Does resilience capacity reduce the negative impact of shocks on household food security? Evidence from the 2014 floods in Northern Bangladesh

Lisa C. Smith
Timothy R. Frankenberger

TANGO, International
Tucson, AZ

DRAFT
Comments welcome

Summary

Using data collected before and after the catastrophic flooding that took place in northern Bangladesh in 2014, this paper contributes to the growing evidence on the factors enhancing households' resilience to shocks, or their "resilience capacities". In addition to disaster preparedness and mitigation, it points to the following factors to consider in future efforts to bolster resilience in Bangladesh and other developing-country areas that are increasingly vulnerable to shocks due to climate change: Social capital, human capital, exposure to information, asset holdings, livelihood diversity, safety nets, access to markets and services, women's empowerment, governance, and psycho-social capabilities such as aspirations and confidence to adapt.

July 2016

1. Introduction

Bangladesh is one of the most shock-prone countries in the world. While there is some debate as to whether climate change is happening within its own borders, there is no doubt that it is highly vulnerable to its impacts (IPCC 2014; Todd 2014; Mondal 2014; Pender 2008). The country is ranked sixth on the 2016 Global Climate Risk Index in terms of exposure to extreme weather events, enduring a total of 222 such events between 1995 and 2014, third only to the Philippines and Vietnam.[1]

Topography, population density, and poverty contribute, but geographic location is a key source of Bangladesh's vulnerability to climate change. It is sandwiched between the Himalayas and the Indian Ocean—the former exposing it to glacial snow melt and the latter to the heavy rainfalls of the annual monsoons, both of which are exacerbated by global warming. The country is part of the world's most dynamic hydrological system and contains one of the biggest active deltas. Three main rivers drain into the Bay of Bengal through Bangladesh: the Ganges, the Brahmaputra, and the Meghna. All have their peak flows during the highest rainfall months of the monsoon season (July, August and September). In normal years they overflow their banks and deposit fertile silt on the floodplains, typically covering 20-25 percent of the country's land area. However, in some years the peak water levels of all three rivers occur at the same time, and severe flooding covering large areas of the country can ensue. The most recent catastrophic flooding took place in 1998 when the "flood of the century" covered near 70 percent of the country in flood waters. Even in a normal year, extreme flooding can occur due to flash floods, coastal floods accompanying storm surges generated by cyclones, and local flooding due to high rainfall in the monsoon season (Bangladesh Water Development Board 2014; Del Ninno et al. 2001).

While 2014 did not mark a year of widespread flooding in Bangladesh—flood waters covered only 25 percent of the country—major catastrophic flooding did take place in its northern regions due to a combination of factors. These include heavier-than-normal monsoon rains, flash flooding, and heavy rainfall upstream in India, leading the Brahmaputra and Meghna to flow above danger levels. The floods left nearly half of million people homeless, devastated the *aman* rice crop, and destroyed public infrastructure, such as roads, schools and health facilities. They also disrupted employment, transportation and access to services, and led to a loss of safe sanitation and drinking water (Todd 2014; Al-Mahmood 2014; CARE Bangladesh 2014).

This paper investigates the impact of the abnormally high flooding in northern Bangladesh during the 2014 monsoons on households' food security. Its main objective is to determine whether the degree of households' resilience to the shock—their ability to maintain their food security in its wake—was boosted by their resilience *capacities* prior to its onset and which types of capacities are likely to matter the most in future shocks of this type.

Formally, resilience is defined as "the ability of people, households, communities, countries, and systems to mitigate, adapt to, and recover from shocks and stresses in a manner that

[1] The Global Climate Risk Index, developed by Germanwatch, ranks countries based on the impacts of extreme weather events both in terms of fatalities and economic losses (Kreft et al. 2015).

reduces chronic vulnerability and facilitates inclusive growth" (USAID 2012). A household that is resilient is able to maintain its well-being even in the face of shocks and stressors. While resilience itself is an ability to manage or recover, resilience capacities are a set of conditions that are thought to enable households to achieve resilience in the face of shocks. Three types of resilience capacity are recognized: (1) absorptive capacity—the ability to minimize exposure to shocks and recover quickly when exposed; (2) adaptive capacity—the ability to make informed choices about alternative livelihood strategies based on changing conditions; and (3) transformative capacity—system-level enabling conditions for lasting resilience (Frankenberger et al. 2013; Béné et al. 2016b).

In recent years the development community has come to realize that building these capacities to withstand shocks, which are becoming more frequent across the developing world, is key to assisting households pull out of poverty. Awareness of the close interactions between short-term shocks and longer-term development is rising. Further, interventions to enhance households' incomes and well-being are increasingly undermined by shocks. Enhancing resilience through boosting households' resilience *capacities* is thought to not only increase the sustainability of impact of such interventions, but also help ensure that the costs incurred by implementing agencies get their expected return in terms of development outcomes (Frankenberger et al. 2012; Von Grebmer et al. 2013).

But would efforts to bolster resilience through enhancing households' resilience capacity help to reduce the negative impacts of shocks on well-being outcomes such as food security? As governments, Non-Governmental Organizations, and donors look ahead to incorporating resilience into their strategies, solid evidence of the importance of resilience capacity in mitigating the negative impact of shocks, including which types of resilience capacity are important in specific settings, is needed. Yet, beyond economic factors such as assets, savings, and formal safety nets (Frankenberger et al. 2013; World Bank 2016), which have been studied in piecemeal fashion, little is known about how resilience capacity intervenes in times of crisis and what aspects of it are most important. Two recent studies, one conducted in the pastoral lowlands of Ethiopia and the other in Sahelian areas of Burkina Faso and Niger, provide some first evidence from semi-arid drought and conflict prone areas (Frankenberger and Smith 2015; Smith et. al. 2016). As done here, these studies take into account the full spectrum of factors that potentially influence resilience based on a comprehensive conceptual understanding of its determinants.

In this paper we contribute to the evidence base on the role of resilience capacity using data collected from households in the target area of the "Strengthening Household Ability to Respond to Development Opportunities II" (SHOUHARDO II) program of CARE Bangladesh. The program was implemented in the most shock-prone areas of Bangladesh—the Chars, the Haors, and the Coastal flood plains—from 2010 through 2015. Fifty percent of its 1,573 participating villages were exposed to the 2014 flooding. Data sets representative of the households residing in program villages collected shortly after the flooding ended (in December 2014) and two years earlier (December 2012) are a rich source of information on households' food security, the extent to which they were exposed to the flooding, and their resilience capacities.

The next section gives some background information on the SHOUHARDO II program and the study area. In Section 3 the data and empirical methods employed in the paper are laid out. Section 4 describes the shocks which households were exposed to over 2014, including flooding, and the state of their food security after the flood waters receded. Next, Section 5 presents the indicators used to measure their resilience capacities. Section 6 reports on the empirical analysis investigating the role of resilience capacity in mitigating the negative impact of the flooding on household's food security. Finally, Section 7 ends with some concluding remarks regarding the implications of the findings for boosting households' resilience to future climate shocks in Bangladesh and elsewhere.

2. Background: SHOUHARDO II and its program area

A Food for Peace Title II program, CARE Bangladesh's SHOUHARDO II program was funded by the United States Agency for International Development (USAID) and the Government of Bangladesh at nearly US$130 million, making it one of the largest non-emergency food security programs in the world. Its overall objective was to "transform the lives of women and men in 370,000 poor and extreme poor households in eleven of the poorest and most marginalized districts in Bangladesh". Typical of a Food for Peace program, SHOUHARDO II's main goals were to 1) enhance household food security; and 2) improve the health and nutritional status of children under two. However, following on its predecessor, SHOUHARDO I (Smith et al. 2013), it also addressed some systemic causes of food insecurity and malnutrition in a cross-sectoral manner, having additional goals to 3) empower women; 4) promote improved governance among local elected bodies and government service providers; and 5) assist households, government institutions, and partner NGOs to be better able to prepare for, mitigate, and respond to disasters and adapt to climate change.

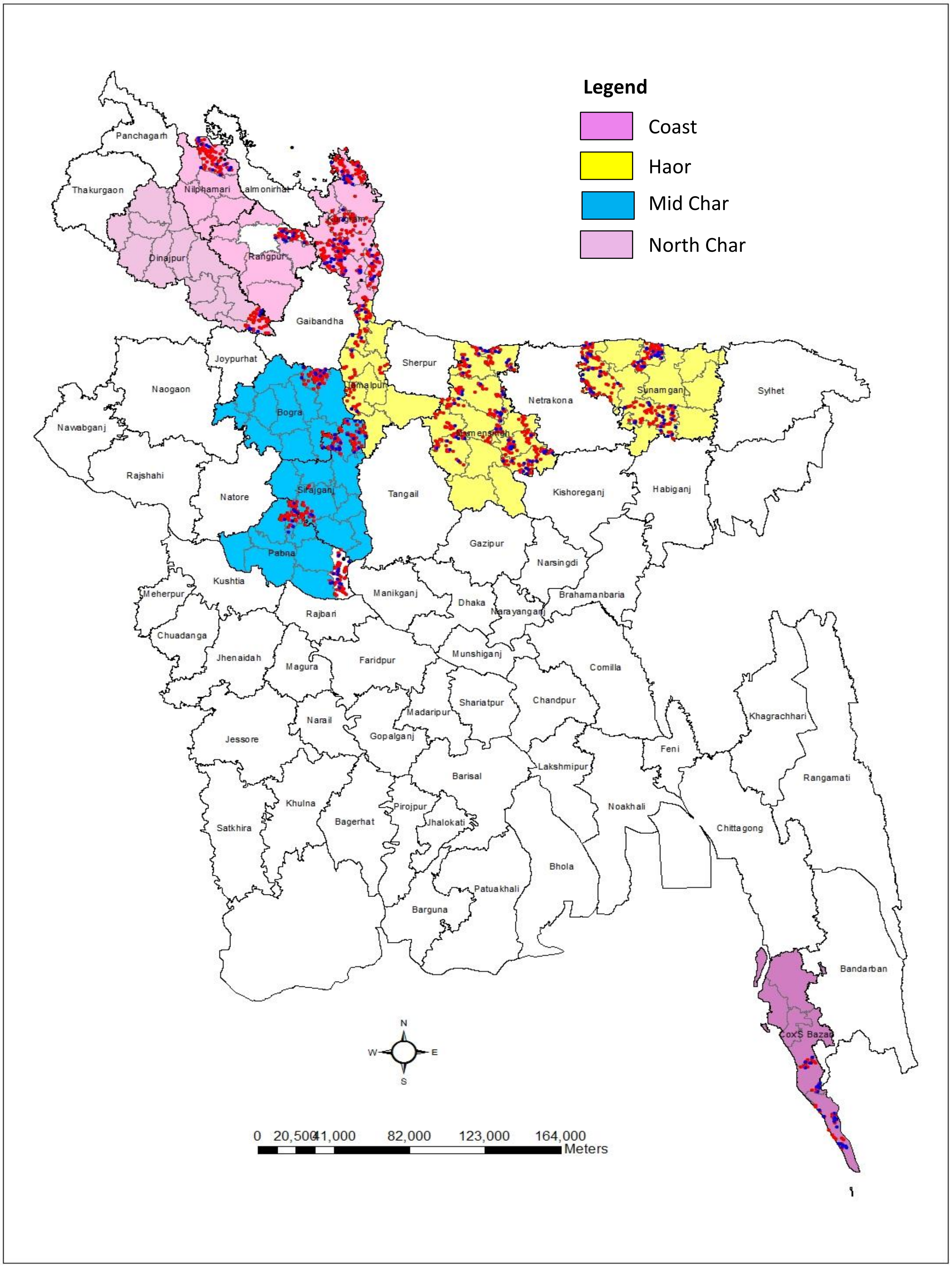
As can be seen, the program had a strong focus on both food security and disaster risk mitigation and reduction, both of which were key in forming the criteria for locating an appropriate target population. National data bases were used to identify the areas in the country most vulnerable to food insecurity and child malnutrition and most susceptible to natural disasters.[2]

Figure 1 locates the resulting four SHOUHARDO II program areas that are the study sites for this analysis—Coast, Haor, Mid Char and North Char—within Bangladesh. The northcentral *Chars* are riverine islands surrounded by water most of the year. They are prone to dramatic erosion and floods, which result in crop loss, isolation, and poor access to markets and services. Also highly flood-prone and with similar food insecurity issues to the Chars is the northeastern *Haor* area, characterized by vast expanses of depressed wetlands with scattered, elevated mounds that become largely inhabitable islands during the wet season. The delta-like *Coast* region is in the deep southeast of the country, where food security is threatened by regular storm surges and slow-onset disasters such as water-logging and land salinization. As will be seen in the next

[2] Other criteria were: remoteness, illiteracy, poverty rates, and avoiding duplication and overlap with other projects.

Section, the Chars and Haor are the program areas that were affected by the extreme flooding in 2014.

Figure 1. Map of SHOUHARDO II program areas



It should be kept in mind that over the course of the 2014 flooding and its aftermath the SHOUHARDO II program area was engaged in an intensive transformation in which it made considerable progress towards its overall objective and five goals listed above (TANGO International 2015). The program's activities ultimately led to substantial improvements in well-being among program participants, including improved household food security and reduced malnutrition among children (stunting declined from 61.7 to 48.8 percent) (Smith, 2015).

