for its self-employment income and investment in lumpy goods. We also find as a result a crowding-out effect of the informal sharing network on the formal insurance against disaster.

We also try to separate the effect of resource pooling within the informal network from the effect of exposure to the disaster on household's risk attitude, thus changing household's investment choices. Cameron and Shah (2013) find that individuals in villages in Indonesia that suffered a flood or earthquake in the past three years exhibit higher levels of risk aversion compared to those in villages that did not experience a disaster. If for example a household became less risk-taking due to the higher level of its exposure and its network's exposure to the disaster, the household might invest less in high-return but lumpy investment and we could not distinguish this effect from the effect of network's resource pooling. To examine the post-disaster risk-taking behaviour, we exploit the experimental data from a risk-taking and risk-pooling game that we conducted with the participation of the same households in 2012, at the same time when we did our follow-up survey. We examine whether a household and its network's exposure to AILA have any effect on the household's risk-taking and risk-sharing behaviour, as measured in the game. We however find no such effect, thus we claim the effect of the network's exposure to AILA was solely due to resource sharing within the network.

2. Informal risk-sharing network

Much in the literature has tested the full insurance model and found informal insurance plays an important role in smoothing household's consumption but is not fully effective at the local community level (Deaton (1992); Gertler and Gruber (2002); Ligon, Thomas, and Worrall (2002); Townsend (1994); Udry (1994)). Townsend (1994) finds household consumptions comove with village average consumption but are still influenced by their own income fluctuations and the landless are less well insured than the farmers. Gertler and Gruber (2002) examine the ability of Indonesian households to insure consumption against illness and find that while the households can fully insure against minor illness, they can only insure less than 40% of income loss from severe illnesses. Udry (1994) looks at risk pooling between households in northern Nigeria and finds the repayments of loans depend on realizations of random production and consumption shocks by both borrowers and lenders but a fully efficient risk-pooling equilibrium is not achieved.

More recent empirical studies on informal insurance arrangements look at risk sharing within networks, usually of friends and relatives, instead of the community or village level. De Weerdt and Dercon (2006) use panel data from a village in Tanzania to test risk-sharing within self-reported insurance networks in the village. Looking at how households cope with health shocks, they could not reject full risk-sharing at the village level for food consumption but find evidence of insurance at the network level for non-food consumption. Grimard (1997) tests whether risk-sharing within ethnic groups in Côte d'Ivoire is fully efficient. Although the complete insurance hypothesis is rejected, there is evidence for partial insurance among members of the same ethnic group, particularly for those who live in regions where formal financial markets are of limited access. Fafchamps and Lund (2003) study risk-coping strategies by rural Filipino households and risk sharing within networks of family and friends. They find that risk sharing takes place through these networks instead of at the village level and households insure against shocks mostly through zero-interest informal loans from family and friends but hardly through sales of livestock and grain. Their results thus support models of quasi-credit where enforcement constraints limit risk sharing. Similarly, Munshi and Rosenzweig (2009), when explaining the persistence of low marital mobility in rural India, find evidence for the important role of risk sharing among members within sub-caste networks. Households in higher-income caste networks are found to be more likely to participate in these risk-sharing arrangements, thus less likely to out-marry and out-migrate. More recently, Angelucci, De Giorgi, and Rasul (2012) use information on surnames from a census data set of rural villages in Mexico to identify households' first-degree relatives in the village. Looking at the impact of PROGRESA, a conditional cash transfer program that offered cash transfer to only eligible households that live in a subset of random treatment villages in the census, the paper shows the networks of extended family are an important informal resource-sharing arrangement and households having relatives in the village allocate resources and invest differently from households without relatives. Households with relatives share resources within their networks, thus can better smooth consumption and invest more in human capital.

While informal risk sharing is deemed to have an important role in poor households' consumption smoothing against adverse shocks, most empirical evidences have rejected the full insurance hypothesis at the village level and show most risk sharing arrangements take place at a lower network level. A number of theoretical papers have been trying to explain for this phenomenon, examining the constraints that limit the extent and effectiveness of informal insurance. According to Barr and Genicot (2008), since informal risk-sharing arrangements are all self-enforced, the informal risk sharing is potentially limited by incentive constraints, information asymmetries and lack of commitment, thus risk sharing is more likely to take place among people with close relationships like friendship, kinship, co-ethnicity, or co-membership in an organization. In their theoretical model of risk-sharing group formation, Genicot and Ray (2003) also attribute the limits to group size to information asymmetries and lack of enforcement. Similarly, Murgai, Winters, Sadoulet, and Janvry (2002) construct a model to examine the role of two types of transaction costs: the association costs of establishing links with insurance partners and the extraction costs of using these links to implement insurance transfers, in the formation of insurance groups. They show that the optimal size of insurance groups can range from partial insurance at the community level, to full insurance in clusters, partial insurance in clusters, and no insurance at all. Another theoretical model by Fafchamps (1999) shows that repeated interaction among group members can support risk sharing, but the risk sharing arrangements with pure gift giving are susceptible to increases in risk or risk aversion while quasi-credit can overcome the constraints of pure gift giving. Bloch, Genicot, and Ray (2008) develop a model where a network risk sharing arrangement results from a collection of bilateral arrangements between linked individuals and the insurance arrangement of each linked pair is a function of their income, identities and net obligations to other individuals in the network. A main implication of this model is under intermediate levels of punishment, thickly and thinly connected networks tend to stable while connections with intermediate density tends to be unstable. More recently, Ambrus, Mobius, and Szeidl (2014) examine the degree and structure of risk sharing networks and show that the degree of insurance is characterised by the expansiveness of the network, which is the per capital number of connections that groups have with the rest of the community. Other related theoretical works include Karlan, Mobius, Rosenblat, and Szeidl (2009) and Bramoullé and Kranton (2007).

