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Natural Disasters, Preferences, and Behaviors: Evidence from the 2011 Mega Flood in Cambodia

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Natural Disasters, Preferences, and Behaviors:

Evidence from the 2011 Mega Flood in Cambodia*

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Abstract: This paper studies the impacts of the 2011 mega flood on preferences, subjective expectations, and behaviors among rice-farming households in Cambodia, a country with weak formal institutions. We find flood victims to have larger risk aversion and altruism, and lower impatience and trust of friends and local governments. The disaster also induced flooded households to adjust upward their subjective expectations of future floods and of natural resources as a safety net. Mediating (partially if not all) through these changes in preferences and expectations, the 2011 flood also affected households' behaviors, some of which could further affect long-term economic development and resilience to future floods. We find flooded households to have lower productive investment, to substitute away social insurance by increasing self-insurance and demand for market-based instruments, and more importantly, to increase the use of natural resources as insurance. These findings shed light on the design of incentive-compatible safety nets and development interventions in an economy with underdeveloped institutions.

Key Words: Natural disasters, preferences, subjective expectation, household behaviors

JEL Classification: D1, O12, O17

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1. Introduction

Natural disasters often create adverse impacts on the livelihood of people, especially those living in developing economies where access to safety nets is limited and formal institutions are weak. Disasters not only destroy physical, human, and social capital of households, catastrophic disasters can also lead to a change in risk, time, and social preferences. In addition, largely unexpected and rare disasters as well as the success or failure of safety net institutions in coping with the disasters may lead to a revision of subjective expectations of future events and assistance. Such impacts could induce changes in behaviors that could in turn affect long-term economic development and resilience to future disasters. Understanding these consequences has crucial policy implications for the design of incentive-compatible safety nets and development programs for households in developing economies.

This paper aims to make a contribution to the growing literature on the impacts of catastrophic events (natural disasters or civil conflicts) on household preferences and behaviors by studying the consequences of the 2011 mega flood in Cambodia on rice-farming households. We use the 2011 mega flood as a natural experiment and utilize the discontinuity generated by this flood to create variations in flood exposure across sampled villages and households. Field surveys and experiments were used to elicit key preferences, expectations, and behaviors.

This paper is related to two strands of literature. First, there is a growing number of studies showing evidence that natural disasters can change risk, time, and social preferences of affected households. For risk preferences, Eckel et al. (2009) found that experiencing Hurricane Katrina in 2005 affected the risk preferences of Hurricane evacuees in the United States. Cameron and Shah (2012) found that individuals who had recently suffered earthquake in Indonesia exhibited higher risk aversion than those living in similar but unaffected villages. Cassar et al. (2011) and Ingwersen (2014) showed that the 2004 Indian Ocean tsunami in Thailand and Indonesia resulted in higher and lower risk aversion, respectively. Page et al. (2012) found that after large negative wealth shocks from the 2011 flood in Brisbane, Australia, individuals became more willing to adopt riskier options in their decision-making process. For time preferences, Callen (2015) showed that exposure to the 2004 Indian Ocean earthquake and tsunami increased the patience of Sri Lankan wage workers. For social preferences, Castillo and Carter (2011) found that a large negative shock caused by Hurricane Mitch in 1998 increased altruism, trust, and reciprocity in small Honduran communities. Cassar et al. (2011) showed that the 2004 Indian Ocean earthquake and tsunami in Thailand also resulted in higher altruism.

Finally, as summarized in Delavande et al. (2011), shocks could also lead households to form and adjust their subjective expectations.[1]

Second, growing theoretical and empirical studies have documented various mechanisms that preference and subjective expectations could affect household behaviors, which in turn affect economic wellbeing of the households and their resilience to future disasters. For example, increasing risk aversion may cause households to reduce risk-taking behaviors, which may include a reduction in productive investment (Dercon 1998). Time preference could affect households' intertemporal decisions, with increasing patience resulting in an increase in savings (Besley 1995). Increasing altruism may enhance public goods contribution and investment in social capital (Carter and Castillo 2002). Subjective expectations have been found to affect various agricultural investment decisions (Giné et al. 2009; Hill 2009; Raschky et al. 2013; Shaik et al. 2008).