With respect specifically to activities related to disaster preparation and mitigation, an extensive set of interventions directly related to what is known as "Disaster and Climate Risk Management" (DCRM) were implemented. At the village level, Village Development Committees (VDCs) were established and trained in community-based planning from which disaster contingency plans were developed. SHOUHARDO II also worked with local governments to develop disaster management committees, and a cadre of volunteers was trained in disaster preparedness, contingency planning, and search and rescue. Additional program activities related to DCRM included provision of improved stoves for cooking, establishment of floating gardens, promotion of flood-tolerant rice varieties, tree planting to prevent erosion, and construction of raised homesteads, storm shelters and village protection walls (Todd 2014).

According to Todd (2014), the fact that there was very little loss of life during the floods, livestock losses were small, and many households were able to take refuge in raised homesteads or flood shelters indicates that the preparedness measures taken by villages and supported by the SHOUHARDO II program were effective. He also points, however, to the obvious continuing vulnerability of households to flooding despite these positive signs. Such vulnerability necessitated emergency relief by CARE and the Bangladeshi government in the form of water purification sachets, food (rice and dry food packs), medications and cash, especially targeting internally displaced people. At the end of 2014, CARE felt the need to undertake post-flood negotiations with USAID to help 70,000 flood-affected households in the SHOUHARDO II program area re-establish their livelihoods (Todd 2014; CARE Bangladesh 2014; Al-Mahmood 2014).

As will be seen in Section 6, the data analysis of this study indicates that the extreme flooding of 2014 in northern Bangladesh did indeed have a negative impact on households' food security. In the absence of the changes described here taking place in the program areas—the improvements in well-being, the disaster preparedness and mitigation measures, and the emergency relief—that negative impact would likely have been far greater.

3. Data and methods

Data

The primary data used for this paper's analysis were collected as part of the SHOUHARDO II program's mid-term and endline surveys. The mid-term data were collected in November/December 2012, the endline data in the same months in 2014. While each survey was cross-sectional, collected using a two-stage, random sampling design,[3] data were incidentally collected from a sub-sample of 358 panel households that were included in both surveys.

The large-sized endline data set, containing data from 8,415 households, allows cross-sectional regression techniques to help detect statistically significant relationships among key variables in the data. While representing a small sample, the panel data allow the use of more rigorous empirical techniques as well as measurement of how households' food security changed over the course of the flooding—and thus to investigate the role resilience capacity played in their actual *resilience* to the flooding.

Note that the panel data set is not a representative sample of households in the SHOUHARDO II program area. Because the four program areas were sampled with an equal number of target households, those in areas with relatively small populations, such as Coast, are over-represented; those in areas with relatively large populations, such as Haor, are under-represented. However, for our purposes this is an advantage since the two regions with the greatest flooding exposure, Mid Char and North Char, represent roughly half of the sample while those reporting the least flooding represent the other half. This breakdown means that the low-flooding group is adequately represented in the regression analyses.

Two secondary sources of data are employed. The first is the Princeton University Global Flood and Drought Monitor (GFDM), a real-time, satellite-based, flood/drought monitoring and seasonal forecast system. Current conditions are compared to an historical, multi-decadal reconstruction of the terrestrial water cycle using data from 1950-2008. The GFDM allows Geographical Information System (GIS) coordinates to be employed to download data from the internet for localized geographical areas—in this case the 193 endline sample villages—with 0.25^{o} spatial resolution (Sheffield et. al. 2014).[4] For this analysis, monthly data on streamflow

[3] Two levels of stratification were employed. The first was a division of the SHOUHARDO II operational area into its four program areas, described in Section 2. The second level of stratification was into intervention arms defining a randomized controlled trial embedded into the project's design to evaluate the effectiveness of two approaches to targeting Maternal and Child Health and Nutrition interventions: (1) an approach whereby only designated poor households are included as participants in the interventions; and (2) an approach whereby all eligible women (pregnant and lactating) and children (under two) in project villages participate, regardless of socio-economic status. Within each of the resulting eight strata, program villages served as primary sampling units. Forty-five households were randomly selected in each village to make up the final sample (Smith 2015). All descriptive statistics presented in this report are calculated using sampling weights reflective of this sampling design.

[4] As of the time of this writing, the GFDM was not yet released to the public. However, the GFDM platform is identical to that of the African Flood and Drought Monitor (AFDM 2016) and the Latin American Flood and Drought Monitor (LAFDM 2016), which are freely available for use on-line and can be consulted for further details.

percentiles of the norm for the year prior to the endline survey (December 2013-December 2014) are employed to capture the magnitude of flooding in each village (see Section 4).

The other secondary data source is a "Village Grading Dataset" collected in 2014 as part of the SHOUHARDO II program's Monitoring and Evaluation (M&E) activities. Program M&E staff visited each village to collect data on the extent to which they were successful in meeting program goals. Each village was given a score for various achievements following pre-established criteria. Information was gathered through Focus Group Discussions, Key Informant Interviews, reviews of the meeting notes of Village Development Committees, training records, and physical observations. The data are used to measure several indicators of resilience capacity, including social capital, support for disaster preparedness and mitigation, and the quality of village governance (see Section 5).

Empirical strategy

The empirical analysis starts by presenting the data on shock exposure and food security as well as household resilience capacity. As laid out in detail in Section 4, shock exposure is measured using households' own reports of their exposure to various shocks in the 12 months prior to the endline survey, including flooding, as well as satellite data from the GFDM on flood levels. Food security is measured using two indicators, one representing household's reports of their ability to provide sufficient food to meet their needs in each month of 2014 and an experiential measure of hunger. Resilience capacity indexes are built using factor analysis, compiled from multiple indicators of the three capacities: absorptive capacity, adaptive capacity, and transformative capacity (see Section 5).

When factor analysis is employed, only the indicators that have a scoring coefficient of the expected sign (positive or negative) based on theoretical understanding of how the indicators work together to measure the overall concept being measured are included. Additionally, only indicators having a Kaiser-Meyer-Olkin (KMO) statistic greater than or equal to 0.5 are retained. KMO is a measure of sampling adequacy, and values less than 0.5 are considered to be "unacceptable" such that the indicators have too little in common to warrant a factor analysis (Statacorp 2013).

Relationship between food security and resilience capacity

Resilience is only meaningful in the context of a shock. In order to understand the relationship between households' food security and their resilience capacity in the face of the flooding that took place in 2014, we thus conduct regression analyses including both shock exposure and resilience capacity as independent variables while controlling for other important household and village characteristics. Starting with the cross-sectional analysis using the endline (EL) survey data (N=8,415), the following is the basic estimating equation for understanding the relationship between food security (Y_i) and resilience capacity (RC_i) in the face of exposure to shocks (SE_i):

$$Y_{i,EL} = \alpha + \beta_1 SE_i + \beta_2 RC_{i,EL} + \beta_3 X_{i,\mathrm{EL}} + \mu + \varepsilon_i, \quad (1)$$

where α, the βs, and μ's are coefficients to be estimated, and ε represents random error. Equation (1) is estimated using Ordinary Least Squares with fixed-effects (OLS-FE). The μ are the fixed-effects terms indicating the area of residence of each household. Controlling for these effects indirectly takes into account factors in households' broader area of residence that influence their food security, such as elevation and cultural or political factors. For the shock exposure indicators measured at the household level, the μ terms are village fixed-effects, one for each of the 193 villages in the sample. For the GFDM shock exposure indicator, which is measured at the village level, they are program area fixed-effects (controlling for residence in Coast, Haor, Mid Char or North Char).

The household characteristics, X_i, that are included as independent variables are:

- Age of the household head;
- Whether the household head is a female;
- Education of adult household members, measured as dummy variables for no education, achievement of a primary education by at least one member, and achievement of a secondary education by at least one member;
- Occupation of household head: farming, agricultural laborer, non-agricultural laborer, salaried employment, self-employment, unpaid household work, or "other";
- Household size;
- Percent of household members in six age-sex groups (female 0-16, female 16-30, female 30+, male 0-16, male 16-30 and male 30+); and
- Household economic status (extreme poor, poor, middle, middle-rich, and rich), as assigned at the beginning of the SHOUHARDO II program.[5]

Because the OLS-FE model is implemented using the large-sample endline survey data, sample size is not likely to be an issue for estimating the regression coefficients. However, the model employs post-shock resilience capacity, yet some aspects of resilience capacity, for example households' asset holdings and savings, are typically themselves affected by households' shock exposure. Such a dependency among the independent variables will lead to bias in coefficient estimates (in this case, the coefficient of resilience capacity is likely to be biased downwards).

To overcome such bias and also focus more directly on *changes* in households' food security—an indicator of their resilience to shocks—we next employ a standard growth model (e.g., Yamano, Alderman and Christiaensen 2015; Hoddinott and Kinsey 2001) as follows:

$$Y_{i,\mathrm{EL}} - Y_{i,\mathrm{MT}} = \alpha + \beta_1 SE_i + \beta_2 RC_{i,\mathrm{MT}} + \beta_3 Y_{i,MT} + \beta_4 X_{i,\mathrm{EL}} + \mu + \varepsilon_i. \quad (2)$$

Here the change in food security is measured from the time of the mid-term (MT) survey to that of the endline. This two-year period was marked by only one major climate shock, the flooding that took place during the monsoons of 2014. Resilience capacity is measured at the time of the midterm, that is, *before* the onset of the 2014 flooding. Also controlled for is initial food

[5] Households were assigned to the five categories based on a Participatory Rural Appraisal wealth ranking exercise whereby each household in program villages was assigned to a category according to pre-defined criteria.

security, which is expected to be negatively associated with the change in food security. The household characteristics X_i, being unlikely to have changed considerably over the two-year period, are measured using the endline data.

Does resilience capacity reduce the negative impacts of shocks on food security?

To address the second main question addressed by this paper, we focus in on resilience capacity specifically as a force mediating the relationship between shocks and food security. To do so, an interaction term between shock exposure and resilience capacity is included in equations (1) and (2), as follows:

$$Y_{i,EL} = \alpha + \beta_1 SE_i + \beta_2 RC_{i,EL} + \gamma SE_i * RC_{i,EL} + \beta_3 X_{i,\mathrm{EL}} + \mu + \varepsilon_i \quad (3)$$

$$Y_{i,\mathrm{EL}} - Y_{i,\mathrm{MT}} = \alpha + \beta_1 SE_i + \beta_2 RC_{i,\mathrm{MT}} + \gamma SE_i * RC_{i,MT} + \beta_3 Y_{i,MT} + \beta_4 X_{i,\mathrm{EL}} + \mu + \varepsilon_i. \ (4)$$

A coefficient on the interaction term between shock exposure and resilience capacity (γ) that is positive (or negative when hunger is the dependent variable) and statistically significant is evidence in support of the protective effect of resilience capacity.

Which types of resilience capacity matter the most?

To answer this question the same estimating equations as above are employed, but "resilience capacity" is replaced by indexes of its three dimensions—absorptive capacity, adaptive capacity, and transformative capacity—followed by the specific indicators used to build each of the indexes. These indicators are laid out in Section 5 below.

A note on causality

Given the nature of the data collected, the regression techniques used to analyze the data do not allow analysis of *causal* impacts of shocks and resilience capacity on households' food security and changes in it.[6] The results of the regression analysis presented here must be considered exploratory and "suggestive". The focus is on determining whether the relationships between the dependent and independent variables (as identified by the signs of regression coefficients) are in the expected, hypothesized directions and deemed to be statistically significant, while controlling for other factors known to influence the dependent variables. While we cannot claim to provide accurate estimates of the magnitude of impact of the resilience capacities being measured, the data do allow us to reasonably identify whether or not they play a role.

[6] Inferring causality more directly would involve the use of different techniques (for example, experimental or instrumental variables methods) and/or a careful triangulation of multiple sources of quasi-experimental and non-experimental data (Smith et al. 2013).

4. Shock exposure and food security

4.1 Shock exposure data from the SHOUHARDO II endline survey

Table 1 reports on the shocks households reported they faced in the year prior to the endline survey, including climate shocks, economic shocks and family events. Note that, overall, 84% of households experienced at least one shock.

Table 1. Percent of households experiencing various shocks in the previous year (2014), by program area

	All	Program area			
		Coast	Haor	Mid Char	North Char
Climate shocks					
Flooding	61.5	3.2	57.5	70.9	67.2
Heavy rainfall	22.7	8.5	23.5	29.4	20.3
Extreme winds	24.6	4.5	24.1	22.9	27.8
Drought	14.9	2.4	6.9	14.1	24.8
Cold wave	1.9	0.3	1.7	1.4	2.4
Hail	3.0	0.2	5.3	3.0	0.9
Erosion	3.8	1.1	0.9	5.8	6.2
Other	2.2	0.8	1.7	3.6	2.3
Economic shocks					
Sharp food price increases	32.9	45.1	21.8	47.1	36.6
Very poor harvest (fields or fish ponds)	14.1	9.4	11.2	16.2	16.6
Deaths of livestock, including fish	8.1	5.1	8.1	6.3	9.3
Loss of income	16.8	20.5	13.1	21.3	18.3
Family events					
Divorce or abandonment	1.4	2.1	1.0	1.4	1.8
Dowry or wedding expenses	3.3	4.1	2.7	3.3	3.9
Court case/legal problems	2.5	3.4	2.6	2.5	2.3
Death of a family member	2.9	2.8	2.4	3.8	3.0

Source: SHOUHARDO II endline data set.

