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Does Social Capital Encourage Disaster Evacuation? Evidence from a Cyclone in Bangladesh

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Abstract

Prompt evacuation is essential to survival from natural disasters, but the mechanisms behind individuals' decisions to evacuate are not well understood. Using unique survey data collected from cyclone-affected households in Bangladesh, we examine the association between social capital and the decision to evacuate. Given the difficulty in controlling for endogeneity of self-reported social capital, we employ the approach of Oster (2017) to assess the severity of omitted variable bias. We find that those with higher social capital are more likely to evacuate. This is because they perceive a lower risk of theft during evacuation, suggesting that social capital compensates for the lack of a well-functioning law enforcement authority. Further, we cannot rule out the possibility that social capital strengthens the effectiveness of an early warning system. These findings could also contribute to our understanding of the interactive roles of communities and institutions during natural disasters.

Keywords: social capital, natural disasters, evacuation, Bangladesh, Cyclone Aila

JEL Codes: D91, H12, H84, Q54

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1. Introduction

Natural disasters cause immense damage, of which the loss of human lives is one of the most crucial for economies and societies (Kahn 2005, Strömberg 2007). Between 1996 and 2015, 1.35 million people have been killed by 7000 natural disasters worldwide (UNISDR and CRED 2016). It is, therefore, essential for most countries to have effective policies to save the lives of their population, such as policies to encourage prompt evacuation. While empirical studies on evacuation behavior exist, they mostly rely on case studies of hurricanes in the U.S.[1] Evidence from developing countries is scarce despite their vulnerability to disaster risks (Mallick et al. 2011, Paul 2012, Tobin and Whiteford 2002). This lack of knowledge is particularly surprising, since many studies have examined how households and states in developing countries mitigate *economic* damages from disasters (Sawada 2007, Skoufias 2003).

This study bridges the gap in the literature by examining the association between social capital and evacuation behavior during a cyclone in rural Bangladesh.[2] It is important to analyze the effects of social capital for two reasons. First, although previous studies have revealed the multifaceted roles of social capital in post-disaster rehabilitation (Aldrich 2012, Aldrich and Meyer 2015, Carter and Castillo 2005, Nakagawa and Shaw 2004), there are few empirical studies on the effects of social capital on evacuation behavior.[3] Exceptionally, Riad et al. (2006) examine two hurricanes in the U.S. to show that a strong perception of social support is positively associated with evacuation. Aldrich and Sawada (2015) also find that social capital

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[1] See Baker (1991), Burnside et al. (2007) Dash and Gladwin (2007), Gladwin and Peacock (1997), Smith and McCarty (2009), Trainor et al. (2006), and Zhang et al. (2004), among others.

[2] Social capital is defined as informal institutions and organizations that are based on social relationships, networks, and associations that create shared knowledge, mutual trust, social norms, and unwritten rules (Durlauf and Fafchamps 2005).

[3] Existing arguments mainly rely on descriptive evidence, such as Airriess et al. (2008), Dynes (2006), Klinenberg (2003), and Zakour (2008).

significantly reduced the mortality rate of tsunami-affected municipalities in Tohoku, Japan. However, to the best of our knowledge evidence from developing countries does not exist.

Second, it is theoretically ambiguous whether social capital encourages evacuation. On the one hand, social capital may have a positive effect; previous studies show various obstacles to evacuation, such as (1) the inaccuracy of the early warning systems and individuals' risk perception, (2) the risk of falling victim to theft during the evacuation, (3) the loss of income-earning opportunities, and (4) poor accessibility of cyclone shelters (Dash and Gladwin 2007, Eisenman et al. 2007, Haque et al. 2012, Mallick et al. 2011, Paul and Dutt 2010, Riad et al. 2006, Smith and McCarty 2009). However, social capital may address these problems as it helps people obtain reliable information about disasters (Fafchamps and Minten 2002, Granovetter 2005) and lowers the perceived risk of theft (Schechter 2007). Those with higher social capital may also receive a larger amount of support from neighbors and the local government, mitigating the income opportunity costs of evacuation (Besley 1995, Fafchamps and Lund 2003, Galasso and Ravallion 2005, Mahmud and Prowse 2012). Further, social capital may facilitate collective actions among villagers and therefore have a positive effect on the condition of roads to the shelter. On the other hand, social capital could also have the opposite effects: evacuees lose the opportunity to benefit from the social capital in the original community, such as risk sharing arrangement. Therefore, the higher the social capital is, the higher the opportunity cost of evacuation will be.

It would be particularly revealing to explore the evacuation behavior of Bangladeshi households, since this country is prone to cyclones; 159 cyclones hit the country between 1877 and 2009 (Mallick et al. 2011). Given that only 10% of the territory sits one meter above the mean sea level (Mohal et al. 2006) and 30% of the total population lives in the coastal areas (Mallick et al. 2011), even incrementally small elevations in the sea level could have severely negative effects.

This study exploits unique survey data collected from 427 households after Cyclone Aila which hit rural Bangladesh in 2009. The data show that 60% of residences were inundated during the cyclone but only 41% evacuated, of which evacuation to emergency shelters accounted for only 15%. Social capital is elicited via three attitudinal measures including generalized trust and two behavioral measures including the size of a household's information sharing network. We also conduct a principal component analysis for robustness. Given the unavailability of appropriate instrumental variables to control for endogeneity of social capital, we employ the Ordinary Least Squares (OLS) Regression and assess the sensitivity of coefficients to omitted variable bias by using the method proposed by Oster (2017).

To preview the results, first, villagers with higher social capital are more likely to evacuate. The sensitivity test of Oster (2017) suggests that the results cannot be explained by unobserved economic status or cyclone damage. This is consistent with the previous descriptive evidence (Airriess et al. 2008, Dynes 2006, Klinenberg 2003, Zakour 2008) and the empirical studies of developed countries (Aldrich and Sawada 2015, Riad et al. 2006). Therefore, our finding confirms that the positive effects of social capital are observed even in a poor and disaster-vulnerable country.

Second, we also find that the significant effect of social capital is mainly driven by the low perceived risk of crime victimization; the impact of social capital is smaller for those who trust law enforcement authorities. Further, we cannot fully rule out the possibility that social capital strengthens the effectiveness of early warning system; those with higher social capital are more likely to receive warning messages from volunteer workers. To the best of our knowledge, this is the first study to empirically uncover the channels through which social capital influences disaster evacuation.

Further, the second finding could also contribute to our understanding of the interactive roles of communities and institutions during natural disasters. Existing studies on disaster resilience emphasize the importance of strong communities and institutions along with the development of physical infrastructure (Ainuddin and Routray 2012, Cutter et al. 2008, Norris et al. 2008, Sherrieb et al. 2010). However, it is largely unexplored whether they play complementary or substituting roles. This study suggests that the relationship could differ across the types of institutions; social capital compensates for the lack of a well-functioning law enforcement authority, while the early warning system does not work without social capital.

The rest of this study is organized as follows. Section 2 summarizes obstacles to evacuation and the potential roles of social capital. The study site and dataset are documented in Section 3. Section 4 discusses our identification strategy and Section 5 presents the results. Section 6 examines the underlying mechanisms, and finally Section 7 concludes.

2. Obstacles to Evacuation and the Roles of Social Capital

Bangladesh has long been considered one of the most disaster-vulnerable countries in the world. The climatic and geographic conditions of this country make it prone to disasters, such as tropical cyclones and floods, while poor disaster management infrastructure and governance make their damages even larger. In the 1970s, it had the highest number of disaster victims among neighboring countries (Figure 1). Although the country has had remarkable success in reducing the number of victims, the risk of disaster still poses a crucial obstacle to achieving its development potential. Bangladesh experienced 97 disasters, including 49 storms and 26 floods, between 2001 and 2015 (Table 1).[4] A total of 10,185 human lives were lost during the same period, of which around half were killed by the storms, particularly tropical cyclones.