This paper makes several contributions to these existing literatures. First, we add to the knowledge by analyzing the potential behavioral impacts of catastrophic floods, which are among the important extreme disasters that affect large population in developing Asian countries. Despite taking place very rarely, this type of disasters is different from other rare events such as earthquake and tsunami which are largely, if not entirely, caused by exogenous geophysical factors and hit limited locations. Severe floods generally spread extensively throughout the country, creating aggregate covariate shocks. In such situations, there is a limit of government's ability and social networks in local communities to cope with the shocks, making household's reassessment of subjective probability and behavioral changes different from shocks concentrated on specific locations. Second, unlike most of the studies that focused on one particular preference or behavior, our study is one of the few that identify flood impacts on various key preferences, namely, time, risk, social preferences, as well as subjective expectations of farming households, and study the impacts on household's key behaviors affecting their long-term wellbeing. Our analysis thus provides a comprehensive view of behavioral impacts of extreme floods and how they could potentially be mediated through induced changes in preferences and expectations. Third, our research design allowed us to analyze and compare the impacts of the

[1] There is also literature on the effects of traumatic and catastrophic civil conflicts on preferences – for example, Voors et al. (2012), Cassar et al. (2013), and Callen et al. (2014). Also conducted in parallel to this study, Chantarat et al. (2016) study the impacts of the 2011 flood on preferences, subjective expectations, and behaviors of Thai rice farmers.

extreme flood in the more flood-prone areas with those in the less flood-prone areas, giving us the insight on impact heterogeneity that provides better targeted policy implications.

The Cambodian 2011 mega flood was a unique natural disaster event. Although floods are the most common natural disaster in Southeast Asia, Cambodia has experienced relatively less frequent floods than its neighbors—only 15 occurrences during 1981-2010. However, unlike other countries in Southeast Asia, the death toll per flood event in Cambodia is the highest in the region, averaging nearly 90 casualties per event, i.e., nearly twice the death tolls in Indonesia and Thailand.[2] The 2011 flood was particularly important since it was the largest and deadliest in recent decades, with a death toll nearly three times of the historical average. Heavy rains and overflows of the Mekong River and the Tonle Sap Lake that began in the second week of August 2011 eventually affected 18 out of 24 provinces of Cambodia. Impacts were especially severe among the rice farming communities, who tend to be poorer and more flood-prone. The flood caused 250 deaths, and over 1.7 million people were affected. More than 400,000 hectares (ha) of rice crops were impacted; of which, almost 230,000 ha (9.3 percent of the cultivated area) were severely damaged or destroyed. Moreover, 1,675 livestock were lost, and more than 70,000 drinking water wells were contaminated. It was estimated that the floods caused US$625 million worth of losses and damage. Infrastructure damages, estimated at US$376 million, included national, provincial, and rural roads, irrigation facilities, water supply and sanitation facilities, schools, and health centers.[3]

Given its rarity and severity, the 2011 mega flood serves as an ideal natural experiment for a study of how a disaster affects households' preferences, subjective expectations, and behaviors. We study the impacts of the flood by comparing flooded and non-flooded households within the flood-prone and non-flood prone areas. We particularly focus on the impacts of the flood on rice-farming households because most of the areas directly affected by the flood were farmland, especially for rice cultivation. Furthermore, these farms were operated by relatively poor households whose access to risk management and risk coping mechanisms was limited. The flood therefore had substantial impacts on

[2] These statistics are based on the Emergency Events Database (EM-DAT), one of the most comprehensive databases on disasters, maintained by the Centre for Research on the Epidemiology of Disasters (CRED) at the University of Louvain (Belgium). See Samphantharak (2014) for more details.
[3] For background on the 2011 Cambodia flood, see Asian Development Bank (2012). In addition, a study by UNICEF found that food security, health, and nutrition status of mothers aged 15-49 years and children aged 0-59 months were stable within a year after the flood. However, financial hardship from income and asset losses as well as debt burden remained relevant by the time the study was conducted in 2012 (UNICEF 2012).

the livelihood of many farming households and understanding these impacts provides important insights for policymaking regarding safety nets of the poor and vulnerable households.[4]

The findings from our study show that the mega flood made the affected Cambodian rice-farming households more risk averse, and this increase in risk aversion appears greatest among poorer households. The mega flood also reduced household's impatience and increased altruistic behavior among the affected households. Surprisingly, the 2011 flood caused a significant reduction in trust of neighbors and local governments. Flood victims revised upward their subjective probability of future severe floods as well as the potential benefits of natural resources as a safety net. Mediating (partially, if not all) through these changes in preferences and expectations, the 2011 flood also affected households' behaviors. We find that flooded households lowered their productive investment and substituted away from social insurance with self- and market-based insurance instruments. More importantly, these households increased the use of natural resources as insurance. These findings shed light on the design of incentive-compatible safety nets and development interventions.