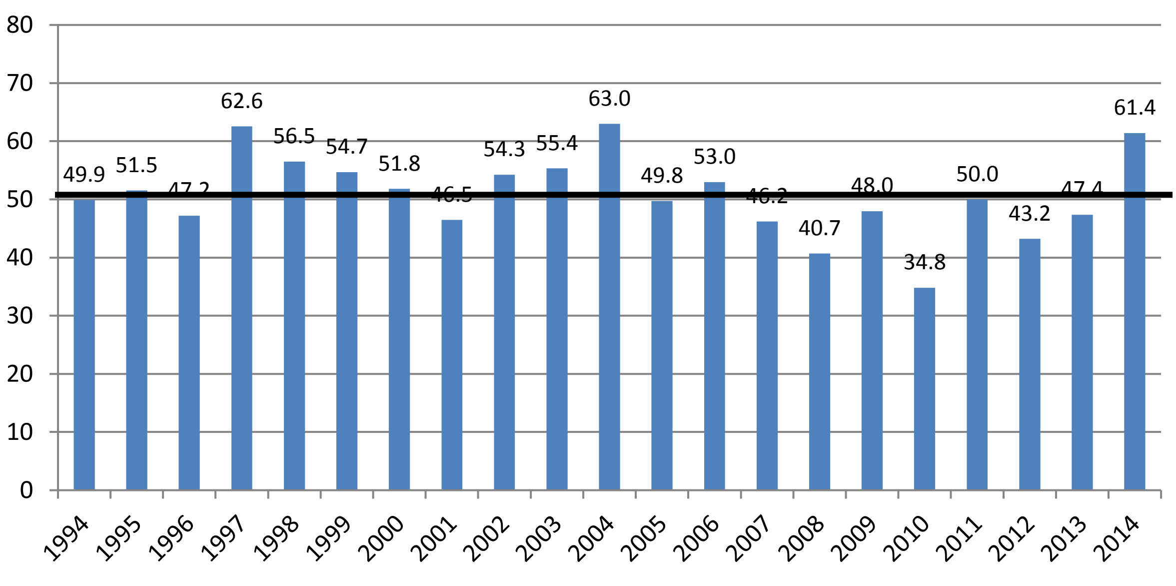
The most commonly-experienced shock was flooding, reported by 62 percent of households. Regionally, flooding was concentrated most strongly in the Char program areas, but was also experienced by near 60 percent of households in Haor. Heavy rainfall was reported by only 23 percent of households, which corroborates information that the flooding was at least partially due to upstream flows outside of Bangladesh itself (CARE Bangladesh 2014). Other commonly-experienced climate shocks were extreme winds and drought. Notably, nearly 25 percent of households in North Char reported experiencing drought.

Among economic shocks, “very poor harvest” and deaths of livestock, which are some of the impacts of the flooding reported by the government’s Disaster Management Information Centre (CARE Bangladesh 2014), were highest in the Chars and Haor. The areas also felt other common impacts: sharp food price increases and loss of income. However, a significant percentage of households in the Coast program area, despite not being exposed to the 2014 flooding, also felt these economic shocks. Shocks associated with family events were relatively rare compared to climate and economic shocks. The most common was dowry or wedding expenses, followed by death of a family member, both experienced by roughly 3 percent of households.

4.2 Flooding exposure data from the Global Flood and Drought Monitor

To put the extent of the 2014 flooding in perspective, Figure 2 documents the historical record, since 1994, of extreme flooding in the study area. The data presented are annual streamflow percentiles from the GFDM specifically for the SHOUHARDO II program villages included in the endline survey (see Section 3). The current streamflow, a measure of the severity of hydrological drought/flooding is compared to the historical norm (1995-2008), with the 50^{th} percentile representing the norm. Streamflow percentiles significantly above the norm indicate flood risk. Streamflow data are derived from satellite precipitation and hydrological modeling to track surface hydrology (Sheffield 2015). The figure shows that for the program area as a whole, the severity of the 2014 flooding, with a streamflow percentile of 61.4, was on par with 1997 and 2004, the years of greatest flooding over the period.

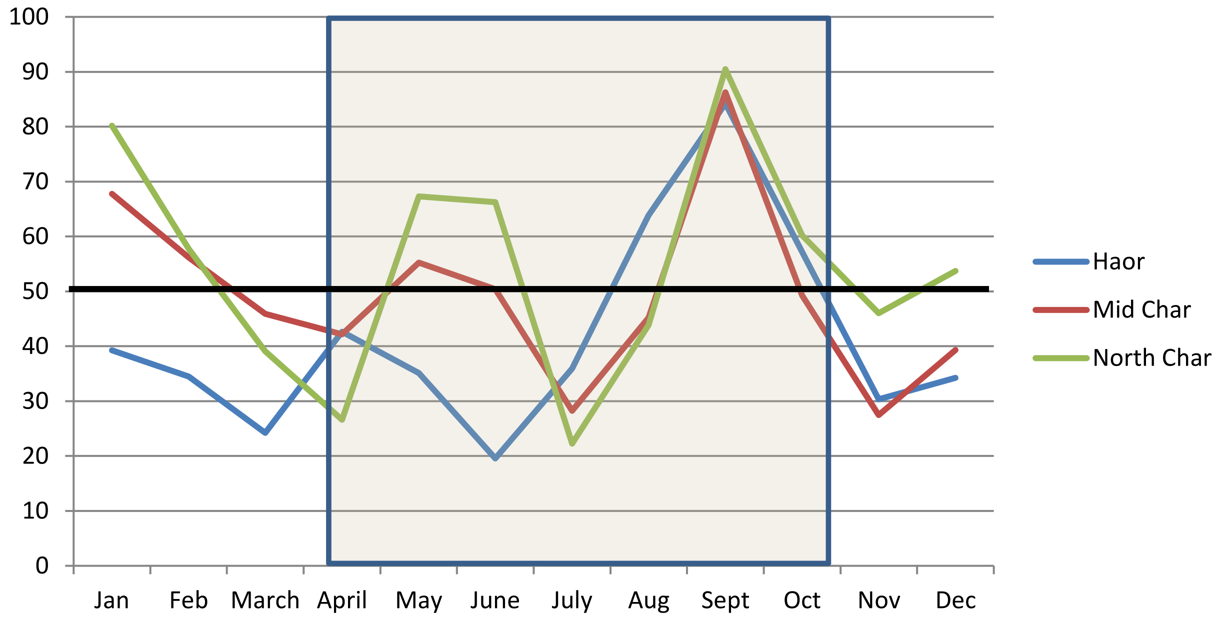
Figure 2. Annual streamflow percentile in the SHOUHARDO II program area, 1994-2004



Source: Global Flood and Drought Monitor.

Figure 3 details the month-by-month streamflow over 2014 focusing in on the SHOUHARDO II regions where the flooding took place. Flooding reached peak levels in all three regions in September. It rose to the 90th percentile in North Char and just below it in Haor and Mid Char, the marker for the most severe flooding possible: "much above normal" (USGS 2016; Climas 2016). The flooding abated rapidly thereafter. Certainly the flooding could be classified as a "rapid onset" shock.

Figure 3. Monthly stream flow percentile in flood-affected areas, 2014



Source: Global Flood and Drought Monitor. The shaded area marks the range of the normal monsoon periods across the three program areas.

4.3 Summary measures of shock exposure

Table 2 reports on some summary measures of shock exposure, starting with those derived from the endline survey data. The first measures the total number of shocks experienced out of the 16 listed in Table 1. The mean number of shocks is 2.1. Flood shock exposure, specifically, is next measured using the data on whether households reported being exposed to flooding in addition to that on three typical downstream economic impacts of climate shocks: price increases, poor harvests and livestock deaths. The index has a value of 0 for households not experiencing flooding, a value of 1 for households experiencing flooding but none of the downstream impacts, and values of 2, 3 or 4 for the rest of the households, depending on the number of downstream impacts experienced. Flood shock exposure in 2014 measured in this manner was highest in Mid Char, followed by North Char and Haor.

Table 2. Means of summary measures of shock exposure in 2014, by program area

Indicator	All	Program area: Coast	Haor	Mid Char	North Char
Self-reported measures					
Shock exposure	2.13	1.13	1.83	2.51	2.38
Flood shock exposure	0.984	0.071	0.855	1.212	1.105
Measures of surface flow hydrology					
Annual streamflow percentile	61.4	56.7	56.1	63.6	67.0
Annual streamflow surplus	107.9	47.4	66.8	108.5	156.3

Sources: SHOUHARDO II endline data set and Global Flood and Drought Monitor (2016).

Two measures of surface flow hydrology from the GFDM are also employed. The first is the annual streamflow percentile for 2014. Because there was considerable monthly variation both above and below the norm (see Figure 3), this measure does not adequately represent the relative extent of exposure to the 2014 floods across the regions. For example, it indicates that Haor had very little flooding yet peak flood levels reached were just as high as those of Mid Char. A measure that zeros in on the extent of flooding is the streamflow *surplus*, measured as the cumulative monthly deviation of streamflow above the 50th percentile. Consistent with that based on self-reported data, this measure of flood exposure indicates that it was greatest in the Chars, followed by Haor.

4.4 Food security in the aftermath of the 2014 floods

Two measures of household food security are employed for this analysis. The first is the number of months of adequate household food provisioning. Survey respondents were asked "Which were the months in the past 12 months in which you did not have enough food to meet your family's needs? This includes any kind of food, such as food you produced yourself, food purchased, food given to you by others, food aid, or food you borrowed." Following, enumerators listed the months and elicited a yes/no response for each. Ranging from 0 to 12, the measure is the number of months in which the household indicated having adequate food to meet the family's needs (Bilinsky and Swindale 2010).

The second measure, the household hunger score, is an index constructed from the responses to three questions regarding people's experiences of acute food insecurity in the previous four weeks (Ballard et al. 2011). The experiences are:

1. There was no food to eat of any kind in the household because of lack of resources to get food;
2. Any household member went to sleep at night hungry because there was not enough food; and
3. Any household member went a whole day and night without eating anything because there was not enough food.

Survey respondents indicate whether or not they or another household member experienced the circumstance in question and, if yes, how often in the last 30 days (rarely, sometimes or often). A score ranging from 0 to 6 is then calculated based on these frequency responses. A prevalence of hunger can be calculated as the percentage of households whose score value is greater than or equal to two, representing "moderate to severe hunger."

Table 3 presents means of the indicators of food security by region. The mean number of months of adequate food is 11.1 and varies little across the regions. Sixty-two percent of households reported *no* months of inadequate food, whether due to lack of exposure to hardship, an ability to overcome it by relying on members' own resources, or humanitarian assistance. The percent of households experiencing the most extreme form of food insecurity, hunger, was 9.6 at the end of 2014, three months after the flooding, and also varied little across the regions.

The food security measures indicate relatively low levels of food insecurity, despite the flooding and despite the fact that the SHOUHARDO II program was located in the most food insecure areas of Bangladesh. One reason for this is that flood-affected households received humanitarian assistance, both food and monetary assistance, in the aftermath of the flooding (see Section 2). Another reason is that food security dramatically improved in the SHOUHARDO II area over the life of the five-year program. The number of months of adequate food provisioning rose from only 5.9 in 2010 to 11.1 in 2014, and the percent of households in hunger fell from 48.8 to 9.6.[7]

Table 3. Household food security, by program area

	All	Program area			
		Coast	Haor	Mid Char	North Char
Number of months of adequate food (2014)	11.1	10.9	11.2	11.0	11.0
Household hunger score (One-month recall, December 2014)	0.351	0.369	0.295	0.383	0.392
Percent of households with moderate-to-severe hunger	9.6	11.2	8.9	10.6	9.6

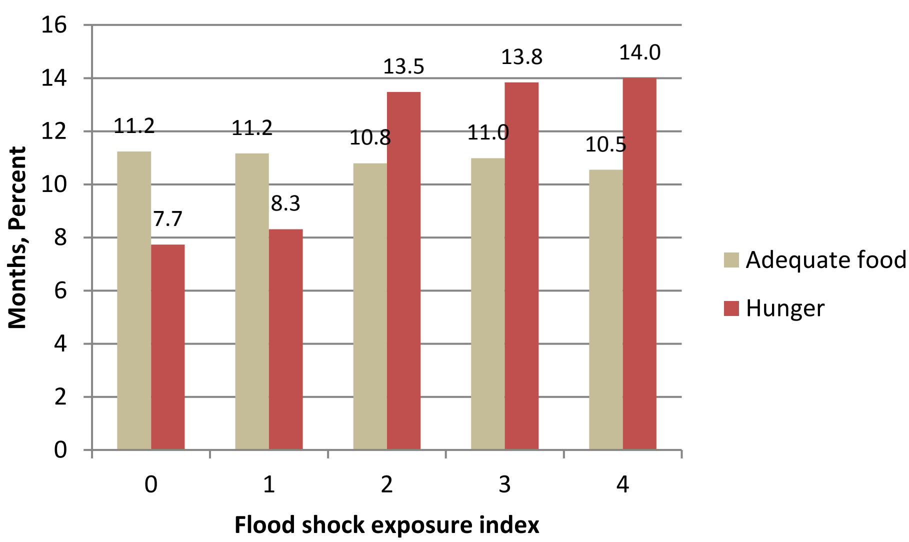
Source: SHOUHARDO II Endline Survey.

[7] The former is from the project endline report (TANGO International 2015), and the latter is calculated by the authors.