[Figure 1]

[Table 1]

[4] Source: EM-DAT.

The significant amount of human loss could be reduced if people at risk evacuate promptly. However, existing studies suggest four major obstacles to evacuation. First, people cannot evacuate promptly without accurate early-warning messages. In Bangladesh, the Cyclone Preparedness Programme (CPP) was initiated in 1972 to a) disseminate cyclone warning signals through an extensive telecommunication network; b) provide first aid, rescue, relief, and rehabilitation operations; c) coordinate with the government; and d) build up the capacity of the community. CPP is made up of local teams of volunteer workers. Nonetheless, people did not pay attention to the warnings during Cyclone Aila in 2009, despite the timely announcement of the evacuation order by the CPP volunteers. This is mainly because they did not trust the accuracy of the warnings, the evacuation orders were issued too long before the storm's landfall, and the warning messages were incomplete (Mallick et al. 2011). This issue is particularly critical in rural Bangladesh because some coastal inhabitants still rely on indigenous early warning indicators of cyclone hazards that are based on an observation of unusual weather, sea patterns, and animal behavior (Howell 2003).

Second, it is reported in many countries that thefts increase during and after natural disasters (Bignon et al. 2017, Harper and Frailing 2010, Mehlum et al. 2006). The increases in crimes were also documented in the case of Cyclone Aila (Azad and Khan 2015, Saha 2015, Shoji 2018b). Thus, people are exposed to a high risk of robbery during the evacuation, which could be a disincentive particularly in regions with ineffective law enforcement authorities (Dash and Gladwin 2007, Eisenman et al. 2007, Riad et al. 2006, Smith and McCarty 2009).

Third, evacuees may suffer from a significant amount of income loss during and even after the evacuation, since some disasters could occur during the planting or harvest period. Agricultural products such as paddy need to be dried after harvest. Therefore, farmers have to protect their products from exposure to heavy rain and inundation during cyclones. If the farmers evacuate and do not take care of their products, they might lose their seasonal income. Further, wage workers could be fired if they evacuate during the busy period (Eisenman et al. 2007).

The fourth obstacle is poor access to emergency shelters. The shelters in the coastal regions play a central role in protecting human lives during cyclones. However, the existing cyclone shelters do not have the capacity to accommodate the entire coastal population, and their geographic distribution continues to be inadequate (Haque et al. 2012, Mallick et al. 2017, Paul and Dutt 2010). The roads to the shelters may not be well maintained. These issues are aggravated by the fact that many existing cyclone shelters are in a dilapidated condition with broken windows and a lack of water and sanitation facilities (Dasgupta et al. 2010).

These arguments suggest four potential roles of social capital in encouraging prompt evacuation. First, social capital facilitates information sharing among community members (Fafchamps and Minten 2002, Granovetter 2005). As such, those with higher social capital may obtain information on disasters more frequently and quickly from the neighbors. Further, even CPP volunteers may disseminate the disaster warning to their friends more carefully or accurately than to the other villagers. Second, people hesitate to evacuate due to the risk of victimization to property crime. However, those who trust their neighbors may anticipate a lower risk of being victimized (Schechter 2007). Third, those with a larger social network may more easily find job opportunities to compensate for the income loss after the evacuation (Calvó-Armengol and Jackson 2004, Ioannides and Loury 2004, Montgomery 1991). Villagers with higher social capital could also ask for supports such as informal loans from neighbors to cope with the income loss (Besley 1995, Fafchamps and Lund 2003). In addition, those who have a network that includes community leaders may be more likely to receive disaster relief than those who don’t (Galasso and Ravallion 2005, Mahmud and Prowse 2012). Finally, social capital facilitates collective actions such as public goods management (Anderson et al. 2004, Bardhan 2000, Bouma et al. 2008, Fehr and Leibbrandt 2010). Therefore, the conditions of roads to emergency shelters may improve as a result of social capital.

3. Dataset

3.1 Study Site and Household Survey

The study site is Satkhira District, located in southwest Bangladesh. Since the district is located in a river delta plain, it is vulnerable to floods and cyclones. In particular, on 25 May 2009 this district was severely affected by Cyclone Aila, a category 1 cyclonic storm with wind speeds reaching 100 km/hour. The water reached approximately 10 to 12 feet above its normal height (Mallick and Vogt 2012). The cyclone killed 190 and affected four million people in the country.[5] In all, 650,000 houses were destroyed fully or partially. It also caused significant economic loss, destroying around 250,000 acres of cropland and killing 150,000 livestock.[6]

Although the magnitude of cyclone was large, the damage to housing and human lives was smaller than those caused by other disasters that hit the country around the same time, such as Cyclone Sidr in 2007. Therefore, there is less possibility of sample selection caused by death and migration, making Cyclone Aila preferable for the study of evacuation behavior.[7]

The household survey was conducted in the district in December 2010, 19 months after the cyclone. We employed a multistage stratified random sampling methodology. In the first stage, we selected the three sub-districts (*upazila*) of Samnagar, Kaliganj, and Ashashoni, based

[5] Based on the EM-DAT: The International Disaster Database by Centre for Research on the Epidemiology of Disasters (CRED), accessed on 13 May 2017; for more details see http://www.emdat.be/disaster_list/index.html.

[6] For more details about the cyclone damage and post-cyclone rehabilitation, see Mallick and Vogt (2012, 2014), Saha (2015), Mahmud and Prowse (2012), Sultana and Mallick (2015), and Mallick et al. (2011).

[7] Mallick and Vogt (2012) and Saha (2015) have found increases in migration after Cyclone Aila from severely affected regions to urban regions. However, Mallick and Vogt (2012, p. 226) claim that only male members of the households migrated. Saha (2015) studies only three of the most-affected villages, which were non-randomly selected, whereas this study uses stratified random sampling to select 24 villages (and the villages he studied are not included). Therefore, there should be no severe bias in the selection of survey households.

on their economic status and the intensity of the cyclone damage. In the second stage, we randomly sampled two *unions* from each sub-district.[8] Figure A1 depicts the location of surveyed unions along with the severity of inundation. In the next stage, four villages from each *union* and one cluster (*para*) from each of the villages were randomly selected. Finally, we selected 18 households from each *para*. Since five households were unavailable for the survey, we obtained a total of 427 of 432 sample households from 24 *para*. Appendix 1 (available in Supplementary Materials) discusses the survey design such as the representativeness of the sample villages, sample size, and questionnaire design.

A challenge in this survey is the elicitation of pre-cyclone social capital in a survey conducted after. Recent studies conduct economic experiments to measure interpersonal trust and cooperativeness (Bouma et al. 2008, Carter and Castillo 2011, Fehr and Leibbrandt 2011, Karlan 2005, Kosfeld and Rustagi 2015, Sawada et al. 2013), but by structure these do not allow us to quantify the social capital of the past. This is crucial, given that the level of social capital could change following the experience of a disaster (Cassar et al. 2017, Shoji 2018a, 2018b). Thus, we consider that the experimental approach is not suitable in the context of this study.

Other researchers use attitudinal and behavioral measures (Anderson et al. 2004, Grootaert et al. 2004). The former elicits the respondents' subjective perception about the relationship with the others, e.g., trust. The latter exploits the behaviors that are closely related with social capital, such as the frequency of communication with neighbors, the amount contributed to community events, or the comfort to leave home with the door unlocked (Anderson et al. 2004). In contrast to the experimental measures, it is easier for respondents to retrospectively report these measures from the pre-cyclone period. However, these measures also have some drawbacks; since the attitudinal measure is based on the subjective perception,

[8] The *union* is an administrative unit in Bangladesh; each *union* contains multiple villages.

measurement errors are likely to be serious. While the behavioral measure is objective, it captures only particular aspects of social capital, such as information sharing and beliefs about the risk of theft.