A growing literature has provided empirical and experimental evidences on the formation of risk-sharing networks. Fafchamps and Gubert (2007) study how risk sharing networks are formed in the rural Philippines and find the major determinant of insurance links is geographic proximity among villagers, which could represent their kinship. However, network links seem not to be the result of purposeful diversification of income and occupation. Foster and Rosenzweig (2001) use three panel data sets from rural India and Pakistan to examine the role of altruism in determining the degree of insurance in informal risk sharing arrangements. Their results show that imperfect commitment restricts efficient risk sharing but are reduced among altruistically linked households. Barr and Genicot (2008) employ an experimental approach to examine the effect of commitment and information in informal risk sharing, thus at the same time distinguishing between intrinsic and extrinsic incentives, which can act to foster commitment. The experiment involves a risk-sharing game where subjects can form groups to share gains from their gambles under three treatments that vary by the level of exogenous commitment and whether information on group members' defections is public or private. The findings show that limiting exogenous commitment leads to less risk sharing while limiting information on defections leads to more risk sharing. This implies that social sanctions can be costly or people have time-inconsistent preferences. Using a similar game design, Barr, Dekker, and Fafchamps (2012) and Attanasio, Barr, Cardenas, Genicot, and Meghir (2012) focus on the social networks of risk-sharing groups. The former examines who commits to share risk with whom under different enforcement mechanisms. They find people who join the same religious group and/or are related by marriage are more likely to form group in the presence of social sanctions. On the other hand, people who are in the same economic organizations are more likely to share risk when commitment is exogenously enforced or by intrinsic incentives but are less likely to share risk when social sanctions are possible. This again points to the high cost of social sanctions, which may be more prominent for members belonging to the same economic organizations. Attanasio et. al. (2012) investigate the roles of social networks and risk attitudes in risk sharing when the enforcement of risk sharing is neither externally enforced nor by social sanctions but is mostly based on trust. They find close friends are relatives are more likely to share risk with each other and assort by risk attitudes.

3. Cyclone AILA

In May 2009 Bangladesh experienced a catastrophic cyclone in some parts of its country. Though flooding is a normal part of the ecology of Bangladesh, the 2009 cyclone, known as "AILA", was particularly severe because of the depth and duration of saline water into homestead and cultivable land. More than a million people have been displaced and over a few hundred killed in just two districts, Satkhira and Khulna, which are worst. 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 other sources. Rice crops, shrimp farms, ponds and trees were also severely damaged.

Thousands of Cyclone AILA survivors hit have been hit again in February and March 2010- this time by flooding and swollen rivers after embankments were breached by high tides. The later has caused many villages inundated in the area when parts of the embankments protecting them were washed away. Hundreds of thousands of people are homeless, clustered into municipal buildings and schools, or are camping outside on higher ground and on road. Communities that were starting to recover have had their homes, crops and infrastructure destroyed again. It was learned that the embankment that were damaged by AILA were either not built at all or not built properly, resulting the wave of flood in early 2010. It is to be noted that unlike other coastal area such flood is very much uncommon in this coastal area of Bangladesh as it is protected largely by Sundarban, largest single block of tidal halophytic mangrove forest in the world. Thus the flood in this area is not common and is particularly a big shock to the households living in the area.

The Government of Bangladesh, in coordination with non-government organizations (NGOs), international organizations and bilateral donors, has rapidly responded to the flood emergency and assisted the affected population. The disaster management ministry with the help of donor agencies started rehabilitation of the AILA victims soon after the cyclone, with the promise of construction of embankments and cyclone centres, and to create employment opportunities in the affected areas. Many NGOs and the International Federation of Red Cross Red Crescent Societies responded rapidly to coordinate relief efforts.

Our main identification strategy is to exploit the variations of the intensity of shocks among the affected households as there are wide variations of flooding and related disaster across locality. There is also variation within a locality, and different households are impacted differently. For example, households in one side of the road are affected severely by flood water whereas households living in other side are not as flood water did not reach there (though both sides experienced cyclone). Therefore the variation in damage between locations and within location provides a potential instrument to identify the causal effect of cyclone on household outcomes.

4. Model and econometric specification

To test for resource sharing within the informal networks of neighbours and relatives following AILA, we examine how a household's and its network's exposure to AILA affect its investment and income. If resource pooling is efficient within the networks, we would expect no effect of household's own AILA exposure and significant effect of its network's AILA exposure on the outcome variables.

4.1. Theoretical framework

We follow the theoretical framework of resource sharing and investment in Angelucci et. al. (2012). This model is extended from the usual framework of insurance for household consumption against income shocks that has been widely used in the literature (pioneer studies include Townsend (1994); Udry (1994)). The model incorporates household's investment decision into the former model where only consumption decision is considered. In the model, we consider a pair of risk-averse households h=j, l, who live for two periods, t=1, 2. In each period each household receives an endowment y_h^t. In period t=1, the households have to make decision on how much to consume and invest. There are two choices of investments: I^s and I^p with rates of return $r^s > r^p$. I^p is continuously divisible while I^s is lumpy, 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, households strictly prefer to invest in I^s than I^p when endowments are high enough. The two households are assumed to have identical Pareto weights, a constant relative risk aversion (CRRA) utility function and a discount rate of 1. If there is complete resource sharing between the two households, the maximization problem for the pair is as followed:

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

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

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

$$c_h^t > 0,\ I_h^p \geq 0,\ I_h^s \geq I_{min}^s$$

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

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

$$I_h^s = 0$$

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:

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

$$I_h^p = 0$$

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

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

Thus if the 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 but does not depend on its own endowment. When the average endowment of other members in the network experienced a negative shock, either of the following scenarios could happen, depending on whether the pre-shock and post-shock total endowment is 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 only reduces the investment of I^p but does not change 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 the investment of I^s and increases the investment of 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 only reduces the investment of I^s but does not change I^p.

Although the direction of change for the investment of I^s and I^p might be ambiguous, we expect the total value of investment and household's income in the second period to be negatively affected by the adverse shock on the network. In another word, we expect households that belong to a network that was more affected by the disaster would have lower investment and lower income.