A third reason for the relatively low food insecurity in the aftermath of the 2014 flooding is that, as we will see in Section 6, many of the interventions implemented by the SHOUHARDO II program were designed to boost households' resilience capacities. They thus likely served to enhance their resilience, protecting their food security in the face of the flooding.

Before moving on to describe the state of households' resilience capacities in the study area, we ask: Does flood exposure have a negative effect on household food security? This important question will be addressed in Section 6, but a preview of the patterns found there is given in Figure 4, which shows the food security indicators across the five numerical categories of the self-reported flood exposure index. The figure indicates that the number of months of adequate food declines with increased exposure to the flooding. The percent of households experiencing hunger increases precipitously, rising from 7.7 in the least-exposed group to 14.0 in the most-exposed.

Figure 4. Relationship between flood shock exposure and food security



Source: Authors' calculations.

It is important to bear in mind that in Bangladesh it is often the most food-insecure households that live in the most shock-prone areas. This is because population pressure pushes the poorest of the poor onto marginal lands like Chars and Haors (Pender 2008). Even within villages the poorest may live closest to the waterways where they are most vulnerable to flooding. The relationship between food security and shock exposure is clouded by this "reverse causality": flooding may increase food security, but the most food secure may also be less vulnerable to shocks in the first place (shocks are not completely exogenous). It can be partially overcome by taking into account the poverty status of households when examining the relationship between food security and shock exposure, which is done in the regression analysis of Section 6.

5. Resilience capacity

The theoretical foundation of resilience capacity measurement used in this paper builds on the work of Barrett and Constas (2014) and that undertaken by the Food Security Information Network Resilience Measurement Technical Working Group (RMTWG) (Constas, Frankenberger and Hoddinott 2014; Constas et al. 2014). This work helped to foster common understanding on the definition of resilience and its conceptual basis, measurement principles, a common analytical framework, data types, and analytical methods.

Resilience capacity is a set of conditions, attributes, or skills that enable households to achieve resilience in the face of shocks. As mentioned in the introduction, three distinct types of resilience capacity are recognized (Frankenberger et al. 2013; Béné et al. 2016b):

- A*bsorptive capacity* is the ability to minimize exposure to shocks and stresses (*ex ante*) where possible and to recover quickly when exposed (*ex post*).
- *Adaptive capacity* involves making proactive and informed choices about alternative livelihood strategies based on changing conditions.
- *Transformative capacity* refers to enabling conditions that foster more lasting resilience. It relates to governance mechanisms, access to markets, services and infrastructure, community networks, and formal safety nets that are part of the wider system in which households and communities are embedded.

Given their complexity, these concepts cannot be measured using one single indicator. Measuring them requires combining a variety of indicators into an overall measure. Figure 5 lays out the indicators of the three capacities that are used to measure them in this paper. In this section the relevance of each indicator to resilience capacity is laid out, along with a description of how each is measured using the SHOUHARDO II data. Both the indicators and resulting indexes of resilience capacity, compiled using factor analysis, are used to understand the conditions, attributes, and skills that are hypothesized to have enabled households in the study area achieve resilience in the face of the 2014 flooding.

As can be seen, some indicators listed in Figure 5 are used to measure more than one capacity. Thus, instead of treating each capacity indicator separately, we address them under these six broad categories:

- Social capital;
- Aspirations and confidence to adapt;
- Economic sources of resilience capacity;
- Human capital, access to information, and women's empowerment;
- Governance; and
- Safety nets and disaster risk reduction.

Figure 5. Indicators employed to measure resilience capacity

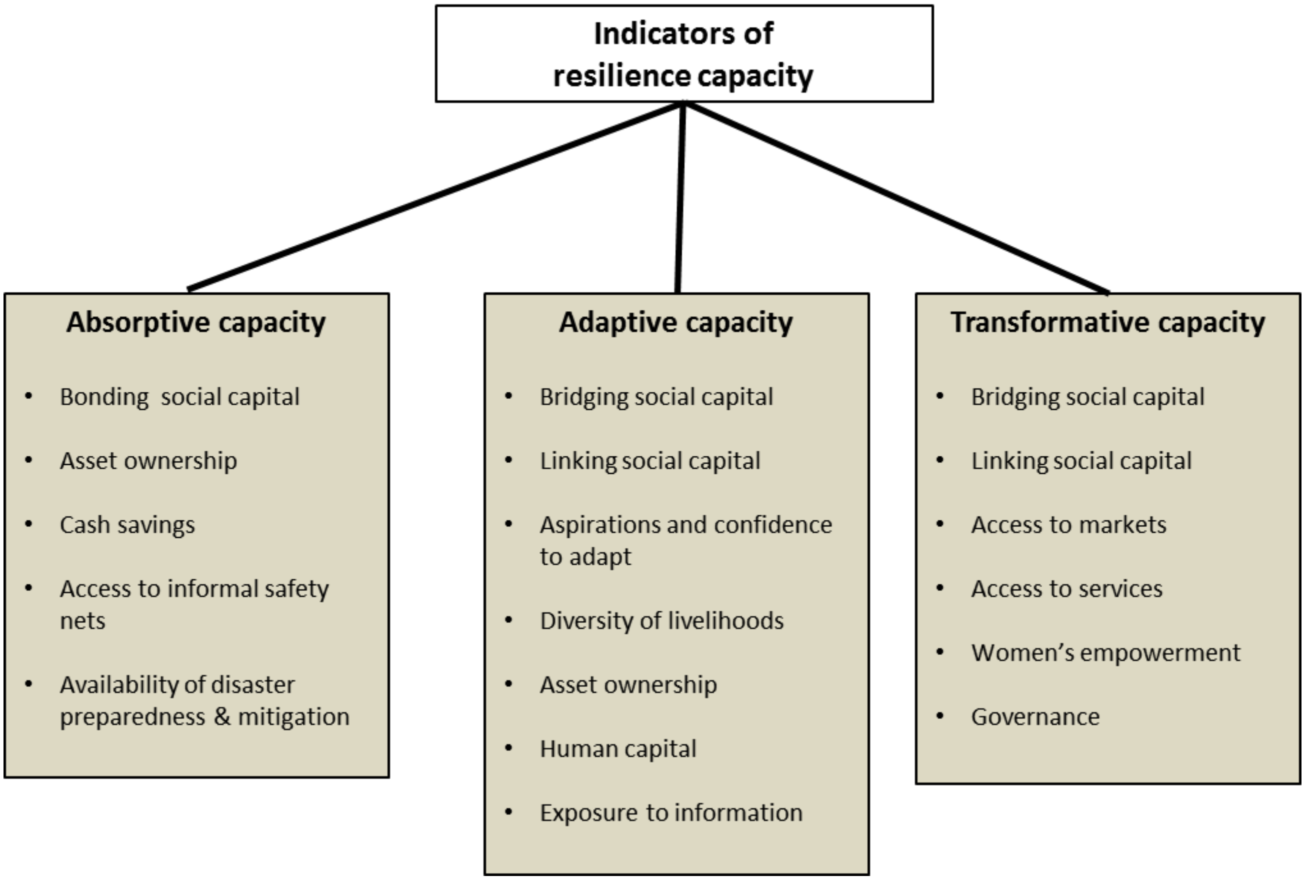


Table 4 contains descriptive statistics for each indicator as measured using the endline survey data.

Table 4. Resilience capacity indicators: descriptive statistics

	Mean	Standard deviation	Minimum	Maximum
Social capital				
Bonding social capital	3.34	1.25	0	4.0
Bridging social capital	0.010	0.704	-0.334	3.001
Linking social capital	0.058	0.789	-1.016	0.998
Aspirations and confidence to adapt				
Index	35.8	17.2	0	100
Economic sources of resilience capacity				
Asset index	5.67	4.56	0	100
Livelihood diversity	1.91	0.94	0	6.0
Savings (Taka)	6,521	41,391	0	1,277,500
Access to markets	3.44	0.43	1.96	3.99
Access to services	69.3	13.3	26.2	99.9
Human capital, access to information, and women's empowerment				
Human capital	54.6	29.5	0	100
Access to information	0.005	0.448	-1.092	1.768
Women's empowerment	0.115	0.810	-1.813	1.835
Safety nets and disaster risk reduction				
Access to informal safety nets	-0.095	0.623	-1.63	0.803
Support for disaster risk reduction	9.42	2.26	2.0	13.0
Governance				
Quality of village governance	0.043	0.834	-2.38	1.43

Source: Authors' calculations using the SHOUHARDO II endline data set.

5.1 Social capital

Social capital can be described as the quantity and quality of social resources (e.g., networks, membership in groups, social relations, and access to wider institutions in society) upon which people draw in pursuit of livelihoods (Frankenberger et al. 2013; Frankenberger and Garrett 1998). It has often been described as the "glue" that binds people in society together. It is based on strong perceptions of local embeddedness, self-regulating moral codes, and the norms, reciprocity and trust that exist between individuals and groups at the community level (Chaskin 2008). Close interaction between people through tight-knit communities, the ability to rely on others in times of crisis, and open communication between stakeholder groups are all generally seen as signs of well-developed social capital.

Three types of social capital are thought to enhance resilience, described as follows:

- ***Bonding social capital*** is seen in the bonds between community members. It involves principles and norms such as trust, reciprocity, and cooperation, and is often drawn on in the disaster context, where survivors work closely to help each other to cope and recover.

- ***Bridging social capital*** connects members of one community or group to other communities/groups. It often crosses ethnic/racial lines, geographic boundaries and language groups, and can facilitate links to external assets and broader social and economic identities. Bridging social capital makes a direct contribution to community resilience in that those with social ties outside their immediate community can draw on these links when local resources are insufficient or unavailable.

- ***Linking social capital*** is seen in trusted social networks between individuals and groups interacting across explicit, institutionalized, and formal boundaries in society. Linked networks are particularly important for economic development and resilience because they provide resources and information that are otherwise unavailable. This type of social capital is often conceived of as a vertical link between a network and some form of authority or power in the social sphere (Aldrich 2012; Wetterberg 2004; Elliott, Haney, and Sams-Abiodun 2010; Woolcock and Narayan 2000).

For this analysis, bonding social capital is measured using an additive index based on household responses to a series of four yes/no questions. The first two ask whether they would be able to borrow money or food from relatives and non-relatives residing in their village in the event the household had an urgent need. The second two ask whether they would be able to do the same for others in their village. The bridging and linking social capital indexes are constructed using factor analysis. Bridging social capital is based on questions regarding regular communication with people outside of one's village, engagement in economic activities with people from other villages, and travel outside of one's village. One variable from the village grading data set is also included: the number of Village Development Committees of other villages that have made cross visits to the household's village for sharing learnings. Linking social capital is measured using information on whether household members are friends or relatives of government officials.

5.2 Aspirations and confidence to adapt

Psychosocial capabilities, such aspirations and confidence to adapt, are thought to be important traits for fostering resilience in the face of shocks. Recent research in Eastern Africa (Ethiopia) has pointed to low self-esteem, low aspirations and a fatalistic view among the poor as linked with their inability to take action to improve their material well-being (Bernard et al. 2012). Aspirations in particular, which are "beliefs, preferences, and capacities relevant to the future and future-oriented behavior" (Béné et al. 2016a), are important in influencing whether households will take steps to invest in their future and thus are important for quick adaptation in order to successfully cope with shocks.

To measure this concept, a factor analysis index is built based on indicators of four factors thought to influence it:

(1) Absence of fatalism, measured using attitudinal questions regarding the roles of working hard, "God's will", and one's own actions in the course people's lives take;
(2) Exposure to alternatives to the status quo, based on questions regarding regular communication with people outside of one's village, engagement in economic activities with people from other villages, getting together with other people to have food, attending a mosque or other religious service, and travel outside of one's village;
(3) Women's freedom of movement, an index build from a count of the number of places women can go alone, including the local market to buy things, a local health center or doctor, the homes of friends in the village, and to a nearby mosque or shrine; and
(4) Women's attitudes about family life, measured using women's responses to questions regarding decision making by women and men, women's paid work outside of the home, who performs household chores, the right to express dissenting opinions, domestic violence, and sending sons versus daughters to school.

The latter two indicators reflect household members' ability to adapt by moving beyond deeply-entrenched beliefs regarding gender relations. The factor analysis index is placed on a scale from 0 to 100.

5.3 Economic sources of resilience capacity

Economic sources of resilience capacity measured for this analysis are: ownership of assets, diversity of livelihoods, holdings of savings, access to markets, and access to services. Note that data are not available to measure an essential aspect of resilience capacity: access to financial services, including credit and savings. These services can be used to increase income and smooth consumption, and relying on them has been one of the most important coping strategies employed by Bangladeshi households in response to past flooding episodes (Del Ninno et al. 2001).

Assets are important components of households' resilience to shocks since they can be used by households to increase income and buffer themselves against shocks. In the aftermath of the widespread 1998 floods in Bangladesh, disposal of assets in order to purchase food was a common strategy used by households (Del Ninno et al. 2001; Del Ninno, Dorosh and Smith 2003). Asset ownership is measured using factor analysis based on the ownership of domestic assets, productive assets, livestock, and land, with the resulting index placed on a 0 to 100 scale.

Concerning livelihood diversity, all livelihood sources are not equally vulnerable to the different risks associated with specific shocks and stresses, suggesting that diversification into multiple livelihood activities, each with different risk profiles, will provide the most effective buffer against future unpredictability (Nelson et al. 2016). It is measured as the total number of livelihood activities each household is engaged in out of 11.