Given these arguments, this study exploits three attitudinal and two behavioral measures. The former includes generalized trust, helpfulness, and fairness,[9] and the latter includes the number of households the respondent would share information with about income-earning activities, and monthly expenditure for ceremonies. For robustness we also conduct the principal component analysis to aggregate these five measures into a single social capital indicator. The survey respondents were asked to answer these questions for four different periods: before the cyclone, the first six months after the cyclone, the next six months, and during the last six months before the survey. This study uses the level of social capital at the pre-cyclone period for the empirical analyses.

Our social capital measures are in line with Putnam's (1993) definition that social capital consists of trust, network, and social norms. Further, Woolcock (2000) categorizes social capital into three types, such as bonding, bridging, and linking social capital.[10] However, our measures cannot completely disentangle the three. We should therefore consider that each measure consists of the three types of social capital.

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[9] Specifically, the respondents were asked the following questions. Generalized trust: *generally speaking, would you say that (1) most people can be trusted, (2) you can't be too careful, or (3) no idea*? Information sharing network: *with how many people could you share information on your income earning activities?* Helpfulness: *would you say that most of the time people (1) try to be helpful, (2) are just looking out for themselves, or (3) no idea*? Fairness: *do you think most people (1) would take advantage of you, (2) would try to be fair, or (3) no idea*?

[10] Bonding social capital is characterized by ties between immediate family members, neighbors, close friends, and business associates sharing similar demographic characteristics. Bridging social capital are ties among people from different ethnic, geographical, and occupational backgrounds but with similar economic status and political influence. Finally, linking social capital is defined as ties between community and those in positions of influence in formal organizations such as banks, agricultural extension offices, schools, housing authorities, or the police.

3.2 Summary Statistics

Table 2 presents the summary statistics for the full sample and the households whose residences were flooded. Panel A summarizes the social capital measures, and Panel B presents the household characteristics. We do not find a systematic difference in the level of pre-cyclone social capital between the flooded and non-flooded households. It appears that the average water level in the home is 1.8 feet (or 0.55 meters). The inundated households have less physical and human capital than the others, while their demographic characteristics are comparable. This is presumably because poor households are more likely to reside in lowland areas.

Panel C shows the patterns of evacuation behavior during the cyclone. Despite the devastating cyclone causing severe damages to their residences, only 15% of the surveyed households evacuated to the emergency shelters while 59% did not evacuate anywhere. Even among the households whose residences were flooded, 34% did not evacuate. Finally, it appears that 21% of survey households and 9% of flooded surveyed households reported that they would not evacuate to the shelter when the disaster alarm is set off next time. This suggests that some obstacles exist that make even those in the highest risk areas hesitate to evacuate.

[Table 2]

What makes these households hesitate to evacuate? Those who answered that they would not evacuate next time were asked about their reasons for this stance. Table 3 summarizes their responses. The poor accessibility of the shelters and inaccuracy of early warning systems are shown to be critical. In addition, the income opportunity costs of evacuation and the risk of falling victim to theft are also mentioned as major reasons not to evacuate. These are consistent with the discussion in Section 2. The most frequent answers, however, appear to be different when focusing on those who experienced flooding. While the proportions of respondents concerned about access to the shelter (72.7%) and risk of theft (59.1%) increased, the other answers were observed less frequently. These results reassure the importance of social capital in the evacuation decision in our study site.

[Table 3]

4. Identification Strategy

We estimate the following OLS model:

$$Evac_{vi} = \alpha_0 + \alpha_1 SC_{vi} + \alpha_2 X_{vi} + \omega_v + \varepsilon_{vi} \qquad (1)$$

where, $Evac_{vi}$ takes unity if household i in village v evacuated during Cyclone Aila regardless of the evacuation site;[11] SC_{vi} denotes the pre-cyclone social capital measure; X_{vi} includes the household's socio-economic status, demographics, and cyclone damage; ω_v denotes the village fixed effects, and ε_{vi} denotes the error terms. The fixed effects control for the heterogeneity in the geographic characteristics, distance to emergency shelters and the accessibility of the other infrastructures. We employ the standard error clustered at the village level.

A key issue in this model is the endogeneity of pre-cyclone social capital. First, since the survey was conducted after the cyclone, retrospectively reported social capital may be influenced by the disaster experience, such as housing loss and evacuation, causing the estimation result to be biased. Hence, we indirectly test this possibility by conducting a falsification test. We regress the social capital variables at the pre-cyclone period on the observed cyclone damages—such as flood levels at home and at the work place—and

[11] It might be helpful to uncover the choice of evacuation sites, such as the shelter and public buildings. However, given the small sample size of our data, the analysis for locational choice may not provide reliable evidence. Thus, we do not pursue this issue in this study. In fact, we conduct a multinomial logit model in the Appendix to examine the locational choice, but the results are unstable across the models.

pre-cyclone household characteristics. We expect that the coefficients of cyclone damage are statistically insignificant. On the other hand, a positive coefficient of cyclone damage indicates a possibility of spurious correlation; more severely affected households are more likely to report higher social capital and more likely to evacuate. Table A2 in the Appendix reports the results. Only two out of 20 coefficients are positive and statistically significant, supporting the validity of our identification strategy.

Second, households residing far away from a river are exposed to lower disaster risk, but have insufficient access to water. Water scarcity enhances the opportunities for collective actions and leads to increases in social capital (Hayami 2009, Nakano and Otsuka 2011, Ostrom 2009). However, controlling for village fixed effects mitigates this issue. More importantly, this type of bias causes a negative correlation between social capital and evacuation behavior. Therefore, as long as we find a positive effect of social capital, it should not alter the interpretation of results, that is the positive coefficient of social capital.

Nonetheless, there might still be unobserved heterogeneity; households with particular characteristics may self-report higher social capital, and they may be more likely to evacuate. A straightforward approach to this is the use of instrumental variable, but our dataset does not include an appropriate variable for the instrument.

Therefore, we assess the severity of omitted variable bias by using the method proposed by Oster (2017). Intuitively, this approach compares the coefficient of interest between the specifications with and without controlling for the observed characteristics. It then considers that the estimation result may be spurious if the coefficient becomes remarkably smaller with the inclusion of observables. More specifically, it computes the degree of selection on unobservables relative to observables that would be necessary to fully explain the estimated effect. A negative value of the degree indicates that fully controlling for omitted variables should cause the absolute value coefficient to be even larger. A large positive value suggests that it is implausible that omitted variable bias explains away the entire effect. Oster (2017) proposes that the degree between zero and one suggests that the estimated effect may be spurious.[12]

5. Results

5.1 Benchmark Results

Table 4 presents the estimation results. The main finding is that those with higher social capital are more likely to evacuate. This is robust to the choice of social capital measures and the restriction of the sample to the residents of flooded homes. The impact of social capital is larger among the flooded households. For example, Column (4) demonstrates that those who find others helpful are 14.9 percentage points more likely to evacuate, given the other characteristics equal.

The results of Oster's (2017) sensitivity test are reported at the bottom of the table. For each column, we assess the sensitivities to unobserved economic status, and unobserved cyclone damage separately.[13] It shows that only three out of 20 results fall between zero and one. Hence, it is implausible to interpret that the spurious correlation caused by unobserved economic status and cyclone damage can fully explain the positive coefficients of social capital.