4.2. Empirical strategy

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

$$\Delta Y_{ijv} = Expose_i + Expose_j + X_i + \Delta X_i + \sigma_v + \varepsilon_{ijv} \text{ (1)};$$

where ΔY_{ijv} is the change in household i's outcome variables between two periods: post-AILA and pre-AILA. For post-AILA outcome variables, we look at two time frames: the short run which is three months after AILA was over in 2010 and the long run which is two years later in 2012. Due to data availability, we only have household monthly income and household monthly self-employment income as the outcome variables in the short run. The household income comprises both wage and home-based income while the self-employment income excludes wage income. For the long run, we have additional variables for livestock values and household's self-reported change in overall condition (whether household's condition is worsen). $Expose_i$ and $Expose_j$ are household i's and its network j's exposure to AILA. X_i and ΔX_i are pre-AILA household's characteristics and change in household's characteristics. σ_v is the village fixed effect. Since we use the change in household's outcome for the dependent variable there was no such community-wide disaster in the area during the period of at least two years before 2009 (so we can consider $Expose_i$ and $Expose_j$ as the change in exposures to disaster between the two periods), equation (2) is a difference-in-difference equation in which the household's and network's fixed effect is controlled for.

We exploit the fact that a household's exposure to AILA is idiosyncratic and unpredictable, thus treating the exposure as an exogenous shock to a household's resource. According to Morduch (1995), if an income shock is expected beforehand, households may have engaged in costly ex-ante smoothing strategies like diversifying crops and activities, thus we would find no effect in a household's ex-post coping mechanisms. This is not the case of AILA since natural disasters like AILA are not common in the area of study, as explained in the previous section. To measure a household's exposure to AILA, we use two variables: household's actual damage value and household's relief rate. The household's actual damage value is the household's total value of damaged assets after deducting its relief amount. The relief rate is the value of household's relief amount as a share of its total value of damaged assets. The value of household's relief amount is the total value of all relief (both in kind and cash) the household received from government and other organizations during AILA and three months later. Both these two variables take into account that a household that lost more from AILA could be compensated by receiving more relief, thus better measuring the shock to a household's resource rather than measuring only the household's damage value. Our main equations of interest are therefore:

$$\Delta Y_{ijv} = Actdamage_i + Actdamage_j + X_i + \Delta X_i + \sigma_v + \varepsilon_{ijv} \ (2a);$$

$$\Delta Y_{ijv} = Relief_i + Relief_j + X_i + \Delta X_i + \sigma_v + \varepsilon_{ijv} \ (2b);$$

Where $Actdamage_i$ and $Actdamage_j$ are the actual damage value of household i and the average actual damage value of network j, of which household i belongs to, respectively. $Relief_i$ and $Relief_j$ are the relief rate of household i and the average relief rate of network j, respectively.

However, there are potential concerns about the endogeneity of the actual damage value and relief rate variable, which could arise if they are correlated with the unobservables that could at the same time affect our outcome variables. For example, households that had more assets damaged during AILA could be those who were more endowed, thus were in better position to recover from AILA. On the other hand, more endowed households might be better protected against disasters, if for example their houses were more concrete and stable. Or households that receive more relief could be those who have better connection with village leaders and government officers, who were in charge of distributing relief. These households were thus likely to be more capable of recovering from the disaster due to better resource endowment and better network connection. Similarly, households whose informal risk-sharing networks receive more relief were also likely to recover better due to the same reason. If this is the case, the coefficients of a household's and its network's relief rate also reflects the effect of the household's resource endowment and social connection, thus overestimating the effect of its exposure to AILA. On the other hand, households that receive more relief could also be the less endowed and/or less connected households, who were more motivated to seek for relief. In this case, the effects of a household's and its network's exposure to AILA would be underestimated.

Another channel through which the endogeneity bias could arise is due to network formation is endogenous. De Weerdt and Dercon (2006) argue that concerns about trust and information flows might make households choose network partners with positively correlated income streams or on the other hand choose networks with negatively correlated income streams to better diversify the aggregate income. In both cases, the factors that determine a household's network partners could directly affect its consumption or in our case, its investment and income. In our case, although AILA is unpredictable, the endogeneity is present if a household chooses its network partners based on its knowledge about the partners' capability to cope with risk in general. However, the issue is partly resolved since we define a household's network by its existing kinship but not its self-reported risk-sharing network as defined in De Weerdt and Dercon (2006). It is thus less likely that households chose its relatives and neighbours taking into account their capability to cope with disasters. Moreover, in rural Bangladesh, a household's location of residence is mostly determined by its family heritance but not much of its own choice.

We address both sources of the endogeneity bias by the instrument variable method. This method can also deal with the issue of measurement error in the relief rate that is due to household's misreporting of the total relief amount and total damage amount. This kind of measurement error would tend to bring an attenuation bias that biases the coefficient towards zero. We instrument a household's and its network's relief rates by the number of days and the average number of days respectively it took for the roads to their home to get back to operation after AILA. A number of AILA aid reports have reported on the issue of roadblock that obstructed the 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 following natural disasters have also discussed the importance of road networks in effective response to disaster relief distribution (for example, Kovács and Spens (2007), Yan and Shih (2009)). We expect the longer it took for the road network to a household to recover, the lower level of relief rate that household would have received. While the roadblock is correlated with our endogenous variable, the relief rate, we believe it does not have any direct effect on the outcome variables or is correlated with a household's unobservables that could affect the outcome variables. Since floods are uncommon in the area, it is unlikely that households chose their residence in location where the road networks were better built to face with disasters. Moreover, our data show all roads were recovered within two to three months, thus we expect no direct long-term effect of the roadblock on household's investment and income. We however cannot find any suitable variable for the actual damage variable, thus we focus on analyzing the findings from using the relief rate variable.

We thus run the first-stage regressions as following:

$$Relief_{ijv} = Road_i + Road_j + X_i + \Delta X_i + \sigma_v + \varepsilon_{ijv} \text{ (3);}$$

and

$$Relief_{jv} = Road_i + Road_j + X_i + \Delta X_i + \sigma_v + \varepsilon_{ijv} \text{ (4)}$$

where $Road_i$ is the time (number of days) it took for the road networks to household i to recover and $Road_j$ is the average time for the network j. The main regression of interest or the second-stage regression is as following:

$$\Delta Y_{ijv} = \widehat{Relief}_i + \widehat{Relief}_j + X_i + \Delta X_i + \sigma_v + \varepsilon_{ijv} \text{ (5);}$$

where $\widehat{Relief}_i$ and $\widehat{Relief}_j$ are the predicted relief rates, which are estimated from the first-stage regressions (3) and (4). The standard errors are thus corrected to take into account the estimated value of the relief rate. We also cluster the standard errors at the village level.