Reliance on savings was the most commonly-reported coping strategy used by household to cope with the 2014 floods in Northern Bangladesh, employed by almost one-quarter of households.[8] It is measured here using the total Taka value of current savings.

Access to markets enables vulnerable households to reduce their risk by providing access to inputs and financial services, thus promoting diversification of assets and income-generation activities (Frankenberger et al. 2013; Frankenberger et al. 2012). It is measured at the village level using data collected from households on the walking distance to markets for buying food, selling food, and purchasing agricultural inputs.

Access to services enables households to maintain their human capital and meet a number of other needs, such as conflict mitigation services and access to infrastructure (Frankenberger et al. 2013). To measure this aspect of household resilience capacity an index is constructed based on households' responses regarding the availability of the following services in their village: health care services, family planning services, a primary school, a preschool, a local government council (or "Union Parishad"), a village dispute adjudication entity (or "Grammo Shalish"), and 11 services provided by various government agencies. The percent of households reporting each of the 17 services in each village is calculated, and the mean across the services is then used to construct the index.

5.4 Human capital, access to information, and women's empowerment

Human capital endows people with the ability to use information and other resources to cope with shocks and stressors. Access to information allows people to put such human capital to use as well as giving them important information for adapting in the face of shocks. Regarding women's empowerment, women in the SHOUHARDO II program area typically have less power to make decisions and less control over resources than do men, yet engage in productive and income generating activities and make major contributions to household physical well-being through their caring practices (Caldwell, Ravesloot and Smith 2011). Their empowerment is expected to increase households' overall capacities to respond to shocks and stressors.

Human capital is measured using a factor analysis index with education, literacy and disability status of household members as components. Access to information is also measured using a factor analysis index, based on the following factors likely to enhance it: access to a cell phone, regular communication with people outside of one's village, number of SHOUHARDO II staff (who are likely to have an expanded knowledge base) members known, and household women's ability to travel to markets, where new information is often shared. Women's

[8] This statistic comes from the SHOUHARDO II endline survey data. To collect the data on coping strategies households were simply asked "How did your household cope…?", and then their responses were recorded by enumerators without being prompted on the list of 24 possible responses. This is not a reliable method for collecting these kind of recall data, which requires specifically asking households about each coping strategy.

empowerment is measured using three aspects of empowerment combined into an index using factor analysis:

- Women's decision making within their homes;[9]
- Women's freedom of movement (see Section 5.2 above);
- The degree to which women hold non-patriarchal values.[10]

5.5 Governance

Representative, responsive, transparent and accountable governance is critical for households to exercise their rights and benefit from laws and policies. It is an enabling condition that provides the foundation for households' access to resources, skills, technology, services, markets and information, thus helping them anticipate, prepare for, respond to, and recover from shocks (Pasteur 2011).

For this study a factor analysis index of the quality of governance in villages is constructed using from the data in the Village Grading data set on the following:
(1) The capacities and functioning of Village Development Committees (VDCs) established by the SHOUHARDO II program. The aspects evaluated are:

- The VDC was formed in a democratic manner, is functioning well, and is well represented in Upazila-level[11] committees;
- The VDC has received training in good governance, human rights, leadership, and problem analysis and planning;
- The VDC has established its own office/meeting place and has developed plans for its sustainability and the sustainability of other community groups linked to it (e.g., women's groups);
- The VDC has a sustainable presence in the village and is able to maintain vertical and horizontal linkages with service providers; and
- Community capacity is strengthened, including capacity on analysis and planning, implementation of activities, external relations, and advocacy.

(2) The implementation of Community Action Plans (CAPs),[12] with these aspects evaluated:

- CAP monitored and updated regularly and displayed in a common/strategic place;

---

[9] Women's decision making power is measured as an index based on information collected from women regarding their ability to make various decisions. Women were asked to what degree they participate in 12 types of decisions ranging from buying small food items to moving to a shelter in times of crisis. To amalgamate their responses into a single index, the following categories of response, and corresponding score values from 1 for "least power" to 4 for "most power", were used: "Can decide alone" (score=4); "Can decide with husband or other adult male family member (3); "Husband makes decision after discussion with wife" (2); and "Not involved" (1). The overall decision-making index is the mean over the 12 decisions that the woman felt were applicable to her situation.

[10] Measured using the attitudinal questions listed in Section 5.2, but with scores for each being positive if the women's response reflects non-patriarchal values.

[11] Upazilas are the second lowest tier of regional administration of the Government of Bangladesh.

[12] Community Action Plans were jointly developed by the VDCs through a participatory process after identification of key problems faced by villages and prioritization of needs that fell within the scope of the SHOUHARDO II program.

- The VDC has presented the CAP to potential funders and obtained resources to support its implementation;
- The CAP is implemented successfully and has contributed to visible change in the livelihoods and empowerment of the poor.

(3) Awareness of community regarding entitlements and responsiveness of government agencies to community needs:

- A large number of village people are aware about their basic entitlements, including the responsibilities of service providers to them;
- Government agencies are responsive and extend effective support for community needs, particularly to women and the poor.

5.6 Safety nets and disaster risk reduction

Formal social safety nets are widely recognized as a means for building resilience, both by providing cash, food, insurance and other resources to help households smooth their incomes in the face of shocks and by promoting human capital development and income generating activities in the longer run (World Bank 2016). Informal safety nets, such as relying on other households or local support groups for food or cash loans, can also be important buffers against the negative impacts of shocks, but they may not be effective in the case of co-variate shocks that affect large geographical areas at one time (Skoufias and Quisumbing 2005; Skoufias 2003).

Data on the availability of formal safety nets are not available in the SHOUHARDO II data set so they could not be used for measure resilience capacity in this study. However, data on informal safety nets are. Here access to them is measured at the village level using factor analysis and three indicators: the existence of a women's group established by the SHOUHARDO II program,[13] the existence of a savings group, and the degree of social support in villages. The latter is measured using the percent of households in each village that would be able to borrow food or money urgently from others in their village (non-relatives) if they were in need.

Data on Disaster Risk Reduction (DRR), which has obvious benefits to households' resilience to climate shocks, are available in the Village Grading data set. Villages are given scores (with ranges in parentheses) based on the following criteria:

(1) Village has improved physical infrastructure to mitigate the impact of shocks (0-3);
(2) Disaster early warning and response systems are in place (0-3);
(3) Disaster volunteers from the village are trained in disaster preparedness, risk reduction and mitigation (0-2);

[13] SHOUHARDO II established "Empowerment, Knowledge and Transformative Action" (EKATA) women's groups for promoting life-skills education, empowerment and social change. Made up of 20 women and 15 adolescent girls recruited from among interested community members, and facilitated bi-weekly by a paid volunteer, the groups provided a platform for empowering women and adolescent girls through education, solidarity, group planning, and rights advocacy.

(4) A commendable number of people in the village are aware of local coping mechanisms, disaster contingencies, and “risk and resource” maps (0-3); and

(5) The village VDC organizes DRR awareness events annually (0-2).

The scores are added to arrive at an overall DRR index.

5.7 Indexes of resilience capacity

Indexes of absorptive, adaptive, and transformative capacity are constructed using factor analysis based on the indicators listed in Figure 5. All indicators making up the transformative capacity index are measured at the village level. For example, bridging social capital, initially measured at the household level, is aggregated to the village level by taking the village mean of the household index values. An overall index of resilience capacity is calculated using factor analysis of the three sub-indexes. All four indexes are placed on a scale running from zero to 100.

Note that the indexes are not comparable to one another, and specific values representing “low” or “high” resilience cannot be established. They can be used, however, for comparisons across geographic and demographic groups and, as will be seen in the next section, provide the variability across households needed for detecting relationships in the regression analysis.

Table 5 presents the means of the indexes by SHOUHARDO II program area. Absorptive capacity is roughly the same across the regions. The Coast region has the lowest adaptive capacity, followed by Mid Char, while Haor has the highest. The Coast region has an especially low value of transformative capacity, while North Char has the highest. Overall, Coast households tend to have the lowest resilience capacity, and Haor and North Char households the highest.

Table 5 Resilience capacity index means, by program area

		Program area			
	All	Coast	Haor	Mid Char	North Char
Absorptive capacity	24.7	24.3	25.2	24.4	24.3
Adaptive capacity	41.3	34.1	43.4	38.9	41.0
Transformative capacity	50.8	28.7	51.3	44.9	55.1
Resilience capacity	31.5	25.2	32.4	29.7	32.1

Source: Authors’ calculations using the SHOUHARDO II endline data set.

6. Regression results

We start this section by presenting the results of a set of regressions looking at whether the basic relationships between shocks and food security, on the one hand, and between resilience capacity and food security, on the other, are in the hypothesized directions. Does shock exposure reduce food security? Does resilience capacity enhance it? Next, in Section 6.2 we focus more specifically on the question of whether resilience capacity actually reduced the negative impact of the 2014 flooding on households' food security. Finally, Section 6.3 asks which of the three dimensions of resilience capacity and which indicators of resilience capacity listed in Figure 5 appear to have mattered the most in bolstering households' food security in the face of the flooding.

6.1 The relationship between shocks, food security and resilience capacity

Cross-sectional regression results

The regressions based on the endline data set alone (N=8,415) indicate that shock exposure indeed has a negative impact on household food security. The results in Table 6 show highly statistically significant regression coefficients (at the 1% level) of the hypothesized sign for all three measures of shock exposure—self-reported overall shock exposure, self-reported flood shock exposure, and streamflow surplus data from the GFDM—and both indicators of food security. The results suggest that shock exposure, and specifically the 2014 flooding, served to reduce the number of months in which households had adequate food and to increase the likelihood that households experienced the most extreme form of food insecurity: hunger. These results hold despite the considerable assistance provided to households in the aftermath of the flooding.

In the case of resilience capacity, as measured using the overall index combining all three of its dimensions, here again the regression coefficients have the expected signs and are significant at the 1% level. The results suggest that resilience capacity serves to increase the number of months of adequate food and reduce the likelihood that a household will experience hunger. Several other variables controlled for also have the expected direction of effect as determinants of food security. Those that are statistically significant are: gender of the household head, education of the household head, occupation of the household head (with laborers showing particular vulnerability to food insecurity), well-being category (poverty status), other shocks (than flooding), and region of residence.

As mentioned in Section 4, to at least partially address the problem of reverse causality related to the fact that food insecure people are more likely to live in shock-prone areas due to their poverty, it is particularly important to control for the poverty status of households when analyzing the effect of shock exposure on food security. The well-being categories employed by the SHOUHARDO II program to classify households into poverty groups serve this purpose well here: they are highly statistically significant as a group and reflect the fact that greater economic well-being serves to increase households' food security.

Table 6. Relationship between food security, shock exposure and resilience capacity: Cross-sectional regression results

	Overall shock exposure (Self-reported, Village fixed-effects)						Flood shock exposure (Self-reported, Village fixed-effects)						Flood shock exposure (Streamflow surplus)					
	Months of adequate food provisioning			Hunger score			Months of adequate food provisioning			Hunger score			Months of adequate food provisioning			Hunger score		
	Coeff-icient	*t*-stat		Coeff-icient	*t*-stat		Coeff-icient	*t*-stat		Coeff-icient	*t*-stat		Coeff-icient	*t*-stat		Coeff-icient	*t*-stat	
Shock exposure	-0.109	-10.04	***	0.0561	8.48	***	-0.153	-7.30	***	0.081	6.15	***	-0.001	-5.15	***	0.001	3.23	***
Resilience capacity	0.053	19.28	***	-0.0308	-18.32	***	0.053	19.42	***	-0.031	-18.33	***	0.044	26.88	***	-0.023	-22.9	***
Age of household head	-0.001	-0.84		0.0004	0.48		-0.001	-0.98		0.001	0.56		-0.002	-1.35		0.001	0.91	
Female household head	-0.088	-1.12		0.0812	1.69	*	-0.090	-1.15		0.081	1.68	*	-0.115	-1.44		0.109	2.23	**
Education of household head: None a/																		
Primary	0.019	0.50		-0.0048	-0.21		0.019	0.50		-0.004	-0.19		0.024	0.64		-0.008	-0.34	
Secondary	0.135	2.86	***	-0.0145	-0.50		0.134	2.84	***	-0.015	-0.50		0.100	2.09	**	0.000	-0.01	
Occupation of head: Farming a/																		
Agricultural laborer	-0.266	-5.39	***	0.1289	4.26	***	-0.264	-5.35	***	0.129	4.26	***	-0.344	-6.95	***	0.171	5.71	***
Non-agricultural laborer	-0.176	-2.85	***	0.0572	1.51		-0.176	-2.83	***	0.057	1.50		-0.316	-5.11	***	0.135	3.59	***
Salaried employment	0.050	0.66		-0.0389	-0.84		0.051	0.67		-0.037	-0.79		0.007	0.09		-0.012	-0.27	
Self employment	0.009	0.18		0.0025	0.08		0.010	0.22		0.002	0.07		-0.042	-0.87		0.043	1.45	
Unpaid household work	0.129	1.58		-0.0207	-0.41		0.132	1.61		-0.022	-0.44		0.106	1.27		-0.006	-0.11	
Other	-0.168	-3.16	***	0.0573	1.76	*	-0.166	-3.12	***	0.057	1.74	*	-0.256	-4.76	***	0.101	3.12	***
Household size	-0.014	-1.39		0.0117	1.88	*	-0.016	-1.56		0.012	1.90	*	-0.010	-0.96		0.003	0.53	
Age-sex composition: % females 0-16																		
Percent females 16-30	0.002	1.03		-0.0005	-0.48		0.001	0.97		0.000	-0.50		0.002	1.42		-0.001	-0.81	
Percent females 30+	-0.002	-1.49		0.0011	1.31		-0.002	-1.52		0.001	1.27		-0.002	-1.40		0.001	1.02	
Percent males 0-16	-0.001	-0.76		0.0004	0.66		-0.001	-0.72		0.000	0.62		-0.001	-0.56		0.000	0.41	
Percent males 16-30	0.003	1.99	**	-0.0009	-1.14		0.003	2.03	**	-0.001	-1.18		0.003	1.92	*	-0.001	-1.24	
Percent males 30+	0.003	1.62		-0.0007	-0.71		0.003	1.70	*	-0.001	-0.78		0.003	1.75	*	-0.001	-1.15	
Well-being category: Extreme poor a/																		
Poor	0.280	5.90	***	-0.0961	-3.31	***	0.272	5.72	***	-0.094	-3.23	***	0.280	6.02	***	-0.095	-3.35	***
Lower middle	0.403	6.61	***	-0.1233	-3.31	***	0.391	6.40	***	-0.120	-3.22	***	0.380	6.25	***	-0.118	-3.22	***
Middle	0.468	7.18	***	-0.1849	-4.63	***	0.459	7.03	***	-0.183	-4.57	***	0.470	7.26	***	-0.196	-5.00	***
Rich	0.551	6.91	***	-0.1369	-2.80	***	0.537	6.72	***	-0.132	-2.69	***	0.610	7.81	***	-0.190	-4.02	***
Other shocks																		
Climate							-0.113	-2.94	***	0.036	1.52		-0.149	-4.27	***	0.053	2.49	**
Economic							-0.248	-5.55	***	0.077	2.82	***	-0.261	-6.27	***	0.068	2.72	***
Family							-0.049	-0.91		0.065	1.95	**	-0.068	-1.24		0.079	2.39	**
Region: Coast a/																		
Haor													-0.034	-0.67		0.100	3.24	***
Mid Char													-0.068	-1.24		0.105	3.15	***
North Char													-0.039	-0.62		0.125	3.32	***
Number of observations		8,415			8,415			8,415			8,415			8,415			8,415	
R-Squared		0.238			0.166			0.237			0.164			0.166			0.108	