Regarding the other characteristics, three points should be mentioned. First, as expected, the likelihood of evacuation increases with the level of flooding of the home. A one-foot (0.3 meters) increase in the height of flooding is associated with a roughly 11 percentage point increase in the likelihood of evacuation. Second, older households are less likely to evacuate, presumably capturing the physical difficulties in evacuation. Third, we do not find a robust association between socio-economic status and evacuation behavior.

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[12] The degree of one suggests that the observables are as important as the unobservables.

[13] In the implementation of this test, we assume Π to be 1.3 as suggested by Oster (2017).

[Table 4]

5.2 Robustness: Principal Component Analysis

So far, we have examined five social capital variables independently. In this section we construct a composite social capital index by using a principal component analysis. We first report the loadings of the five principal components and the corresponding eigenvalues in Table A3 in the Appendix. Kaiser–Harris criterion suggests retaining components with eigenvalues that are greater than one. Following this criterion, we keep the first two components in the estimations. These explain around 50% of variation in the original social capital measures.

Although the estimation results are not reported in the paper, it reassures us that social capital is positively and significantly related with the likelihood of evacuation (Table A4). One standard deviation increase in the first component is associated with a 7.4 percentage points increase in the likelihood. The estimated effect increases up to 10.4 percentage points for flooded households. The second component also demonstrates qualitatively the same results.

6. Underlying Mechanisms

How does an individual's social capital increase his/her likelihood of evacuation? This section tests four potential channels. First, social capital may help people obtain reliable information on the disaster from neighbors and CPP volunteers (Fafchamps and Minten 2002, Granovetter 2005). We test this possibility by estimating the impact of social capital on two indicators: whether the respondents received information on the cyclone from neighbors and CPP volunteers. The control variables are the same as Equation (1). Positive coefficients of social capital support this hypothesis. Table 5 shows that, counter to our expectation, access to information from neighbors does not differ with social capital. However, Table 6 suggests that we cannot fully rule out the possibility that the cyclone warning from volunteers is more likely to reach to those with higher social capital.

[Table 5]

[Table 6]

Second, those with higher social capital may anticipate a lower risk of victimization of theft during evacuation, and therefore evacuate. This hypothesis predicts that the impact of social capital should in particular be larger for those who believe that law enforcement in the local community is not well-functioning. Therefore, in Equation (1), we additionally control for the interaction term between social capital and pre-cyclone trust in law enforcement authority.[14] Table 7 presents the results. As expected, the impact of social capital on evacuation appears to be larger for those who do not trust law enforcement authorities. Further, trust in law enforcement authorities is positively associated with the probability of evacuation. These are consistent with the hypothesis that social capital reduces the perceived risk of thefts and encourages evacuation.

[Table 7]

The third channel is the reduction of income opportunity costs. Evacuation causes a significant amount of income loss, as documented in Section 2. However, social capital may reduce the loss if it helps people find job opportunities after the evacuation (Calvó-Armengol and Jackson 2004, Ioannides and Loury 2004, Montgomery 1991). Further, those with higher social capital may be more likely to receive supports from community members and the local government (Besley 1995, Fafchamps and Lund 2003, Galasso and Ravallion 2005, Mahmud and Prowse 2012). To test these possibilities, we explore whether social capital is associated with (1) the change in labor income between before and after the cyclone, (2) receiving informal

[14] Trust in police was measured by the question similar with the generalized trust. Unlike the trust in people, this question captures the expected ability of police.

loans without interest, and (3) receiving disaster relief from the government. Positive and significant coefficients of social capital in these estimations are consistent with this hypothesis. The results are presented in Tables 8, 9, and 10, and show that the data do not fit this hypothesis; the coefficients of social capital are statistically insignificant for most specifications.

[Table 8]

[Table 9]

[Table 10]

Finally, social capital facilitates collective actions to maintain the roads to shelters, which would make it easier for the affected households to evacuate. We test this channel by analyzing whether the availability of roads to cyclone shelters increases with social capital. The estimation model is similar to Equation (1), but the dependent variable takes unity if the respondent considers that the road to the shelter was usable during the cyclone, and zero otherwise. Table 11 reports the estimation result. The coefficient of social capital is negative, ruling out this hypothesis.

[Table 11]

7. Conclusions

Using unique survey data collected from cyclone-affected households in rural Bangladesh, we found that social capital is positively and significantly associated with the likelihood of evacuation. The results cannot be fully explained by the bias driven by unobserved socio-economic status and unobserved cyclone damage. We also provide evidence that the significant effect of social capital is mainly attributed to the reduction of perceived risk of crime victimization. Further, we cannot rule out the possibility that those with higher social capital benefit from better access to the early warning system.

The following policy implication can be derived. Current policies for disaster risk reduction are mainly concerned with the development of physical infrastructure, such as emergency shelters and coastal embankment, while they pay less attention to trust and networks of community members (Aldrich and Meyer 2015). Our findings suggest that policymakers can benefit from developing both of them. For example, previous studies have consistently shown that individuals who experience collective actions with their community members exhibit higher trust (Schechter 2007, Durante 2009, Shoji 2018a, Shoji et al. 2012, Feigenberg et al. 2013, Gneezy et al. 2016). However, we should be careful how the policies for developing social capital and physical infrastructure are combined.

Finally, since the government and NGOs have expended large efforts to reduce the number of disaster victims, the behavioral patterns of households could have changed since the 2009 cyclone. Unfortunately, there is no empirical study on social capital and disaster evacuation during more recent disasters, and therefore, we cannot discuss the current situation. In order to draw conclusions regarding the design of effective disaster risk reduction policies to encourage evacuation, further studies are required.

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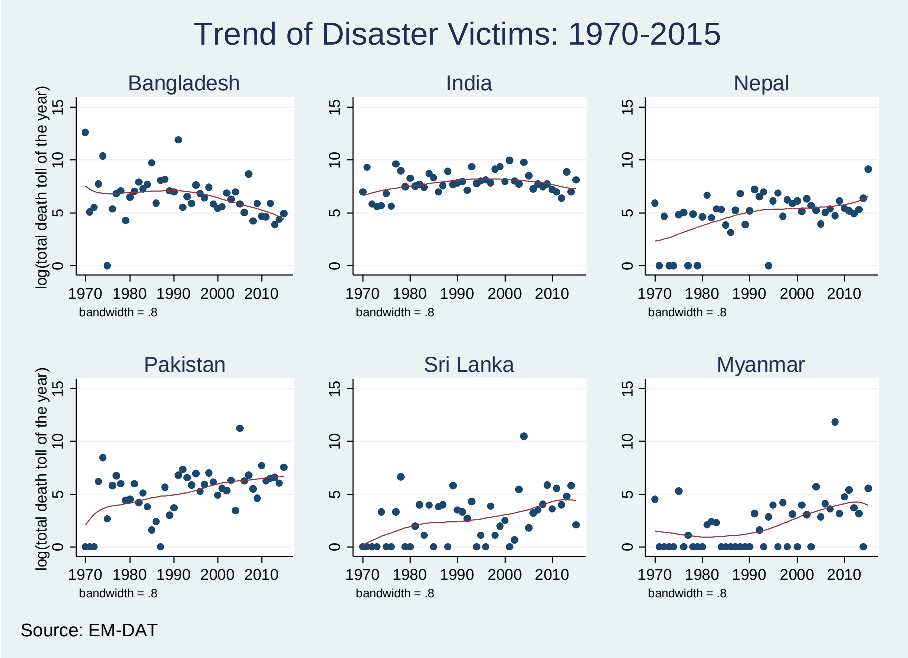