A crucial assumption that we use in our model is the household's CRRA utility function is fixed, thus we assume there is no change to its risk behaviour after the disaster. This assumption may not hold in our context. If for example a household became less risk-taking due to the higher level of its exposure and its network's exposure to the disaster, the household might invest less in high-return but lumpy investment and we could not distinguish this effect from the effect of network's resource pooling. To examine the post-disaster risk-taking behaviour, we exploit the experimental data from a risk- taking and risk-pooling game that we conducted with the participation of the same households in 2012, at the same time when we did our follow-up survey. We examine whether a household and its network's exposure to AILA have any effect on the household's risk-taking and risk-sharing behaviour. Therefore we also run regression (5) for two additional dependent variables, which are measured from 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

Our survey dataset is a panel of two rounds in 2010 and 2012. The 2010 survey was conducted in June 2010, about three months after the cyclone AILA was over. We surveyed a total of 1,526 households in 50 affected villages in the two districts of Khulna and Satkhira. The survey comprises of questions about main household characteristics at both pre-AILA and post-AILA levels and specific questions about household's situation during and after AILA. Around the same time we had a separate survey of other 2,000 households which are in the same districts but are in villages that are not affected by AILA. This survey was conducted for another project but includes similar data on household characteristics as our survey of affected households.

In the 2nd round in 2012, we revisited and surveyed the same affected households as in 2010 survey. The follow-up survey focuses more on post-AILA coping mechanisms, migration and employment situation. The total number of affected households that we could follow is 1,447 households. Thus the attrition rate between the two rounds is 5.2%, which is relatively low. We randomly followed 1,024 households in the unaffected area. Thus in total we have a panel data set of 2,471 households. However, for the purpose of this paper we need information on the relationship between households within each village. The information is only available for a much smaller sample, which comprises of only households that participate in our experiment (as discussed later in the next section). Therefore, our final dataset comprises of 505 households in the affected villages and 461 households in the unaffected villages.

5.2. Experimental data

At the same time when we did the follow-up survey in 2012, for another project we conducted a risk-taking and risk-pooling game on a subset of our survey sample. The experiment follows Attanasio et. al. (2012) and Barr et. al. (2012), to examine the effects of pre-existing social networks and enforcement mechanisms on risk-sharing group formation. The game involves two rounds. In the first round, subjects were asked to choose one gamble out of six gamble options, ranked from the least to the most risky. In the second round, subjects play the gamble choice game again but have the option to form sharing groups with other subjects. Before playing the game, each subject was randomly allocated to one of three treatment groups, which are different in terms of whether or not and in which way (privately/publicly) subjects can choose to leave the sharing group after they know their own gamble outcome. We also collect data on the pre-existing relationship between each pair of subjects in the same session, so within a same village, which allows us to examine who share risk with whom under different enforcement mechanisms and whether their risk preferences affect the decision of whom to group with. Our main results show that subjects are most likely to group with relatives, and secondly with neighbours under all enforcement mechanisms. However, when the possibility of social sanction is present, the propensity to form groups with relatives is reduced. For the purpose of this paper we only use data on subject's level of risk-taking and risk-sharing which was measured in the first round and the second round of the game respectively. We do not account for different enforcement mechanisms that subjects were allocated in the second round. As the treatments are randomly allocated, we believe they do not affect our results.

5.3. Descriptive statistics

We report the descriptive statistics of our main dependent and independent variables in table 1. We observe a wide variation in households' exposure to the cyclone, in terms of the relief amount, value of damaged assets, relief rate, and damage rate. For example, the mean value of actual damaged value is 87,554 taka and the standard deviation is 94,902 taka while the mean relief rate is 19.9% with a standard deviation of 22.5%. The damage rate of 59.5% seems very high, partly due to our calculation that based on a proxy of total asset holdings but not the actual asset holdings. Since we do not have data on household's total value of assets, to calculate the damage rate we use 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 how much the damages were. The damage rate is calculated as the total of listed damage value divided by the total of listed asset value. However, we use the total damage amount which was reported separately to calculate the relief rate. The spread of the relief rate and the instrument variable, the roadblock time, is also relatively large. These statistics are consistent with our expectation that households in the affected area were affected differently, mostly due to the variation in their resident location.

The descriptive statistics of our outcome variables are reported at the bottom panel of table 1. In general the mean household's self-employment income and livestock holding were lower in 2012 compared with the levels before AILA. We only see an increase in the total household income. However, we might not attribute the decrease in self-employment income and livestock holding to the effect of AILA as we observe a similar trend among households who live in the unaffected villages. The household incomes in 2012 however were higher than the levels of the post-AILA level in 2010. This thus suggests households were severely hit shortly after the disaster but at least partly recovered two years later. For the amount of annual premium a household's willing to pay for formal insurance against disaster there is also a significant reduction in 2012 compared with 2010. This could be explained by their recovery from the disaster two years later, thus lowering their need for insurance. We also report the mean and standard deviation for variables on risk attitude. The 'risk-love' is a dummy variable and is constructed from the first stage of our risk-pooling game. The variable takes the value of one when the subject chose the two riskiest options in the game and takes the value of zero otherwise. The "risk-share" variable is also a dummy variable and based by subjects' decision whether to join a risk-pooling group in the second stage of the game. We find 44% of the subjects are risk loving and 91% of the subjects chose to share risk.

Table 2 shows statistics on household's mechanisms to cope with AILA and general health shocks. There are in general four main coping mechanisms: drawing from household's own money, borrowing from financial institutions or/and moneylenders, getting help from neighbours or/and relatives, and selling assets. In the specific case of AILA, another mechanism is to get relief from the government or/and NGOs. For general shocks, we only focus on the health shock as this is the most frequently reported shock and the existing literature on the effect of health shock on household outcomes is well establish (for example: Asfaw and Von Braun (2004), Dercon and Krishnan (2000), (De Weerdt & Dercon, 2006), Gertler and Gruber (2002), Wagstaff (2007). To cope with AILA, we look at how households finance the house repairing expenses and how they recover their damaged assets. We observe a few differences between coping mechanisms for general health shocks and for recovering from AILA. The most frequently reported mechanism for health shocks outside drawing from own money is getting help from neighbours and relatives while the main coping mechanism for AILA is getting relief. This shows the crucial role of receiving relief on household's recovering from a disaster. Only 10% or 12% of households reported getting help from neighbours and relatives to repair house or to recover damaged assets respectively while 25% seek for the help when faced with health shocks. This suggests the important role of network's resource sharing in insuring households against shocks: when all households in the network are affected by a common shock (like in the AILA case), the extent to which a household can seek help from another network member is limited. In this case, households have to resort to other coping mechanisms such as drawing from own money (which includes savings with interest) and selling valuable assets, which might be more costly in the long run. For example, we find 13% of households sold assets to recover from AILA while only 3% of them did so to cope with a health shock.