Stars represent statistical significance at the 1%(***), 5%(**) and 10% (*) levels.

Panel growth model results

The panel regression results are reported in Table 7. Here the dependent variables are *changes* in the food security indicators from before the flooding to after, which is a direct measure of households' actual resilience to the flooding. As mentioned in Section 3, households' resilience capacity is measured before the flooding as well which, despite the small sample size (N=358), renders these results more valid from a methodological standpoint.

The panel results, too, indicate that shock exposure, whether overall shock exposure or that related specifically to the 2014 monsoon flooding, has a negative influence on household food security.
With respect to the change in the number of months of food provisioning, the coefficient for overall shock exposure is significant at the 1% level, and that for self-reported flooding shock exposure is significant at the 5% level. The coefficient when streamflow surplus is employed is not significant. The respective coefficients for the change in the hunger score show lower statistical significance (at the 5 or 10 percent level), but are all positive as hypothesized.

The panel growth model results for resilience capacity also mirror those of the cross-sectional regressions. They concur that it likely served to bolster households' food security—making them more resilient—over a period in which there was a major climate shock.

Table 7. Relationship between food security, shock exposure and resilience capacity: Panel growth model regression results

	Overall shock exposure (Self-reported, Village fixed-effects)				**Flood shock exposure (Self-reported, Village fixed-effects)**				**Flood shock exposure (Streamflow surplus)**			
	Change in months of adequate food provisioning		Change in hunger score		Change in months of adequate food provisioning		Change in hunger score		Change in months of adequate food provisioning		Change in hunger score	
	Coeff-icient	*t*-stat	Coeff-icient	*t*-stat	Coeff-icient	*t*-stat	Coeff-icient	*t*-stat	Coeff-icient	*t*-stat	Coeff-icient	*t*-stat
Shock exposure	-0.164	-2.69 ***	0.056	1.91 *	-0.279	-2.00 **	0.137	1.99 **	-0.002	-0.9	0.001	1.71 *
Resilience capacity	0.020	2.06 **	-0.015	-3.17 ***	0.021	2.16 **	-0.015	-3.21 ***	0.019	3.28 ***	-0.010	-3.59 ***
Initial level of dependent variable	-0.920	-22.79 ***	-0.974	-29.03 ***	-0.934	-23.12 ***	-0.970	-28.24 ***	-0.943	-27.09 ***	-0.998	-34.83 ***
Age of household head	0.003	0.26	0.007	1.5	0.004	0.37	0.007	1.44	0.008	0.88	0.003	0.63
Female household head	0.441	0.98	-0.231	-1.05	0.540	1.21	-0.214	-0.97	0.371	0.91	-0.168	-0.85
Education of household head: None a/												
Primary	-0.185	-0.88	-0.013	-0.13	-0.130	-0.62	-0.009	-0.08	-0.247	-1.27	0.015	0.16
Secondary	-0.108	-0.36	0.105	0.73	-0.087	-0.29	0.110	0.75	0.009	0.03	0.119	0.93
Occupation of head: Farming a/												
Agricultural laborer	-0.379	-1.35	0.399	2.92 ***	-0.338	-1.21	0.411	2.98 ***	-0.353	-1.35	0.412	3.24 ***
Non-agricultural laborer	0.121	0.35	-0.094	-0.55	0.194	0.56	-0.085	-0.5	0.006	0.02	-0.002	-0.01
Salaried employment	0.278	0.62	0.165	0.75	0.439	0.98	0.152	0.69	0.139	0.35	0.173	0.89
Self employment	-0.316	-1.17	-0.010	-0.07	-0.313	-1.16	-0.002	-0.02	-0.186	-0.76	0.044	0.37
Unpaid household work	-0.078	-0.18	0.358	1.71 *	-0.169	-0.4	0.358	1.7 *	-0.127	-0.32	0.413	2.15 **
Other	-0.387	-1.28	-0.011	-0.08	-0.385	-1.26	0.028	0.18	-0.437	-1.61	0.032	0.24
Household size	-0.108	-1.86 *	0.019	0.67	-0.104	-1.82 *	0.020	0.72	-0.084	-1.61	0.022	0.87
Age-sex composition: % females 0-16												
Percent females 16-30	0.004	0.41	-0.010	-2.36 ***	0.004	0.45	-0.010	-2.3 **	0.001	0.09	-0.007	-1.87 *
Percent females 30+	-0.012	-1.43	-0.004	-1.01	-0.013	-1.56	-0.003	-0.84	-0.009	-1.24	-0.003	-0.7
Percent males 0-16	-0.005	-0.92	-0.002	-0.82	-0.004	-0.76	-0.002	-0.74	-0.002	-0.39	-0.003	-1.12
Percent males 16-30	0.002	0.25	-0.003	-0.88	0.002	0.26	-0.003	-0.71	0.003	0.42	-0.004	-1.28
Percent males 30+	0.004	0.36	-0.004	-0.81	0.006	0.52	-0.004	-0.76	0.000	0.04	-0.002	-0.39
Well-being category: Extreme poor a/												
Poor	-0.016	-0.05	-0.049	-0.34	-0.155	-0.52	-0.032	-0.22	-0.113	-0.42	-0.066	-0.5
Lower middle	0.163	0.39	-0.157	-0.77	-0.012	-0.03	-0.159	-0.77	0.070	0.20	-0.214	-1.24
Middle	-0.067	-0.16	-0.019	-0.09	-0.148	-0.35	0.000	0.00	-0.072	-0.20	-0.078	-0.45
Rich	0.334	0.65	-0.111	-0.45	0.200	0.39	-0.061	-0.24	0.336	0.74	-0.122	-0.56
Other shocks												
Climate					0.199	0.87	-0.057	-0.51	-0.039	-0.19	0.043	0.43
Economic					-0.728	-3.25 ***	0.010	0.09	-0.621	-3.21 ***	0.066	0.71
Family					0.176	0.55	0.057	0.35	0.105	0.35	0.036	0.24
Region: Coast a/												
Haor									-0.329	-0.85	0.021	0.11
Mid Char									-0.206	-0.77	0.232	1.77 *
North Char									-0.112	-0.32	-0.036	-0.21
Number of observations		358		358		358		358		358		358
R-Squared		0.802		0.857		0.807		0.858		0.738		0.813

Stars represent statistical significance at the 1%(***), 5%(**) and 10% (*) levels.

6.2 Does resilience capacity reduce the negative impact of shocks on food security?

The analysis of the last section suggests that shock exposure undermines household food security and resilience capacity enhances it. Resilience marks the ability of households to withstand and recover from shocks, maintaining their well-being even in the face of shocks. Focusing specifically on the floods of 2014, in this section we ask: Did resilience capacity actually work to protect households from the negative impacts of the flooding on their food security? Table 8 contains the regression results (both cross-sectional and panel) when an interaction term between the flooding indicators and food security indicators is included. A coefficient on this term that is statistically significant and of the expected sign indicates that this protective pathway was in action. Only the results for the main variables of interest are reported.

Table 8. Does resilience capacity reduce the negative impact of flooding shocks on food security?

	Self-reported flood shock exposure						Streamflow surplus					
	Months of adequate food provisioning			Hunger score			Months of adequate food provisioning			Hunger score		
	Coeff-icient	*t*-stat		Coeff-icient	*t*-stat		Coeff-icient	*t*-stat		Coeff-icient	*t*-stat	
Cross-sectional regression results (N=8,415)												
Shock exposure	-0.302	-5.49	***	0.187	5.56	***	-0.004	-5.72	***	0.001	3.38	***
Resilience capacity	0.050	16.5	***	-0.028	-15.2	***	0.035	12.2	***	-0.019	-11.3	***
Shock exposure*resilience capacity	0.004	2.76	***	-0.003	-3.43	***	0.00008	3.96	***	-0.00003	-2.26	**
R-Squared		0.239			0.166			0.167			0.109	
Panel growth model regression results (N=358)												
Shock exposure	-0.943	-2.19	**	0.764	3.65	***	-0.004	-1.18		0.004	2.34	**
Resilience capacity	0.016	1.65	*	-0.011	-2.28	**	0.012	1.28		-0.003	-0.76	
Shock exposure*resilience capacity	0.012	1.63		-0.012	-3.17	***	0.00006	0.85		-0.00006	-1.75	*
R-Squared		0.809			0.863			0.739			0.815	

Note: The independent variables controlled for in each regression are the same as those listed in Tables 6 and 7.
Stars represent statistical significance at the 1%(***), 5%(**) and 10% (*) levels.

The interaction term is statistically significant at least at the 5% level in all of the cross-sectional regressions. Its sign is positive when the months of adequate food is the dependent variable, meaning that the negative effect of the flooding was diminished the greater was households' resilience capacity. The implied empirical relationship between flood exposure (FE), household resilience capacity (*RC*), and the months of adequate food (MAF) when streamflow surplus is employed as the measure of flood exposure is:

$$MAF = -0.004 * FE + 0.035 * RC + 0.00008 * FE * RC + D,$$

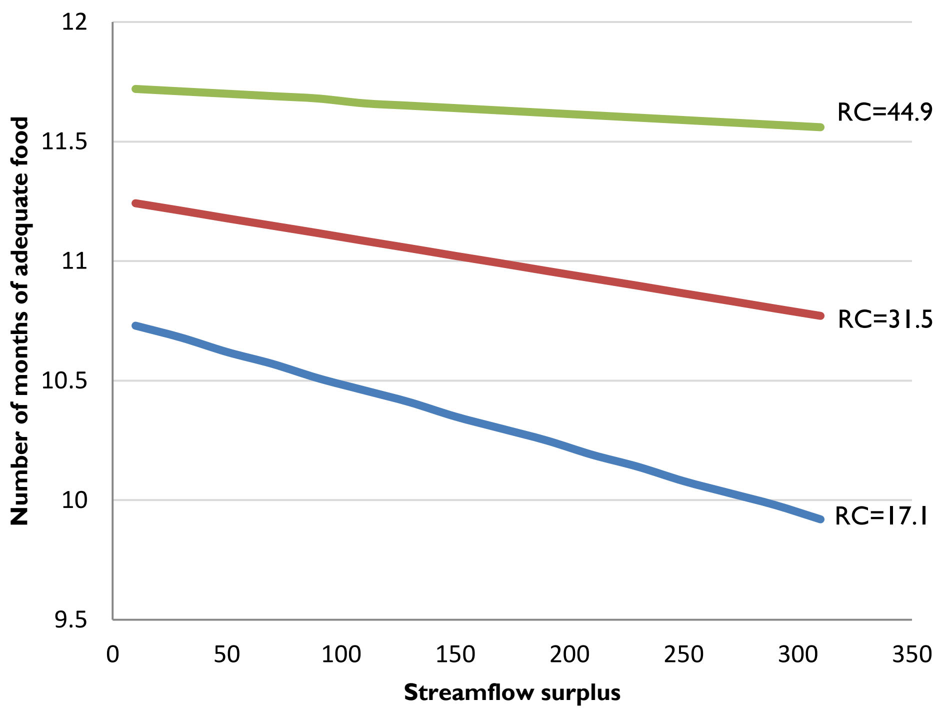
where *D* represents the contribution to the equation of the constant term and the remaining independent variables controlled for.