Figure 1: Trend of Disaster Victims: 1970-2015

Table 1: Frequency and Total Deaths of Natural Disasters in Bangladesh: 2001-2015

Disaster Type	Freq.	%	Deaths	%
Storm (convective storm, tropical cyclone)	49	50.5	5,842	57.3
Flood (riverine flood, flash flood)	26	26.8	2,615	25.6
Extreme temperature (cold wave, heat wave, severe winter conditions)	11	11.3	1,420	13.9
Epidemic (viral, bacterial, parasitic)	5	5.2	214	2.1
Landslide	4	4.1	103	1.0
Earthquake (ground movement, tsunami)	2	2.1	4	0.0
Total	97	100.0	10,198	100.0

Source: EM-DAT

Table 2: Summary Statistics

	Full Sample		Inundated	
	Mean	S.D.	Mean	S.D.
Panel A: Social Capital Measures (SC_{vi})				
Attitudinal Measures				
Generalized trust	0.86	0.34	0.86	0.35
Helpfulness	0.64	0.48	0.61	0.49
Fairness	0.50	0.50	0.43	0.50
Behavioral Measures				
1 if expenditure for ceremonies >=150 (BDT/month)	0.16	0.36	0.11	0.31
1 if HHs to share information >=10	0.14	0.35	0.20	0.40
Aggregated Measures				
1st principal component	0.00	1.24	-0.14	1.22
2nd principal component	0.00	1.05	-0.01	1.05
Panel B: Household Characteristics (X_{vi})				
Height of inundation at home (feet)	1.78	1.71	2.96	1.17
Height of inundation at working place (feet)	2.56	1.97	3.53	1.66
Land asset (BDT 10^6)	0.13	0.36	0.10	0.29
Livestock asset (BDT 10^6)	11.53	35.18	11.49	41.64
Jewelry (BDT 10^3)	6.01	13.52	3.79	6.73
Schooling years of head	4.37	3.79	4.12	3.62
Age of head	43.97	13.19	43.55	12.90
Household size	4.30	1.56	4.30	1.48
1 if Muslim	0.57	0.50	0.57	0.50
Panel C: Evacuation				
1 if evacuated during Aila ($Evac_{vi}$)	0.41	0.49	0.66	0.48
1 if evacuated to shelter	0.15	0.36	0.24	0.43
1 if evacuated to the other place	0.27	0.44	0.42	0.49
1 if will evacuate to shelter when the alarm is set off next time	0.79	0.41	0.91	0.28
Observations	427		257	

Table 3: Reasons for Not Evacuating to the Shelter

Sample: will not evacuate to the cyclone shelter when the alarm is set off next time.

	Full Sample	Inundated
Evacuation site is too far	69.7%	72.7%
I do not think the waves will reach my house	60.7%	13.6%
To secure the income of the day	55.1%	40.9%
To prevent burglars	47.2%	59.1%
To keep my livestock around	34.8%	9.1%
Worried about separating family	28.1%	18.2%
The road to go to evacuation site is bad	11.2%	27.3%
Others	6.7%	13.6%
Observations	89	22

Note: Multiple answers allowed.

Table 4: The Impact of Social Capital on Evacuation Behavior

Sample:	Full	Inundated	Full	Inundated	Full	Inundated	Full	Inundated	Full	Inundated
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Generalized trust	0.115	0.186*								
	(0.072)	(0.107)								
Helpfulness			0.101***	0.149**						
			(0.033)	(0.053)						
Fairness					0.173***	0.255***				
					(0.039)	(0.066)				
Expenditure for ceremonies							0.115**	0.110*		
							(0.051)	(0.060)		
Information sharing									0.101**	0.113*
									(0.045)	(0.057)
Height of inundation at home	0.110***	0.110**	0.116***	0.112**	0.109***	0.078*	0.110***	0.105**	0.107***	0.110**
	(0.031)	(0.041)	(0.030)	(0.042)	(0.030)	(0.043)	(0.031)	(0.043)	(0.030)	(0.042)
Height of inundation at working place	-0.011	-0.006	-0.010	-0.004	-0.002	0.008	-0.012	-0.006	-0.010	-0.005
	(0.015)	(0.018)	(0.015)	(0.019)	(0.014)	(0.018)	(0.015)	(0.019)	(0.015)	(0.018)
Land asset	0.009	0.006	-0.001	0.032	0.002	-0.021	-0.023	-0.005	0.008	0.026
	(0.050)	(0.138)	(0.047)	(0.145)	(0.042)	(0.140)	(0.044)	(0.145)	(0.047)	(0.141)
Livestock asset	-0.001	-0.000	-0.001*	-0.000	-0.000	-0.000	-0.000	-0.000	-0.001*	-0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Jewelry	-0.001	-0.006	-0.001	-0.005	-0.001	-0.003	-0.002	-0.006	-0.001	-0.005
	(0.001)	(0.004)	(0.001)	(0.004)	(0.001)	(0.004)	(0.001)	(0.004)	(0.001)	(0.004)
Schooling years of head	0.000	0.007	0.001	0.006	0.001	0.002	-0.001	0.006	0.000	0.006
	(0.005)	(0.007)	(0.005)	(0.007)	(0.004)	(0.007)	(0.006)	(0.007)	(0.005)	(0.007)
Age of head	-0.003*	-0.005**	-0.003*	-0.005**	-0.003**	-0.005**	-0.003*	-0.005**	-0.003*	-0.005**
	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)
Household size	0.014	0.023	0.009	0.017	0.009	0.013	0.011	0.020	0.011	0.018
	(0.014)	(0.025)	(0.014)	(0.026)	(0.014)	(0.026)	(0.015)	(0.027)	(0.015)	(0.027)
1 if Muslim	-0.090	-0.220	-0.099	-0.219	-0.097*	-0.179	-0.056	-0.170	-0.087	-0.184
	(0.059)	(0.133)	(0.060)	(0.149)	(0.049)	(0.129)	(0.054)	(0.129)	(0.056)	(0.131)
Observations	427	257	427	257	427	257	427	257	427	257
R-squared	0.583	0.435	0.587	0.440	0.605	0.471	0.583	0.423	0.582	0.427

Sensitivity to unobserved economic status	-0.23	-0.76	-0.42	3.78	1.51	0.64	-0.12	-0.78	-0.11	-1.05
Sensitivity to unobserved cyclone damages	27.58	-77.79	-0.82	-4.47	-7.00	1.07	15.88	0.74	0.95	-5.02

The OLS coefficients are reported, and the clustered robust standard errors at the village level are in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10%, respectively.

Table 5: Association between Social Capital and Information from Neighbors

Dependent Variable: 1 if receive information on Cyclone Aila from neighbors

	Full (1)	Inundated (2)	Full (3)	Inundated (4)	Full (5)	Inundated (6)	Full (7)	Inundated (8)	Full (9)	Inundated (10)	Full (11)	Inundated (12)
Generalized trust	0.024	-0.001										
	(0.043)	(0.040)										
Helpfulness			0.034	-0.079								
			(0.057)	(0.053)								
Fairness					0.047	-0.054						
					(0.043)	(0.055)						
Expenditure for ceremonies							-0.056	0.095				
							(0.061)	(0.069)				
Information sharing									0.032	0.095*		
									(0.049)	(0.049)		
Principal component 1											0.019	-0.025
											(0.016)	(0.015)
Principal component 2											-0.006	0.044*
											(0.020)	(0.022)
Demographics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Socio-economic status	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cyclone damages	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	427	257	427	257	427	257	427	257	427	257	427	257
R-squared	0.175	0.239	0.176	0.248	0.178	0.243	0.177	0.244	0.175	0.247	0.178	0.256

The OLS coefficients are reported, and the clustered robust standard errors at the village level are in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10%, respectively. All the models control for the same independent variables as Table 4.