The paper is organized as follows. Section 2 describes our sampling strategy, survey, and summary statistics of the sampled households and villages. Section 3 discusses the empirical strategy we employed to identify causal impacts of the 2011 mega flood. Section 4 reports our empirical results. Section 5 concludes the paper with policy implications.

2. Data

The data used in this study are from our survey conducted in April 2014. The survey includes a standard household socioeconomic survey with detailed questions on the 2011 flood experience, other risks experienced by households over the previous 10 years, risk management strategies, key behaviors related to farm investment, savings and other safety net decisions, as well as experimentally elicited preference and subjective expectation questions.[5]

2.1 Sampling Strategy

[4] A poor household is defined by comparing their consumption or income with an official poverty line, while a vulnerable household is defined by looking at probability that household's consumption or income falling below poverty line.

[5] One limitation of our study is that the survey was conducted post-disaster. This is a common limitation for the study of the impacts of natural disasters, with the rare exception of Ingwersen (2014) that studies the impacts from the Indian Ocean tsunami using both pre- and post-disaster household data.

There are several important considerations that guide our sampling strategy. First, we confine our study to rice growing areas and households because they were the majority of Cambodia population.[6] In addition, they were poor and vulnerable to adverse shocks. To make our sample more generalizable, we conduct the survey in various regions of the country to reflect variations across the country. We also ensure that our sample had sufficient within-region cross-sectional variations. In particular, we follow the stratified random sampling method described below in which the stratification is at the provincial, commune, and village levels.

Provinces: Our sampled households are from four of Cambodia's key rice-growing provinces: Prey Veng, Kampong Thom, Banteay Meanchey, and Battambang.[7] As shown in Figure 1, these four provinces were severely affected by the 2011 flood. Prey Veng is located in the southeastern plain on the crossing of the Upper Mekong and Lower Mekong rivers, the two major rivers in Cambodia. With annual flows of water from both rivers, the province is one of the high-potential agricultural zones of the country. Apart from rice, farmers often diversify into other cash crops. The province also has good access to market and financial services due to its close proximity to the capital city, Phnom Penh. The other three provinces are located in the Tonle Sap Biosphere Reserves, meaning that people there also greatly rely on forests and other natural resources for their livelihood. Kampong Thom is located on the eastern floodplain of Tonle Sap Lake and occupies key core biodiversity areas in the reserves. The province is among the largest in the country so people have good access to employment and financial services (World Bank 2018). Banteay Meanchey occupies the extended lowland floodplain of Tonle Sap Lake in the northwest. The province also has a border with Thailand and its people benefit from cross-border labor migration opportunities. Battambang is the country's largest rice production province in Cambodia and its rice is predominantly a high-yield variety. The province also serves as a commercial and tourist hub in the northwestern region, with extended market access and alternative livelihood, making the province wealthier than the other three. The four provinces also represent variations in geographical settings, rice cultivation and agricultural production systems, access to market opportunities, and the extent to which household livelihood are prone to floods. These variations in turn contribute to the variations in the nature of the 2011 flood experience, as well as the

[6] Despite rapid economic development of Cambodia in the past two decades, agriculture remains the most important sector for the country's economy, accounting for 74 percent of total employment in 2011 (World Bank). Within agricultural sector, rice is the most important crop, occupying 75 percent of the country's cultivated land (FAO).
[7] These provinces ranked among the top of the country in term of proportion of land used for rice plantation based on government statistics.

capacity and the strategies of the households and the communities in coping with and managing flood damages.

[Figure 1]

Communes: Next, we use official statistics of rice production by commune and village from the Cambodian Council of Agricultural and Rural Development to identify our sampling frames in each province, i.e., the rice-producing communes and villages (i.e., those with more than 50 percent of area growing rice), and use remote sensing maps of inundated areas from 2000 to 2011 produced by the World Food Program (WFP) to identify area severely affected by floods (i.e., areas covered with floodwater for more than 15 days).[8] Using the WFP flood data, we then stratify communes in each province into flood-prone (those with long-term mean proportion of flooded area greater than overall provincial average) and non-flood-prone. Finally, to ensure that our sample consisted of sufficient flooded households, for each province we select four rice-growing communes—two flood-prone and two not flood-prone—that were the most severely affected by the 2011 flood in term of proportion of areas.

Villages: Within each commune, there was a variation in flood experience across rice-growing villages. We then utilize the discontinuity generated by the 2011 flood to construct a variation in flood experience. This discontinuity allows us to compare villages and households that were directly hit by the flood with those who did not directly experience the flood. Using GIS village locators and the satellite based flood maps, we first stratify villages in each commune into two groups: (1) severely flooded villages (i.e., those flooded for more than 15 days), and (2) not (severely) flooded villages.[9] For each commune, we then randomly select two villages, one from each strata.