In table 3 we look at how frequent households seek help from neighbours and relatives to check whether our construction of the sharing network is appropriate. In the survey we asked whether a household received help from their neighbours or relatives when they are in need in general. The percentage of households that reported seeking help from relatives and neighbours is 54% and 52% respectively for money and 16% and 35% respectively for food. We also look at whether households during the last one month of the survey date borrowed from or lent to their relatives and neighbours who are also in our surveyed sample. Among households who had at least one neighbor in the sample, 53% reported borrowing from their neighbor(s) and 42% reported lending to their neighbours(s). Among 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 neighbours and relatives are an important source of resource sharing for households in our surveyed area.

6. Estimation results

6.1. What determines household's actual damage value and relief rate?

Before presenting our main results, we analyse factors that determine a household's actual damage value and relief rate and at the same time might affect the outcome variables. While we cannot look at a household's unobservable characteristics, some observable measures could offer an insight into which direction the OLS estimate of the effect of the variables is likely to be biased to. We look at three main factors: damage rate, social capital index, and per-capita income. The damage rate is defined as a household's value of damaged assets as a percentage of its total asset value. The social capital index is a proxy for household's connection with the local government and is calculated based on our eight survey questions on social capital. There has been a discussion in the literature on the issue of corruption in relief distribution post-disaster (for example, Garrettt & Sobel,). The literature suggests households with more political connection are favoured for more relief distribution. For the household's per-capita income, we use the pre-AILA level.

The results are presented in tables 4 and 5. We find all the three variables have significant effect on a household's actual damage and relief rate, either when we use them separately or together in one regression. The damage rate is positively correlated with the relief rate while the social capital index and the per-capita income are negatively correlated. The effect of the variables on the household's actual damage value is on the opposite direction. There seems to be no evidence that corruption took place during post-AILA relief distribution. The correlations thus suggest that households that were poorer, having less connection with government and more damaged by AILA were targeted by relief distribution policies and/or more motivated to seek for relief, thus more likely to receive more relief. Also, these less endowed households were likely to have lower value of assets damaged during AILA since they possessed fewer assets before the disaster. We also run similar regressions to test the relationship between a network's average actual damage and average relief rate and its damage rate, social capital index and per-capita income. The results are much similar to the household level results. These findings suggest that any effect of a household's relief rate or a network's relief rate, if it exists, would be biased downwards (in absolute value) since we expect households that were better off and less damaged would be in a better position to invest and recover from AILA. Similarly, we expect any effect of a household's and its network's actual damage to be biased downwards.

6.2. Main results: Role of informal sharing network in investment and income

6.2.1. OLS estimates

Tables 6 and 7 report the OLS estimates of the network's resource pooling equation. The results in table 6 are from using the household's and its network's relief rate. Although the results are not systematically consistent, most of the estimates show that households are fully insured either within its network or its village. The only exceptions are for the short-run change in self-employment income and the self-reported assessment of change in household situation (specifications (2) and (10)). Households with a higher relief rate seem to earn more self-employment income a few months after AILA passed and less likely to report that their household situation was worsen by AILA two years later. There is no effect of the network's average relief rate on these two measures. However, the network matters for household's long-run change in income, especially for self-employment income (specifications (4)-(6)). The magnitudes of these effects however are relatively small. For example, a 10%-point increase in a network's relief rate could lead to a 326 taka and 139 taka increase in household's total and per-capita monthly self-employment income respectively.

The results in table 7 reflect a similar trend. Network matters for household's long-run change in self-employment income and its self-reported assessment of general household situation (specifications (6) and (10). In both tables 6 and 7, although mostly not statistically significantly, the magnitude of the effect of network's exposure to AILA is higher than that of the household's exposure. As previously discussed on the potential endogeneity bias of the relief rate variable, the OLS estimates are prone to be biased downwards.

6.2.2. IV estimates

Before reporting our main results of the IV estimates for the effect of household's and its network's relief rate, we report the first-stage results in table 8. Both the instrument variables: household's roadblock time and network's roadblock time, are significantly (at lower than 1% level) correlated with the household's relief rate and network's relief rate respectively. The longer was the roadblock period the lower relief rate households would have received. In particular, one standard deviation of the roadblock time could lower household's relief rate by 3.5%-points and network's relief rate by 3.97%-points. The joint F-tests of excluded variables for both regressions are above 10 (columns (1) and (2)). The Kleibergen-Paap Wald F-statistics[1] is also high at 7.08, so we can reject the null hypothesis of weak identification at 10% maximal IV size. The results when we include non-AILA villages in the sample are similar (columns (3) and (4)) but with higher F-statistics[2].

The second-stage results are reported in table 9. We find household's relief rate consistenly did not have any significant effect on all outcome variables, both in short run and long run, suggesting households share resources efficiently within their village or informal network. We also find no effect of network's relief rate on household incomes in the short run. Thus, household's and network's exposure to the disaster might not matter in the short run when households were mostly affected by the general situation of the whole village when common facilities including water and electricity were still in bad condition. However, the informal network seems to matter in the long run. We find the network's relief rate has a positive and significant effect on household's long-run change in self-employment income (columns 5 & 6) but not in total income (columns 3 & 4). In particular, a 10%-points increase in a network's relief rate could lead to a 1,890 taka increase in self-employment monthly income or a 555 taka increase in self-employment monthly per-capita income for a household in the network. Therefore, households were fully insured within their informal network for the self-employment income. However, in the long run household's total income was not affected by either household or its network's exposure to AILA, thus households seem to be fully insured within the village for their wage income. This is understandable as wage income is more

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

[2] For households in non-AILA villages, the relief rate is inputted as one and the roadblock time is zero.

likely to be affected by the general change in the labour market in the whole village or district.