Table 6: Association between Social Capital and Information from CPP Volunteers

Dependent Variable: 1 if receive information on Cyclone Aila from CPP volunteers

	Full (1)	Inundated (2)	Full (3)	Inundated (4)	Full (5)	Inundated (6)	Full (7)	Inundated (8)	Full (9)	Inundated (10)	Full (11)	Inundated (12)
Generalized trust	-0.027	0.015										
	(0.066)	(0.057)										
Helpfulness			0.163**	0.186**								
			(0.064)	(0.068)								
Fairness					0.109*	0.160*						
					(0.062)	(0.086)						
Expenditure for ceremonies							-0.079	-0.119				
							(0.075)	(0.121)				
Information sharing									-0.093	-0.045		
									(0.079)	(0.078)		
Principal component 1											0.051*	0.069**
											(0.028)	(0.029)
Principal component 2											-0.042*	-0.040
											(0.024)	(0.029)
Demographics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Socio-economic status	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cyclone damages	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	427	257	427	257	427	257	427	257	427	257	427	257
R-squared	0.129	0.192	0.156	0.230	0.142	0.216	0.132	0.197	0.133	0.193	0.153	0.230

The OLS coefficients are reported, and the clustered robust standard errors at the village level are in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10%, respectively. All the models control for the same independent variables as Table 4.

Table 7: The Interactive Role of Trust in Police and Social Capital in Evacuation Behavior

	Full	Inundated	Full	Inundated	Full	Inundated	Full	Inundated	Full	Inundated	Full	Inundated
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Trust in police	0.092	0.169	0.136**	0.226***	0.156***	0.254***	0.078**	0.124**	0.030	0.090	0.030	0.059
	(0.133)	(0.193)	(0.058)	(0.076)	(0.049)	(0.061)	(0.033)	(0.053)	(0.033)	(0.056)	(0.032)	(0.045)
Generalized trust	0.127	0.205*										
	(0.075)	(0.112)										
× Trust in police	-0.050	-0.071										
	(0.139)	(0.198)										
Helpfulness			0.134***	0.195***								
			(0.038)	(0.058)								
× Trust in police			-0.145**	-0.211**								
			(0.068)	(0.101)								
Fairness					0.243***	0.370***						
					(0.052)	(0.072)						
× Trust in police					-0.203**	-0.344***						
					(0.082)	(0.100)						
Expenditure for ceremonies							0.167**	0.148**				
							(0.062)	(0.067)				
× Trust in police							-0.156*	-0.123				
							(0.090)	(0.166)				
Information sharing									0.060	0.080		
									(0.073)	(0.072)		
× Trust in police									0.052	0.020		
									(0.101)	(0.123)		
Principal component 1											0.104***	0.145***
											(0.020)	(0.028)
× Trust in police											-0.088**	-0.135**
											(0.033)	(0.050)
Principal component 2											0.062***	0.052**
											(0.022)	(0.022)
× Trust in police											-0.036	-0.015
											(0.032)	(0.037)

Demographics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Socio-economic status	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cyclone damages	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	427	257	427	257	427	257	427	257	427	257	427	257
R-squared	0.586	0.444	0.591	0.453	0.616	0.505	0.588	0.434	0.583	0.433	0.624	0.510

The OLS coefficients are reported, and the clustered robust standard errors at the village level are in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10%, respectively. All the models control for the same independent variables as Table 4.

Table 8: Association between Social Capital and Income Loss

Dependent Variable: First Difference of Monthly Labor Income

	Full	Inundated	Full	Inundated	Full	Inundated	Full	Inundated	Full	Inundated	Full	Inundated
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Generalized trust	-0.422	-0.472										
	(0.532)	(0.922)										
Helpfulness			-0.272	-0.501								
			(0.316)	(0.550)								
Fairness					0.148	-0.098						
					(0.228)	(0.407)						
Expenditure for ceremonies							-0.902	-1.885**				
							(0.579)	(0.840)				
Information sharing									-0.104	-0.421		
									(0.490)	(0.503)		
Principal component 1											-0.108	-0.227
											(0.146)	(0.264)
Principal component 2											-0.182	-0.369
											(0.185)	(0.222)
Demographics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Socio-economic status	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cyclone damages	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	427	257	427	257	427	257	427	257	427	257	427	257
R-squared	0.132	0.140	0.132	0.143	0.131	0.138	0.138	0.163	0.130	0.140	0.135	0.156

The OLS coefficients are reported, and the clustered robust standard errors at the village level are in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10%, respectively. All the models control for the same independent variables as Table 4.

Table 9: Association between Social Capital and Informal Credit

Dependent Variable: 1 if receive loans without interest rate after the cyclone

	Full (1)	Inundated (2)	Full (3)	Inundated (4)	Full (5)	Inundated (6)	Full (7)	Inundated (8)	Full (9)	Inundated (10)	Full (11)	Inundated (12)
Generalized trust	0.039	0.019										
	(0.053)	(0.065)										
Helpfulness			0.075**	0.050								
			(0.029)	(0.037)								
Fairness					0.044	0.038						
					(0.040)	(0.042)						
Expenditure for ceremonies							0.041	0.081				
							(0.062)	(0.083)				
Information sharing									0.023	-0.005		
									(0.051)	(0.064)		
Principal component 1											0.031**	0.021
											(0.014)	(0.018)
Principal component 2											0.010	0.009
											(0.021)	(0.024)
Demographics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Socio-economic status	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cyclone damages	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	427	257	427	257	427	257	427	257	427	257	427	257
R-squared	0.114	0.183	0.124	0.187	0.117	0.185	0.115	0.187	0.113	0.182	0.125	0.188

The OLS coefficients are reported, and the clustered robust standard errors at the village level are in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10%, respectively. All the models control for the same independent variables as Table 4.

Table 10: Association between Social Capital and Receipt of Disaster Relief

Dependent Variable: 1 if receive disaster relief between June 2009 and December 2010

	Full (1)	Inundated (2)	Full (3)	Inundated (4)	Full (5)	Inundated (6)	Full (7)	Inundated (8)	Full (9)	Inundated (10)	Full (11)	Inundated (12)
Generalized trust	0.065	0.112										
	(0.074)	(0.075)										
Helpfulness			0.030	0.088								
			(0.055)	(0.058)								
Fairness					0.098*	0.025						
					(0.049)	(0.060)						
Expenditure for ceremonies							-0.009	-0.002				
							(0.089)	(0.103)				
Information sharing									-0.024	0.016		
									(0.055)	(0.056)		
Principal component 1											0.033	0.039
											(0.023)	(0.027)
Principal component 2											-0.005	-0.005
											(0.025)	(0.024)
Demographics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Socio-economic status	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cyclone damages	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	427	257	427	257	427	257	427	257	427	257	427	257
R-squared	0.371	0.528	0.370	0.529	0.378	0.523	0.369	0.523	0.370	0.523	0.375	0.530

The OLS coefficients are reported, and the clustered robust standard errors at the village level are in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10%, respectively. All the models control for the same independent variables as Table 4.