The estimated impact of flood exposure on food security is thus:

$$\frac{\partial\, MAF}{\partial FE} = -0.004 + 0.00008 * RC.$$

The resilience capacity-mediated relationship between flood exposure and food security implied by the above equation is illustrated in Figure 6. It shows the estimated impact of flood exposure on the months of adequate food at three values of the resilience capacity index: the mean (red line), the cut-off defining the bottom decile (blue line), and the cut-off defining the top decile (green line). The negative slope of the line is steeper the lower is the level of resilience capacity. Further, any given level of flood exposure (for example, a streamflow surplus of 150) is associated with a higher level of food security the higher is resilience capacity.

Figure 6. Resilience capacity –mediated relationship between flood exposure and food security



Source: Authors' calculations.
Notes: This figure shows the implied impact of flood exposure (measured as streamflow surplus) on food security (measured as the number of months of adequate food), as implied by the regression results in Table 8, at three values of the resilience capacity index: the mean (red line), the cut-off defining the bottom decile (blue line), and the cut-off defining the top decile (green line).

The sign of the interaction term is negative in the equations of Table 8 where the hunger score is the dependent variable. For that employing the self-reported flooding exposure measure, for example, the mathematical expression of the “pathway” relationship is:

$$\frac{\partial\ hunger\ score}{\partial\ FE} = \ 0.187 + \text{-}0.003\text{*RC.}$$

The panel growth model results for the hunger score (see lower panel of Table 8) concur with the cross-sectional results. However, the coefficients of the interaction terms in the number of months of adequate food equations are not statistically significant. The fact that the coefficient for the equation using self-reported flooding exposure is almost statistically significant (at the 10% level) indicates that the small sample size may be limiting our ability to detect the relationship using the panel data.

To summarize: These results, especially those for hunger, suggest that indeed households' resilience capacity worked to enable their resilience, as measured by their ability to maintain their food security in the face of the 2014 flooding.

6.3 Which dimensions of resilience capacity matter the most?

In this section we focus in specifically on the three dimensions of resilience capacity—absorptive, adaptive and transformative—and the indicators from which their indexes are constructed. The latter are potential supporting factors in households' ability to withstand shocks that could be the focus of program interventions and policies. Here again the analysis centers on understanding the *interaction* between flood exposure and these aspects of resilience capacity in influencing the food security outcomes.

Table 9 reports the results for the three dimensions of resilience capacity. Only the regression coefficients for the interaction terms between the capacities and shock exposure are given. The cross-sectional regression results give evidence of a role for all three dimensions, but the strongest is for absorptive capacity, the ability of households to minimize exposure to shocks and recover quickly when exposed. This capacity is shown to reduce the negative effect of flood exposure (measured using both self-reports and streamflow levels) on the number of months in which households have adequate food. It is similarly shown to mitigate the power of flooding to increase hunger among exposed households. These results are supported by those from the panel growth regressions when streamflow surplus is employed as the measure of flood exposure. A strong role for absorptive capacity would be expected in this situation of a rapid-onset climate shock as households give priority to minimizing their exposure and recovering in the shock's immediate aftermath.

The cross-sectional regression results indicate a role for adaptive capacity in mitigating the negative impact of flooding, although the panel growth regression results do not. They indicate a role for transformative capacity in mediating the impact of flooding on hunger. Although not strongly statistically significant (t=1.67), the panel results concur when the streamflow surplus measure of shock exposure is employed.

Table 9. Does resilience capacity reduce the negative impact of shocks on food security? Results for the three dimensions of resilience capacity

	Self-reported flood exposure						Streamflow surplus					
	Months of adequate food provisioning			Hunger score			Months of adequate food provisioning			Hunger score		
	Coeff-icient	*t*-stat		Coeff-icient	*t*-stat		Coeff-icient	*t*-stat		Coeff-icient	*t*-stat	
Cross-sectional regression results (N=8,415)												
Absorptive capacity	0.007	3.56	***	-0.006	-4.85	***	0.000	4.75	***	-0.001	-3.17	***
Adaptive capacity	0.001	0.77		0.000	-0.93		0.000	4.12	***	-0.00002	-2.6	***
Transformative capacity	0.001	1.50		-0.001	-2.47	**	0.000	6.99		-0.00003	-5.5	
Panel growth model regression results (N=358)												
Absorptive capacity	0.017	1.58		-0.137	-1.39		0.0002	2.06	**	-0.00020	-2.09	**
Adaptive capacity	0.002	0.66		-0.001	-0.14		0.00002	0.64		-0.00005	-1.29	
Transformative capacity	0.006	1.40		-0.003	-0.82		0.00003	0.63		-0.00007	-1.67	*

Note: Coefficients are those of the interaction term between the dimension of the capacity and the flood exposure measure. The independent variables controlled for in each regression are the same as those listed in Tables 6 and 7.
Stars represent statistical significance at the 1%(***), 5%(**) and 10% (*) levels.

Turning to the specific factors supporting households' resilience in the face of the 2014 flooding, Table 10 summarizes both the cross-section and panel regression results for each sub-component of the resilience capacity indexes listed in Figure 5.[14] The cross-sectional results are reported as stars when the relevant interaction term is in the expected direction and statistically significant at least at the 10% level, with the stars representing significance levels. Cells of the table are shaded if the panel results indicate statistical significance at least at the 10% level.

[14] Separate regressions were run for each index sub-component rather than including all in a single regression. This modeling decision was in consideration of the substantial inter-correlations of the components and the fact that some are known to causally affect others. For example, the quality of village governance is likely to have a positive impact on access to services, disaster preparedness and mitigation, and bridging and linking social capital.

Table 10. Does resilience capacity reduce the negative impact of shocks on food security?
Results for the index sub-components

	Self-reported flood shock exposure		Streamflow surplus	
	Months of adequate food provisioning	Hunger Score	Months of adequate food provisioning	Hunger Score
Absorptive capacity				
Bonding social capital		***	***	***
Asset ownership	**	***	***	***
Savings a/		*		
Informal safety nets	***	*	***	***
Disaster preparation and mitigation			***	***
Adaptive capacity				
Linking social capital				
Bridging social capital			***	**
Aspirations and confidence to adapt			***	***
Livelihood diversity				
Asset ownership	**	***	***	***
Human capital				
Exposure to information			***	**
Transformative capacity				
Linking social capital in village b/				
Bridging social capital in village	***	***	***	***
Access to markets c/			***	***
Access to services	*	**	***	***
Women's empowerment in village		*	***	***
Quality of village governance			***	***

Notes: This table documents whether an interaction term between the factors supporting resilience capacity, listed in the left-most column, and the flooding exposure variables, the top column headings, has the expected sign and is statistically significant at least at the 10% level. Stars indicate the cross-sectional regression results, with *** indicating significance at the 1% level, ** at the 5% level, and * at the 10% level. Shaded cells indicate that the panel growth regression result coefficients have statistical significance at least at the 10% level. The independent variables controlled for in each regression are the same as those listed in Tables 6 and 7.

a/ The interaction term coefficient in both panel regressions is positive and statistically significant at least at the 5% level when the hunger score is the dependent variable.

b/ The interaction term coefficient in the cross-sectional regression is negative and statistically significant at the 10% level in the months of food regression.

c/ The interaction term coefficient in the cross-sectional regression is negative and statistically significant at the 10% level in the months of food regression.

To summarize, the resilience supporting factors for which this analysis gives the strongest evidence, that is evidence from both the cross-sectional and panel regressions, are:[15]

- Bonding social capital;
- Bridging social capital;[16]
- Access to services;
- Exposure to information;
- Women's empowerment;
- Village governance; and
- Informal safety nets.

Supporting factors for which evidence is given from the cross-sectional regressions (which have the advantage of an ample sample size), but not the panel regressions, are:

- Aspirations and confidence to adapt;
- Asset ownership;
- Access to markets; and
- Disaster preparedness and mitigation.

Supporting factors for which evidence is given from the panel regressions (which have the advantage of a more rigorous estimation technique), but not the cross-sectional regressions are:

- Livelihood diversity; and
- Human capital.

All of the above listed factors supporting households' resilience likely helped mitigate the negative impact of the floods on household food security. Not only is there a convincing conceptual basis for their role (see Section 5), but here we have found evidence that they reduced the negative impact on household's food security of an actual climate shock, the 2014 extreme flooding in Northern Bangladesh.

In interpreting these results, we ask the reader to keep the following in mind. First, it is not possible to judge the relative strength of impact of the factors listed above, only the strength of the empirical evidence we put forth here. Second, recall that two factors that likely played an important role could not be included in this study: access to financial services and access to formal safety nets. Finally, we know conceptually and from previous studies that the factors measured here that did not show up in the above lists—relying on savings and linking social capital—do potentially play a role in assisting households to cope with disasters like floods. They certainly should not be ruled out as possible contributing factors in future studies. In the case of savings, the panel regression results for the hunger score yielded coefficients with the

[15] The evidence is considered to be "strong" if the interaction term regression coefficient is of the expected sign and statistically significant at least at the 5 percent level in both the cross-sectional and panel regressions for one or more combinations of the shock exposure measures and food security indicators.

[16] When bridging social capital is measured at the community level both regression methods provide supportive evidence (see results for transformative capacity).

opposite sign to what would be expected (as documented in the notes to the table),[17] that is, they suggest that the more savings households had prior to the onset of the flooding the greater was the negative impact of flooding on households' hunger. This perverse result could be due to the fact that the purpose of the SHOUHARDO II savings groups, established in 65% of all program villages, was to assist households in accumulating savings specifically to be used in the event of climate shocks (Russell 2016). The savings groups of this type could have been purposefully targeted to the most flood-vulnerable areas, and households in these areas may have saved more in anticipation of need.

7. Conclusion

This paper has investigated the role of households' resilience capacity in mediating the food security impact of the severe flooding in northern Bangladesh that took place during the 2014 monsoons. CARE's SHOUHARDO II program was being implemented at the time in shock-prone areas of the country that were directly hit by the flooding. The paper draws on the rich data collected as part of the program's midterm and endline surveys to determine whether the degree of households' resilience to the shock was boosted by their resilience capacities prior to its onset, and which types of capacities are likely to matter the most in future shocks of this type.

The regression results provide suggestive evidence confirming that the flooding indeed undermined the food security of households, despite the humanitarian assistance they received, and that their resilience capacity served to enhance it. They also indicate more specifically that the negative effect of the flooding was mitigated the greater was households' resilience capacity. These results suggest that indeed households' resilience capacity worked to enable their resilience, as measured by their ability to maintain their food security, in the face of the 2014 flooding.

Although all three dimensions of resilience capacity—absorptive capacity, adaptive capacity and transformative capacity—were found to be important in mitigating the impact of the flooding, the evidence for absorptive capacity is the most robust. A strong role for absorptive capacity would be expected in this situation of a rapid-onset climate shock as households gave priority to minimizing their exposure to the flood and recovering in its immediate aftermath.

A number of factors supporting households' resilience capacity were found to have been important for enabling their resilience in the face of the flooding. The finding that social capital and human capital were important in this case corroborates prior evidence from studies of households' resilience to drought in Ethiopia and Sahelian West Africa. Informal safety nets,

[17] The regression results yielded coefficients with the opposite sign to what would be expected in two other cases, both in cross-sectional regressions, one for linking social capital and one for access to markets. The statistical significance for these are very low, however (t=1.67 for the former and t=1.79 for the latter).

which help spread risk in shock-prone environments, and access to markets were also found to be important in the drought context of Ethiopia, and disaster preparedness and mitigation in the West Africa context (Frankenberger and Smith 2015; Smith et al. 2016; Woodson et al. 2016). The results on assets are as expected given that asset divestment is typically an important coping mechanism in response to climate shocks; They corroborate numerous past analyses (Frankenberger et al. 2013).

This study contributes to the building evidence on the role of aspirations and confidence to adapt—psycho-social dimensions of resilience capacity—which have also been found to foster resilience to shocks in Ethiopia, Ghana, Fiji, Vietnam and Sri Lanka (Béné et al. 2016a). A recent qualitative study in Kenya also highlights their role as a resilience capacity (Cramer 2015).

As discussed by Nelson et al. (2016), livelihood diversification may only come into play when it comes to resilience to climate shocks in areas where opportunities to engage in high return activities and significant non-climate-sensitive livelihood options exist. In settings where these opportunities were not available, livelihood diversification has not been found to improve households' resilience to climate shocks. We have found some evidence from the panel data analysis here that in the Bangladesh setting opportunities are such that diversification likely does make a difference.

The roles of two factors supporting transformative capacity that were shown in this paper to have likely helped mitigate the impacts of the flooding have not been investigated in other contexts: women's empowerment and governance. Hopefully future studies will be able to explore them more fully. In the case of women's empowerment, several outstanding questions are of interest. What are the roles of the different aspects of empowerment, such as relative decision making power within households, control over assets, freedom of movement, freedom from violence, women's education, and women's participation in political and civic life? Future studies should also take into account gender differences in vulnerabilities, exposure to risk, and impacts of shocks (see Kumar and Quisumbing 2014), which we were not able to do here. Regarding governance, some key questions are: 1) Which aspects matter the most when it comes to shock recovery? Representativeness, responsiveness, transparency, accountability?; and 2) How specifically does governance serve to increase households' resilience, that is, which more proximate factors supporting resilience are enhanced by governance?