To understand about how the household's self-employment income is insured within its network, we look at the long-run change in its livestock holdings as a proxy for a household's investment[3]. We also look at two kinds of livestock: big livestock (cows, goats) and small livestock (poultry) separately. As argued in Angelucci et. al. (2012) and modelled in our theoretical framework, resource pooling within a network can relax liquidity constraints, channelling aggregate resources towards the high-return and lumpy goods. We find the network's relief rate has a significant and positive effect on the long-run change in household's total value of livestock and value of big livestock but not in the value of small livestock (columns 7-9). This is consistent with our hypothetical Scenario 3 where the aggregate network resource was high enough for households to invest in lumpy assets both before and after AILA. In particular, a 10%-point increase in a network's relief rate led to 4,160 taka and 4,640 taka increases in household's total livestock value and value of big livestock respectively. The finding suggests resource pooling within a household's informal network allowed the household to make more profitable investment, thus improving its self-employment income. This also means that a household that belongs to a network that was more exposed to AILA would have been limited in investment choices and opportunities to increase self-employment income.

We also look at the household's self-reported assessment of their household situation post AILA. The result is consistent with the results for income and investment. We find full resource pooling within the informal network as households were less likely to report their situation to be worsening when the network they belong to received a higher relief rate (column 10). In particular, a 10%-point increase in the network's relief rate lowered a household's propensity to report their household situation to be worsening by 0.25.

In table 10 we report a same set of long-run results as table 9 for the combined sample of all AILA and non-AILA villages, except for three outcome variables: total livestock holdings, small livestock holding, and propensity to report worsening situation, due to the lack of data

[3] Our data for household's other asset holdings are not sufficient and reliable enough to perform the investigation.

for the non-AILA villages. All the results are similar to the results for the sample of AILA villages only, with only the magnitudes of the effects are slightly smaller.

6.3. Does informal insurance crowd out formal insurance?

We test whether resource pooling within an informal network of neighbours and relatives reduces a household's need for a formal insurance against disaster. The results are reported in table 11. We use three outcome variables which are based on survey questions on how much annual premium the respondent was willing to pay for an insurance against disaster. In particular, the questions ask how much he/she wants to pay for an insurance company to provide with the full value of damaged assets/ half value of damaged assets/ the need of facilities during and after the disaster. The survey questions were asked both in 2010 just after AILA and in 2012. Since we are interested in the long-run effect of network sharing, we use the same specification as in the first-stage equation (3) and (4) and the second-stage equation (5), thus the dependent variable is the change in the annual premium the respondent was willing to pay between 2010 and 2012.

Our results reported in section 2 suggest that resource pooling within the informal network was efficient in the long run for a household to recover from AILA through investment and self-employment income. Therefore, if the informal network crowded out the formal insurance, we would expect households which belong to a network that was less exposed to AILA to have a reduced need for formal insurance during the period 2010-2012, compared with households which belong to a more exposed network. The results in table 11 support this hypothesis. Households that belong to a network with a higher relief rate were willing to pay less for the insurance premium against disaster. For example, a 10%-point increase in the network's relief rate lowered the premium by 1,695 taka for a full insurance and by 1,067 taka for a half insurance against asset loss. The crowding-out effect on the insurance that caters to the facility needs during and after AILA is relatively smaller. This could be due to the effect of network's resource sharing, which was channeled through the network's relief rate, was present mostly in the long run when the recovery from the disaster took place rather than during and shortly after the disaster.

6.4. Does exposure to AILA change risk attitude?

Table 12 reports the results on whether household and network's exposure to AILA have any effect on household's risk-taking behaviour. If the household's risk-taking behaviour changed due to its exposure and its network's exposure to AILA, we might not disentangle this effect from the effect of the network's resource pooling and any change in a household's long-run investment and income might be due to either/both of these effects. We use two outcome variables obtained from our risk game to measure a household's risk-taking behaviour: 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 a household and its network received changed the household's risk-taking and risk-sharing behaviour. While the risk attitude could be different between those who experienced a disaster and those who did not as suggested by the findings in Cameron & Shah (2013), our results show that there is no difference among those who are exposed to AILA at different levels. Therefore, the effect of network's relief rate on a household's investment and income is most likely to be fuelled by the efficient resource-pooling within the network.

7. Conclusion

Our paper has provided evidence on resource sharing within the informal network of neighbours and relatives for the rural households to recover from a natural disaster. While our findings show the disaster still had effect on household's investment and income two years after the cyclone AILA passed, the effect is efficiently shared within the household's informal network. We find no significant effect of household's own exposure to the disaster but only significant effect of its network's exposure on household's investment and income. Households who belong to a network of which member households in average were less affected by the disaster invested more in lumpy assets like big livestock, and as a result had lower self-employment income two years after the disaster, compared with those who belong to a more affected network. We also find a crowding-out effect of the informal sharing network on the formal insurance against disaster. Households who belong to a less affected network were willing to pay less for the formal insurance against disaster. We also find evidence that household's risk attitude was not affected by household's and its network's exposure to the disaster. Therefore, we can exclude this effect and attribute the effect of the network's exposure to AILA solely to the sharing of resource within the informal network.

Our findings have affirmed the important role of the informal resource-sharing network in insurance against income shock. The informal network does not only matter in household's consumption smoothing but also in household's investment and income. Even when households are faced with a community-wide disaster like cyclone AILA to which all network members are exposed, resource sharing within the network was fully efficient in the long-run process of recovering from the disaster. Moreover, the findings also offer important policy implications for formal insurance against disaster and post-disaster policies, such as those regarding relief distribution. It is necessary to take into account the interaction among affected households within the community as part of the externality of the policy.