Table 11: Association between Social Capital and Access to Shelter

Dependent Variable: 1 if the road to the shelter is usable during the cyclone

	Full	Inundated	Full	Inundated	Full	Inundated	Full	Inundated	Full	Inundated	Full	Inundated
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Generalized trust	0.004	-0.041										
	(0.070)	(0.102)										
Helpfulness			-0.112*	-0.225***								
			(0.062)	(0.075)								
Fairness					-0.221***	-0.256**						
					(0.070)	(0.101)						
Expenditure for ceremonies							-0.094	-0.003				
							(0.076)	(0.126)				
Information sharing									0.039	0.080		
									(0.106)	(0.139)		
Principal component 1											-0.068**	-0.098***
											(0.024)	(0.032)
Principal component 2											-0.017	0.029
											(0.037)	(0.051)
Demographics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Socio-economic status	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cyclone damages	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	427	257	427	257	427	257	427	257	427	257	427	257
R-squared	0.110	0.132	0.121	0.179	0.155	0.185	0.113	0.131	0.110	0.135	0.135	0.187

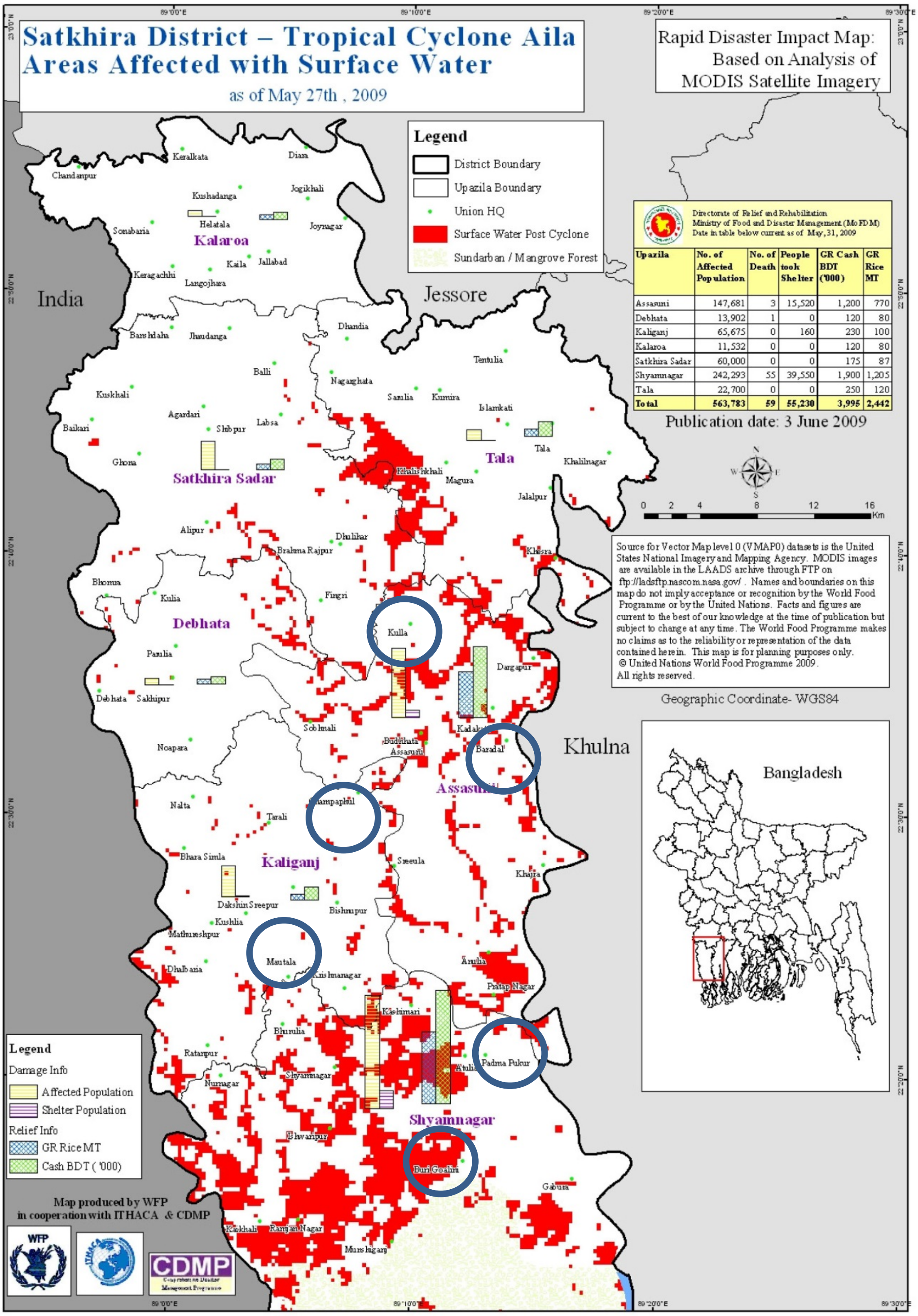
The OLS coefficients are reported, and the clustered robust standard errors at the village level are in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10%, respectively. All the models control for the same independent variables as Table 4.

Appendix 1: Further Discussion of the Survey Design

Our survey data consist of 427 households in 24 villages including both severely affected and moderately affected/non-affected villages. The total sample size and villages examined in this study are comparable or larger than in other quantitative and qualitative studies on Cyclone Aila, such as Mallick and Vogt (2012, 2014), Saha (2015), Mahmud and Prowse (2012), Sultana and Mallick (2015), and Mallick et al. (2011).

Table A1 employs the Population and Housing Census 2011 (Bangladesh Bureau of Statistics 2014) to compare socioeconomic characteristics between the surveyed and non-surveyed villages in Satkhira. No significant differences in demographics, industrial structure, or access to infrastructure are found, although a significant difference is observed in housing materials. This confirms the representativeness of the surveyed areas.

The questionnaire consists of 13 modules: (1) the experience of post-cyclone crime victimization; (2) self-reported cyclone damage; (3) evacuation behaviour; (4) geographical characteristics; (5) bilateral relationships among the surveyed households; (6) demographic characteristics and time allocation; (7) self-reported social capital; (8) asset holdings and savings; (9) disaster relief provided by the government and NGOs; (10) membership in microfinance institutions; (11) consumption; (12) labor and non-labor incomes; and (13) experience of unanticipated shocks (e.g. floods, pest, asset loss). Although the survey was conducted only once in December 2010, retrospective data on the pre- and post-cyclone periods were collected for modules (7) to (13).



*Sou*rce: Ithaca http://www.ithacaweb.org/ (accessed on September 19, 2017).
Note: Circles indicate the surveyed unions.

Figure A1: Map of Study Site

Table A1: Socio-Economic Characteristics of Surveyed and Not Surveyed Villages

	Not Surveyed		Surveyed		
	Mean	S.D.	Mean	S.D.	Difference
The number of households	299.47	310.85	271.43	173.99	
Household size	4.23	0.37	4.23	0.33	
Literacy rate	50.62	11.67	46.33	12.20	
Proportion of the employed (age>6)	0.36	0.09	0.36	0.07	
Agriculture	0.83	0.24	0.82	0.23	
Industry	0.03	0.08	0.02	0.05	
Service	0.14	0.22	0.15	0.21	
Proportion of the household work (age>6)	0.46	0.10	0.46	0.09	
% Pucca (high quality material) house	12.12	10.07	8.61	7.83	**
% access to sanitary toilet	60.62	31.80	66.98	26.00	
% access to tap water	4.29	16.67	5.07	12.02	
% access to electricity	33.30	20.89	29.93	19.32	
Observations	1,177		24		

Source: Computed from Population and Housing Census 2011. The villages in Satkhira Sadar Upazila are not included, since they are located in the urban areas and therefore not appropriate for the comparison group. * p<0.1. ** p<0.05. *** p<0.01.