In conclusion, we have presented evidence in this paper that all three dimensions of resilience capacity, and a variety of factors supporting them, combined together to boost households' resilience in the face of the flooding of 2014 in Bangladesh. The SHOUHARDO II program was designed to strengthen most of these factors, based upon an understanding of their importance for supporting households' food security, particularly in times of disaster. The program helped strengthen bridging social capital through its Village Development Committees, it prioritized interventions that strengthened transformative capacity such as those focused on women's empowerment and better governance, it sought to increase asset holdings, strengthen access to markets and basic services, and diversify livelihoods through climate smart agriculture. It also supported a number of Disaster Risk Reduction interventions to protect households in the event of extreme flooding, and provided emergency relief.

This paper's identification of the factors that potentially influence households' resilience was based on a comprehensive conceptual understanding of its determinants. The empirical results—and the example of the SHOUHARDO II program's success in supporting households' resilience to the flooding—point, above all, to the importance of taking a cross-sectoral, multi-intervention approach to building households' resilience capacities in Bangladesh and other developing-country areas that are increasingly vulnerable to climate shocks. The paper provides evidence that this approach appears to work.

References

Aldrich, D. 2012. Building resilience: Social capital in post-disaster recovery. The University of Chicago Press.

Al-Mahmood, Syed Zain. 2014. Flooding in Bangladesh leaves nearly half a million people homeless. *Wall Street Journal*, August 25, 3014.

AFDM. 2016. African Flood and Drought Monitor. Princeton University. http://stream.princeton.edu/AWCM/WEBPAGE/interface.php?locale=en

Ballard, T., J. Coates, A. Swindale, and M. Deitchler. (2011). Household Hunger Scale: Indicator Definition and Measurement Guide. Food and Nutrition Technical Assistance II Project, FHI 360, Washington, D.C.

Bangladesh Water Development Board. 2014. Annual Flood Report 2014. Flood Forecasting and Warning Centre. Processing and Flood Forecasting Circle, Ministry of Disaster Management and Relief. Dhaka, Bangladesh.

Barrett, Christopher B. and Mark A. Constas. 2014. Toward a theory of resilience for international development applications. *Proceedings of the National Academy of Sciences* 111(4): 14625-14630.

Béné, C., Frankenberger, T., Langworthy, M., Mueller, M. and Martin, S. 2016a. The Influence of Subjective and Psycho-social Factors on People's Resilience: Conceptual Framework and Empirical Evidence. Report prepared by the Technical Consortium, a project of the CGIAR. Technical Report Series No. 2: Strengthening the Evidence Base for Resilience in the Horn of Africa. Nairobi, Kenya: A joint International Livestock Research Institute (ILRI) and TANGO International publication.

Béné, Christophe, Derek Headey, Lawrence Haddad and Klaus von Grebmer. 2016b. Is resilience a useful concept in the context of food security and nutrition programmes? Some conceptual and practical considerations. *Food Security* 8(1): 123-138

Bernard, T., S. Dercon, P. Krishnan, S. Krutikova, and A.S. Taffesse. (2012). Aspirations matter: Shaping aspirations can play a crucial role in enabling people to pull themselves out of poverty. Improving Institutions for Pro-Poor Growth (IIG) Briefing Paper No. 19. CSAE Economics Department, University of Oxford, United Kingdom.

Bilinsky, Paula; and Swindale, Anne. 2010. Months of Adequate Household Food Provisioning (MAHFP) for Measurement of Household Food Access: Indicator Guide (v.4). Washington, D.C.: FHI 360/FANTA.

Caldwell, Richard, Bruce Ravesloot and Lisa Smith. 2011. CARE Bangladesh SHOUHARDO II Program: Baseline Study Report. TANGO International, Inc. Tucson, AZ

CARE Bangladesh. 2014. Flooding in North East and North West Bangladesh: Emergency update. Update # 1. September. CARE Bangladesh: Dhaka.

Chaskin, R.J. (2008). Resilience, community, and resilient communities: conditioning contexts and collective action. *Child Care in Practice*, 14(1), 65-74.

Climas. 2016. Figure 07. Streamflow conditions. Climate Assessment for the Southwest. A NOAA RISA Team. http://www.climas.arizona.edu/content/figure-07-streamflow-conditions

Constas, M., Frankenberger, T., & Hoddinott, J. 2014. Resilience measurement principles: Toward an agenda for measurement design. Food Security Information Network (FSIN) Resilience Measurement Technical Working Group. Technical Series No. 1. Rome: World Food Programme.

Constas, M., T. Frankenberger, J. Hoddinott, N. Mock, D. Romano, C. Béné and D. Maxwell. 2014. A Common Analytical Model for Resilience Measurement: Causal Framework and Methodological Options. Resilience Measurement Technical Working Group. Technical Series 2. Rome: Food Security Information Network. November.

Cramer, Laura. 2015. Measuring resilience: beyond income and assets to the intangible and subjective. Change for the Better: The CCAFS Annual Report. CGIAR research program on climate change, agriculture and food security. https://ccafs.cgiar.org/blog/measuring-resilience-beyond-income-and-assets-intangible-and-subjective#.V3bsWI-cHcs

Del Ninno, Carlo, Paul A. Dorosh and Lisa C. Smith. 2003. Public Policy, Markets and Household Coping Strategies in Bangladesh: Avoiding a Food Security Crisis Following the 1998 Floods. *World Development.* Vol. 31, No. 7, pp. 1221-1238.

Del Ninno, Carlo, Paul A. Dorosh, Lisa C. Smith and Dilip K. Roy. 2001. *The 1998 Floods in Bangladesh: Disaster Impacts, Household Coping Strategies, and Response.* IFPRI Research Report No. 122. Washington, D.C.: International Food Policy Research Institute.

Elliott, J.R., T. Haney, and P. Sams-Abiodun. (2010). Limits to Social Capital: Comparing Network Assistance in Two New Orleans Neighborhoods Devastated by Hurricane Katrina. *Sociological Quarterly*, 51(4), 624-648.

Frankenberger, Tim, Kimberly Swallow, Monica Mueller, Tom Spangler, Jeanne Downen, and Sara Alexander. 2013. Feed the Future Learning Agenda Literature Review: Improving Resilience of Vulnerable Populations. Prepared for the Feed the Future FEEDBACK project of the United States Agency for International Development. TANGO, International, Tucson, AZ.

Frankenberger, Timothy R. and Lisa C. Smith. 2015. Ethiopia Pastoralist Areas Resilience Improvement and Market Expansion (PRIME) Project Impact Evaluation: Report of the Interim Monitoring Survey 2014-2015. Prepared for the Feed the Future FEEDBACK project of the United States Agency for International Development. TANGO, International, Tucson, AZ.

Frankenberger, Timothy, Mark A. Constas, Suzanne Nelson, and Laurie Starr. 2012. Resilience programming among nongovernmental organizations: Lessons for policy makers. International Food Policy Research Institute, Washington D.C.

Frankenberger, T.R. and J. Garrett. (1998). Getting connected: Reducing livelihood insecurity by investing in social capital. December.

Hoddinott, J. and Kinsey, B. (2001). Child Growth in the Time of Drought Oxford Bulletin of Economics and Statistics. 63 (4), 409–436. September.

IPCC. 2014. What does the IPCC say about Bangladesh? Intergovernmental Panel on Climate Change, United Nations Environmental Programme and World Meteorological Organization.

Kreft, Sönke , David Eckstein, Lukas Dorsch and Livia Fischer. 2015. Global Climate Risk Index 2016. Who Suffers Most From Extreme Weather Events? Weather-related Loss Events in 2014 and 1995 to 2014. Germanwatch: Bonn.

Kumar, Neha and Agnes Quisumbing. 2014 Gender, shocks, and resilience. Brief 11. 2020 Conference on Building Resilience for Food and Nutrition Security, May 15-17, 2014. Addis Ababa, Ethiopia.

LAFDM. 2016. Latin American Flood and Drought Monitor. Princeton University. http://stream.princeton.edu/LAFDM/WEBPAGE/interface.php?locale=en

Mondal, P. 2014. Integrating Disaster Risk Reduction and Climate Change Adaptation in Development Programs: Experience from Northern Chars in Bangladesh. Paper presented to the CBA Conference, Dhaka.

Nelson, S., Frankenberger, T., Langworthy, M., Finan, T. and Bower, T. (2016). The Effect of Livelihood Diversity on Recovery and Shock Impact in Ethiopia, Kenya and Uganda. Report prepared by The Technical Consortium, a project of the CGIAR. Technical Report Series No 2: Strengthening the Evidence Base for Resilience in the Horn of Africa. Nairobi, Kenya: A joint International Livestock Research Institute (ILRI) and TANGO International publication.

Pasteur, K. 2011. From vulnerability to resilience: A framework for analysis and action to build community resilience. Rugby: Practical Action.

Pender, James S. 2008. What is climate change? And how will it affect Bangladesh? Briefing Paper. Church of Bangladesh Social Development Programme. Dhaka, Bangladesh.

Russell, Mara. 2016. Personal communication. Food Security Director, CARE U.S.A., June 28, 2016.

Sheffield, Justin. 2015. Streamflow flood monitoring and forecasting over Africa with little data. Hydrological Ensemble Prediction Experiment. (HEPEX). March 6, 2015 http://hepex.irstea.fr/streamflow-flood-monitoring-and-forecasting-over-africa-with-little-data/

Sheffield, J., E.F. Wood, N. Chaney, K. Guan, S. Sadri, X. Yuan, L. Olang, A. Amani, A. Ali, S. Demuth, and L. Ogallo. (2014). A drought monitoring and forecasting system for SubSahara African water resources and food security. *Bulletin of the American Meteorological Society* 95, 861–882.

Skoufias, E. 2003. Economic crises and natural disasters: coping strategies and policy implications. *World Development* 31(7): 1087-1102.

Skoufias, E. and A. R. Quisumbing. 2005. Consumption insurance and vulnerability to poverty: A synthesis of the evidence from Bangladesh, Ethiopia, Mali, Mexico and Russia. *European Journal of Development Research* 17(1): 24-58.

Smith, Lisa C., Timothy R. Frankenberger, Sabrina Aguiari, and Carrie Presnall. 2016. Resilience in the Sahel-Enhanced (RISE) Project Impact Evaluation: Baseline Survey Resilience Analysis. Prepared for the Feed the Future FEEDBACK project of the United States Agency for International Development. TANGO, International, Tucson, AZ.

Smith, Lisa C. 2015. Quantitative impact evaluation of the SHOUHARDO II project in Bangladesh. Commissioned by CARE Bangladesh. TANGO International, Inc., Tucson.

Smith, L.C., K. Faheem, T.R. Frankenberger, and A.K.M. Abdul Wadud. 2013. Admissible Evidence in the Court of Development Evaluation? The Impact of CARE's SHOUHARDO Project on Child Stunting in Bangladesh. *World Development*, 2013, 41(C): 196-216.

StataCorp. 2013. Stata: Release 13. Statistical Software. College Station, TX: StataCorp LP.

TANGO International. 2015. SHOUHARDO II Final Quantitative Performance Evaluation. SHOUHARDO II Multi-Year Assistance Program (MYAP). Technical Assistance to NGOs, Inc. Tucson, AZ.

Todd, Ian. 2014. Improving the disaster and climate change resilience of SHOUHARDO II communities". November. SHOUHARDO II project: Dhaka.

USAID. 2012. Building resilience to recurrent crisis: USAID Policy and program guidance. United States Agency for International Development. Washington, D.C. http://www.usaid.gov/sites/default/files/documents/1870/USAIDResiliencePolicyGuidanceDocument.pdf.

USGS. 2016. USGS current water data for the nation. National Water Information System: Web interace. United States Geological Service. Reston, VA. http://waterdata.usgs.gov/nwis/rt

Von Grebmer, Klaus, et al. 2013. Global Hunger Index: The challenge of hunger: Building resilience to achieve food and nutrition security. Welt Hunger Hilfe, International Food Policy Research Institute, and Concern Worldwide.

Wetterberg, A. 2004. Crisis, Social Ties, and Household Welfare: Testing Social Capital Theory with Evidence from Indonesia. The World Bank. Washington, D.C.

Woodson, L., Frankenberger, T., Smith, L., Langworthy, M. and Presnall, C. 2016. The effects of social capital on resilience capacity: Evidence from Ethiopia, Kenya, Uganda, Niger and Burkina Faso. Report prepared by the Technical Consortium, a project of the CGIAR. Technical Report Series No 2: Strengthening the Evidence Base for Resilience in the Horn of Africa. Nairobi, Kenya: A joint International Livestock Research Institute (ILRI) and TANGO International publication.

Woolcock, M. and D. Narayan. (2000). Social capital: Implications for development theory, Research, and policy. World Bank Research Observer, 15(2), 225-249.

World Bank. 2016. *Closing the gap : building resilience to natural disasters and man-made shocks through social safety nets*. Closing the Gap. Washington, D.C. : World Bank Group. http://documents.worldbank.org/curated/en/2016/04/26238912/closing-gap-building-resilience-natural-disasters-man-made-shocks-through-social-safety-nets

Yamano, Takashi, Harold Alderman, and Luc Christiaensen (2005). Child growth, shocks, and food aid in rural Ethiopia. *American Journal of Agricultural Economics.* 87(2): 273-288.