Table 1: Main household descriptive statistics				
No. obs=448	**2010**		**2012**	
Variable	**mean/%**	**s.d**	**mean/%**	**s.d**
relief amount (taka)	13,514	12,981		
damage value (taka)	101,068	94,508		
actual damage value (taka)	87,554	94,902		
relief rate (%)	19.87	22.45		
damage rate (%)	59.46	29.40		
roadblock time (no. days)	50.50	40.81		
water height (ft)	6.57	1.32		
water stay (no. days)	6.52	0.87		
head's age	46.42	13.07		
head's schooling (no. years)	3.49	3.99		
female head	0.03	0.17		
no. adult members	3.21	1.30		
no. child members	1.51	1.10		
monthly household income (taka)	5,677	2,993	7,072	5,559
monthly household income after AILA (taka)	3,667	2,400		
monthly self-employment income (taka)	2,891	3,279	2,226	3,384
monthly self-employment income after AILA (taka)	1,643	1,988		
monthly per-capita (adult equiv.) income (taka)	1,451	622	1,808	1,312
monthly per-capita (adult equiv.) self-employment income (taka)	767	868	602	939
total livestock value (taka)	6,258	8,334	2,962	5,485
big livestock value (taka)	4,790	7,998	1,935	4,962
small livestock value (taka)	1,467	1,588	864	1,092
% subjects who are risk-loving			44	
% subjects who joined risk-sharing groups			91	
willingness to pay for full insurance (taka)	6,153	4,484	1,066	1,092
willingness to pay for half insurance (taka)	4,393	3,003	686	698
willingness to pay for facility insurance (taka)	2,824	1,856	457	423

Table 2: Coping mechanisms			
% households	**health shock (N=225)**	**repair house after AILA (N=454)**	**recover 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/neighbours	25	10	12
selling assets	3		13
getting relief		56	62

Table 3: Borrowing/lending activities among relatives and neighbours	
% households receive help from relatives/neighbours (N=505)	
from relatives for money	54
from relatives for food	16
from neighbours for money	52
from neighbours food	35
% households borrowing from/lending to relatives/neighbours in the sample	
borrow from neighbours (N=497)	53
borrow from relatives (N=173)	47
lend to neighbours (N=497)	52
lend to relatives (N=173)	49

Table 4: What determines relief rate?

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

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

Table 5: What determines actual damage value?

	(1)	(2)	(3)	(4)
damage rate (%)	-0.0046***			-0.0047***
	(0.0012)			(0.0011)
social capital index (%)		0.029***		0.030***
		(0.0051)		(0.0043)
log(income per capita)			0.32***	0.33***
			(0.098)	(0.091)
No. obs	474	474	474	474
R-sq	0.098	0.109	0.097	0.161

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

Table 6: OLS estimates: effect of household and network relief rate on short-run and long-run 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	6.42	10.7**	-10.8	-2.73	14.7
	(5.95)	(3.76)	(9.56)	(2.71)	(10.4)
network's relief rate	-6.48	-19.2	9.53	11.1	23.0
	(16.3)	(12.5)	(23.8)	(6.86)	(21.1)
N	445	445	445	445	445
R-sq	0.422	0.344	0.097	0.133	0.112
	(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	3.08	30.9	25.0	0.22	-0.0029*
	(2.94)	(31.3)	(30.7)	(6.45)	(0.0015)
network's relief rate	12.4*	26.4	27.9	-6.08	-0.0064
	(6.16)	(55.3)	(53.5)	(14.6)	(0.0048)
N	445	445	445	445	445
R-sq	0.165	0.036	0.031	0.016	0.036

All specifications include 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 number of adult members, change in number of children. All specifications control for village fixed effect and correct standard errors for village clusters. The corrected standard errors are in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 7: OLS estimates: effect of household and network actual damage value on short-run and long-run outcomes

	(1)	(2)	(3)	(4)	(5)
	SR income	SR self-employment income	LR income	LR per-capita income	LR self-employment income
household's actual damage	-290.3***	-405.6***	747.2	189.2	-329.4
	(54.8)	(59.4)	(602.8)	(149.1)	(249.5)
network's actual damage	42.9	5.87	503.2	-3.27	-556.6
	(344.2)	(275.0)	(474.4)	(100.7)	(396.2)
N	448	448	448	448	448
R-sq	0.448	0.361	0.107	0.141	0.115
	(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 actual damage	-72.6	-300.2	-403.0	123.8	0.030
	(64.9)	(710.3)	(745.7)	(140.0)	(0.030)
network's actual damage	-180.9*	-1074.2	-815.7	-242.6	0.17*
	(102.3)	(1772.4)	(1775.9)	(305.2)	(0.088)
N	448	448	448	448	448
R-sq	0.160	0.020	0.017	0.022	0.033

All specifications include 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 number of adult members, change in number of children. All specifications control for village fixed effect and correct standard errors for village clusters. The corrected standard errors are in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 8: IV first-stage: effect of household and network relief rate on short-run and long-run 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***	-0.020***	-0.093***	-0.020***
	(0.017)	(0.0048)	(0.017)	(0.0046)
network's roadblock time	-0.032	-0.13***	-0.029	-0.13***
	(0.049)	(0.035)	(0.047)	(0.034)
N	445	445	873	873
R-sq	0.141	0.193	0.114	0.189
F-test	19.63	13.66	25.75	14.50
Weak identification test:				
Kleibergen-Paap Wald rk F-test	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		

All specifications include 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 number of adult members, change in number of children. All specifications control for village fixed effect and correct standard errors for village clusters. The corrected standard errors are in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 9: IV second-stage (AILA villages only): effect of household and network relief rate on short-run and long-run 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	31.9	-520.9	-128.2	-75.3
	(35.7)	(30.6)	(518.0)	(126.3)	(102.1)
network's relief rate	32.7	13.4	464.9	132.9	189.0*
	(65.3)	(45.6)	(384.3)	(95.2)	(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	-114.8	-128.3	41.1	0.0038
	(26.4)	(157.9)	(127.3)	(48.0)	(0.012)
network's relief rate	55.5**	416.0*	464.0**	-49.8	-0.025**
	(28.2)	(232.6)	(184.5)	(63.4)	(0.012)
N	445	445	445	445	445

All specifications include 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 number of adult members, change in number of children. All specifications control for village fixed effect and correct standard errors for village clusters. The corrected standard errors are in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 10: IV second-stage (AILA and non-AILA villages): effect of household and network relief rate on short-run and long-run 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	-120.4	-61.8	-8.03	-47.3
	(490.1)	(118.8)	(91.8)	(23.4)	(116.3)
network's relief rate	452.0	128.0	174.3*	51.8**	398.1**
	(366.9)	(90.6)	(90.5)	(25.7)	(170.1)
N	873	873	873	873	873