Table A2: Determinants of Social Capital

	Generalized trust		Helpfulness		Fairness		Expenditure for ceremonies		Information sharing	
Sample:	Full	Inundated	Full	Inundated	Full	Inundated	Full	Inundated	Full	Inundated
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Height of inundation at home	0.005	0.000	-0.055*	-0.014	0.010	0.125***	0.003	0.044	0.035*	-0.004
	(0.013)	(0.025)	(0.028)	(0.036)	(0.039)	(0.032)	(0.020)	(0.026)	(0.019)	(0.021)
Height of inundation	-0.010	-0.003	-0.016	-0.023	-0.057***	-0.057***	-0.004	-0.011	-0.022	-0.020
at working place	(0.011)	(0.014)	(0.022)	(0.028)	(0.016)	(0.018)	(0.017)	(0.022)	(0.015)	(0.023)
Land asset	-0.037	0.085	0.058	-0.073	0.017	0.166	0.242***	0.240***	-0.035	-0.038
	(0.064)	(0.074)	(0.072)	(0.110)	(0.068)	(0.130)	(0.054)	(0.068)	(0.039)	(0.114)
Livestock asset	0.000	0.001	0.001**	0.001**	0.000	-0.001	-0.000	0.000	0.002***	0.002***
	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)
Jewelry	0.002	0.002	-0.002	-0.005	-0.001	-0.010	0.005***	-0.000	-0.000	-0.004
	(0.001)	(0.003)	(0.002)	(0.007)	(0.002)	(0.007)	(0.001)	(0.005)	(0.001)	(0.005)
Schooling years of head	-0.000	-0.006	-0.003	0.002	-0.003	0.015	0.011**	0.003	0.002	0.001
	(0.004)	(0.007)	(0.008)	(0.011)	(0.009)	(0.010)	(0.004)	(0.006)	(0.004)	(0.008)
Age of head	0.002	0.001	0.002	0.001	0.003	0.003	0.001	0.002	0.001	0.001
	(0.001)	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)	(0.001)	(0.001)	(0.001)	(0.002)
Household size	-0.010	-0.015	0.035***	0.019	0.020	0.028	0.012	0.006	0.014	0.018
	(0.012)	(0.017)	(0.012)	(0.020)	(0.018)	(0.017)	(0.015)	(0.014)	(0.010)	(0.015)
1 if Muslim	-0.006	0.149**	0.083	0.183	0.035	-0.049	-0.302***	-0.197*	-0.040	-0.067
	(0.060)	(0.068)	(0.094)	(0.149)	(0.112)	(0.103)	(0.073)	(0.100)	(0.060)	(0.186)
Observations	427	257	427	257	427	257	427	257	427	257
R-squared	0.097	0.147	0.091	0.127	0.104	0.264	0.261	0.197	0.123	0.140

The OLS coefficients are reported, and the clustered robust standard errors at the village level are in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10%, respectively.

Table A3: Principal Component Analysis

	Component 1	Component 2	Component 3	Component 4	Component 5
Generalized trust	0.534	-0.073	0.318	0.679	-0.385
Helpfulness	0.643	-0.176	0.142	-0.190	0.707
Fairness	0.541	0.113	-0.464	-0.480	-0.499
Expenditure for ceremonies	0.088	0.758	-0.428	0.382	0.298
Information sharing	0.039	0.614	0.693	-0.357	-0.118
Eigenvalue	1.446	1.098	0.974	0.846	0.637
Proportion	0.289	0.220	0.195	0.169	0.128

Table A4: The Impact of Social Capital on Evacuation Behavior (Principal Component Analysis)

Sample:	Full	Inundated
	(1)	(2)
Principal component 1	0.074***	0.104***
	(0.015)	(0.024)
Principal component 2	0.046***	0.041**
	(0.015)	(0.017)
Height of inundation at home	0.110***	0.092*
	(0.031)	(0.044)
Height of inundation at working place	-0.002	0.006
	(0.016)	(0.021)
Land asset	-0.022	-0.026
	(0.047)	(0.151)
Livestock asset	-0.001***	-0.001*
	(0.000)	(0.000)
Jewelry	-0.001	-0.004
	(0.001)	(0.003)
Schooling years of head	-0.001	0.004
	(0.005)	(0.006)
Age of head	-0.004**	-0.005***
	(0.001)	(0.002)
Household size	0.006	0.015
	(0.014)	(0.026)
1 if Muslim	-0.062	-0.204
	(0.056)	(0.133)
Observations	427	257
R-squared	0.614	0.484
Sensitivity to unobserved economic status: Component 1	-0.71	8.11
: Component 2	-0.15	-0.46
Sensitivity to unobserved cyclone damages: Component 1	-2.04	3.23
: Component 2	1.58	1.33

The OLS coefficients are reported, and the clustered robust standard errors at the village level are in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10%, respectively.

Table A5: The Impact of Social Capital on Locational Choice for Evacuation

Sample:	Full	Inundated	Full	Inundated	Full	Inundated
	(1)	(2)	(3)	(4)	(5)	(6)
Shelter						
Generalized trust	-0.015	-0.048				
	(0.034)	(0.056)				
Helpfulness			0.099**	0.144**		
			(0.042)	(0.065)		
Fairness					0.141***	0.225***
					(0.035)	(0.052)
Others						
Generalized trust	0.132***	0.210***				
	(0.051)	(0.079)				
Helpfulness			-0.012	-0.005		
			(0.035)	(0.059)		
Fairness					0.025	0.015
					(0.038)	(0.074)
Demographics	Yes	Yes	Yes	Yes	Yes	Yes
Socio-economic status	Yes	Yes	Yes	Yes	Yes	Yes
Cyclone damages	Yes	Yes	Yes	Yes	Yes	Yes
Observations	427	257	427	257	427	257

Sample:	Full	Inundated	Full	Inundated	Full	Inundated
	(7)	(8)	(9)	(10)	(11)	(12)
Shelter						
Expenditure for ceremonies	0.096*	0.174**				
	(0.050)	(0.077)				
Information sharing			-0.002	-0.003		

	(1)	(2)	(3)	(4)	(5)	(6)
			(0.048)	(0.079)		
Principal component 1					0.055***	0.083***
					(0.017)	(0.027)
Principal component 2					0.023	0.042
					(0.015)	(0.026)
Others						
Expenditure for ceremonies	0.069	-0.030				
	(0.076)	(0.104)				
Information sharing			0.099	0.126		
			(0.065)	(0.110)		
Principal component 1					0.016	0.013
					(0.012)	(0.022)
Principal component 2					0.041*	0.031
					(0.024)	(0.038)
Demographics	Yes	Yes	Yes	Yes	Yes	Yes
Socio-economic status	Yes	Yes	Yes	Yes	Yes	Yes
Cyclone damages	Yes	Yes	Yes	Yes	Yes	Yes
Observations	427	257	427	257	427	257

Marginal effects at the mean are reported, and the clustered robust standard errors at the village level are in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10%, respectively.

Abstract (In Japanese)

要約

自然災害による人的被害を軽減するうえで、迅速な避難行動は不可欠である。しかし既存研究では、人々の避難行動における意思決定メカニズムは十分明らかにされていない。そこで本稿は、バングラデシュのサイクロン被災家計から収集した独自のデータを用いて、避難行動における社会関係資本の役割を分析した。実証分析において社会関係資本の内生性を完全に除去することは容易でないため、本稿では Oster (2017)の手法を用いて推定結果のバイアスへの脆弱性を数値化することで対処した。この分析から、社会関係資本が高い村人は被災時に避難する確率が有意に高いことが示された。またそのメカニズムを明らかにする一連の分析から、社会関係資本によって避難時の窃盗被害リスクの認識が低下したこと、および災害警報が多くの村人に情報共有されたことを示唆する結果も得られた。これらの知見は、災害時におけるコミュニティと政府の役割を理解するうえでも重要な貢献を果たすことが期待される。

キーワード：社会関係資本, 自然災害, 避難行動, バングラデシュ, サイクロンアイラ

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