All specifications include 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 number of adult members, change in number of children. All specifications control for village fixed effect and correct standard errors for village clusters. The corrected standard errors are in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 11: Does informal insurance crowd out formal insurance?			
	(1)	(2)	(3)
	full insurance	half insurance	facility insurance
household's relief rate	158.8	96.8	65.4
	(120.7)	(76.7)	(49.4)
network's relief rate	-169.5***	-106.7**	-56.4*
	(63.7)	(45.6)	(30.9)
N	445	445	445

All specifications include 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 number of adult members, change in number of children. All specifications control for village fixed effect and correct standard errors for village clusters. The corrected standard errors are in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 12: Risk attitude				
	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	0.0041	-0.0072	0.0032
	(0.011)	(0.0054)	(0.010)	(0.0055)
network's relief rate	0.0047	0.0033	0.0045	0.0040
	(0.010)	(0.0064)	(0.0099)	(0.0060)
N	445	445	873	873

All specifications include 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 number of adult members, change in number of children. All specifications control for village fixed effect and correct standard errors for village clusters. The corrected standard errors are in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%

References

Ambrus, A., Mobius, M., & Szeidl, A. (2014). Consumption Risk-Sharing in Social Networks. *American Economic Review, 104*(1), 149-182.

Angelucci, M., De Giorgi, G., & Rasul, I. (2012). Resource Pooling Within Family Networks: Insurance and Investment.

Asfaw, A., & Von Braun, J. (2004). Is consumption insured against illness? Evidence on vulnerability of households to health shocks in rural Ethiopia. *Economic Development and Cultural Change, 53*(1), 115-129.

Attanasio, O., Barr, A., Cardenas, J. C., Genicot, G., & Meghir, C. (2012). Risk pooling, risk preferences, and social networ. *American Economic Journal: Applied Economics, 4*(2), 134-167.

Barr, A., Dekker, M., & Fafchamps, M. (2012). Who shares risk with whom under different enforcement mechanisms? *Economic Development and Cultural Change, 60*(4), 677-706.

Barr, A., & Genicot, G. (2008). Risk sharing, commitment, and information: an experimental analysis. *Journal of the European Economic Association, 6*(6), 1151-1185.

Bloch, F., Genicot, G., & Ray, D. (2008). Informal insurance in social networks. *Journal of Economic Theory, 143*(1), 36-58.

Bramoullé, Y., & Kranton, R. (2007). Risk-sharing networks. *Journal of Economic Behavior & Organization, 64*(3), 275-294.

Cameron, L., & Shah, M. (2013). Risk-taking behavior in the wake of natural disasters: National Bureau of Economic Research.

De Weerdt, J., & Dercon, S. (2006). Risk-sharing networks and insurance against illness. *Journal of Development Economics, 81*(2), 337-356.

Deaton, A. (1992). Saving and income smoothing in Cote d'Ivoire. *Journal of African Economies, 1*(1), 1-24.

Deaton, A. (1997). *The analysis of household surveys: a microeconometric approach to development policy*: World Bank Publications.

Dercon, S., & Krishnan, P. (2000). In sickness and in health: Risk sharing within households in rural Ethiopia. *Journal of Political Economy, 108*(4), 688-727.

Fafchamps, M. (1999). Risk sharing and quasi-credit. *Journal of International Trade & Economic Development, 8*(3), 257-278.

Fafchamps, M., & Gubert, F. (2007). The formation of risk sharing networks. *Journal of Development Economics, 83*(2), 326-350.

Fafchamps, M., & Lund, S. (2003). Risk-sharing networks in rural Philippines. *Journal of Development Economics, 71*(2), 261-287.

Foster, A. D., & Rosenzweig, M. R. (2001). Imperfect commitment, altruism, and the family: Evidence from transfer behavior in low-income rural areas. *Review of Economics and Statistics, 83*(3), 389-407.

Garrett, T. A., & Sobel, R. S. (2003). The political economy of FEMA disaster payments. *Economic Inquiry, 41*(3), 496-509.

Genicot, G., & Ray, D. (2003). Group formation in risk-sharing arrangements. *The Review of Economic Studies, 70*(1), 87-113.

Gertler, P., & Gruber, J. (2002). Insuring Consumption Against Illness. *The American Economic Review*.

Grimard, F. (1997). Household consumption smoothing through ethnic ties: evidence from Cote d'Ivoire. *Journal of Development Economics, 53*(2), 391-422.

International Federation of Red Cross and Red Crescent Societies. (2009). Emergency appeal no MDRBD004, Glide no TC-2009-000105-BGD.

Karlan, D., Mobius, M., Rosenblat, T., & Szeidl, A. (2009). Trust and social collateral. *The Quarterly Journal of Economics, 124*(3), 1307-1361.

Kovács, G., & Spens, K. M. (2007). Humanitarian logistics in disaster relief operations. *International Journal of Physical Distribution & Logistics Management, 37*(2), 99-114.

Ligon, E., Thomas, J. P., & Worrall, T. (2002). Informal insurance arrangements with limited commitment: Theory and evidence from village economies. *The Review of Economic Studies, 69*(1), 209-244.

Morduch, J. (1990). Risk, production and saving: Theory and evidence from Indian households. *Harvard University, Manuscript*.

Morduch, J. (1995). Income smoothing and consumption smoothing. *The journal of economic perspectives*, 103-114.

Munshi, K., & Rosenzweig, M. (2009). Why is mobility in India so low? Social insurance, inequality, and growth: National Bureau of Economic Research.

Murgai, R., Winters, P., Sadoulet, E., & Janvry, A. d. (2002). Localized and incomplete mutual insurance. *Journal of Development Economics, 67*(2), 245-274.

Townsend, R. M. (1994). Risk and insurance in village India. *Econometrica: journal of the Econometric Society*, 539-591.

Udry, C. (1994). Risk and insurance in a rural credit market: An empirical investigation in northern Nigeria. *The Review of Economic Studies, 61*(3), 495-526.

Wagstaff, A. (2007). The economic consequences of health shocks: evidence from Vietnam. *Journal of health economics, 26*(1), 82-100.

Yan, S., & Shih, Y.-L. (2009). Optimal scheduling of emergency roadway repair and subsequent relief distribution. *Computers & Operations Research, 36*(6), 2049-2065.