Households: Finally, within each village we identify the localized areas around the flood limit, i.e., there was a variation of the 2011 flood experience across households with both flooded and non-flooded households in the village. We use the official records of flood victims who experienced rice

[8] The WFP flood maps were based on the near real time remote sensing NASA-MODIS product with 1-km resolution. The MODIS inundation maps have been available every 15 days since 2000.

[9] Since the 2011 mega flood was largely covariate, it was not possible to find completely non-flooded villages. Our distinction of the flooded and non-flooded villages was thus the intensity of the 2011 flood extent, observed through the length of inundation. Our village-level analysis of impacts from flood therefore explores marginal variations in the village flood experience.

farm losses in 2011 and their land sizes collected by local government.[10] Given a relatively small sample size per village, we make sure that our sample is representative of the population. Specifically, for each village, we first stratify households in each village into flooded and non-flooded groups. We then ranked the households in each group by their land size and selected households proportional to the those in each strata, picking households in every X ranking.

In summary, our study is conducted in deliberately selected four provinces (to ensure the nationwide coverage of major rice growing regions), four selected communes per province (to ensure that our sample consists of both flooded and non-flooded villages), two randomly selected villages per commune, and eight randomly selected households per village. In total, our sample thus consists of households from 16 communes, 32 rice-growing villages, and 256 households. Figure 1 shown earlier also illustrates the surveyed villages in the four provinces overlaid with the 2011 flood map.

2.2 Summary Statistics of Survey Data

Table 1 shows descriptive statistics of flood experience in our sample. The sample size by province is shown in Panel A. Note that the sample size is unbalanced following the actual proportion of flooded households in the selected villages, communes, and provinces. The flooded households largely outnumbered non-flooded households for Kampong Thom, Banteay Meanchey, and Battambang, where the majority of rice farms were flooded in 2011. Our sample is relatively more balanced in Prey Veng (29 flooded households out of 64 households).

[Table 1]

Panel B shows the variation of flood experience across the four provinces. Since the 2011 flood had resulted from the overflow of rainwater from the Mekong River toward Tonle Sap Lake, it hit Prey Veng slightly earlier, in late August, before continuing to Kampong Thom, Banteay Meanchey, and Battambang in early September. Flood heights were also different with the majority of households in Prey Veng experiencing knee-high flood, whereas the other three provinces in the Tonle Sap region experienced chest-high flood. Households also reported the number of days that their rice fields were completely submerged by floodwater. We use this information to generate the total number of days

[10] This official record was collected and verified by the local government for government assistant purposes. The data include the names of household head who experienced crop loss from the 2011 flood, land sizes, and locations.

that each household experienced the 2011 flood.[11] On average, the 2011 flood resulted in 26 submerged days, with a maximum of 180 days experienced in Kampong Thom. The flood damaged 89 percent of rice fields and resulted in US$994 loss in rice income (63 percent of total rice income) and US$50 loss in assets (3 percent of total non-land assets) for the median households in the four provinces. The relatively wealthy rice farmers in Battambang suffered the largest loss (75 percent rice income loss and eight percent asset loss for the median households). Among important asset losses were productive farm assets (34 percent, including livestock). Only seven percent of households reported damaged housing and one percent reported having lost family members. Following the 2011 flood, 24 percent of our sampled households reported they had to reduce consumption, nine percent had to cut back child schooling, and 15 percent lowered spending on health care, with slightly greater impacts in Kampong Thom.

Panel C of Table 1 shows coping strategies the flooded households used during the 2011 flood across the four provinces. Strikingly, despite great variations, reliance on natural resources as a safety net was the most salient mechanism in all four provinces—it was adopted by 39 percent of flooded households. Social mechanisms and reliance on assistance from government or non-governmental organizations (NGOs) were quite limited and varied greatly across the four provinces. Specifically, 22 percent of flooded households relied on remittances and borrowing from friends and relatives, although shares varied from only three percent in Prey Veng to 31 percent in Kampong Thom. Fifteen percent of flooded households relied on the government and 19 percent on NGOs, but the bulk of such assistance was concentrated in Kampong Thom.

Apart from natural resources, our sampled rice-farming households relied more on various self-coping mechanisms—29 percent of flooded households reported using borrowing to cope with the 2011 flood, more than half of which from informal institutions such as microfinance institutions and savings groups. Use of credit to cope with the flood varied across provinces, ranging from 45 percent in Prey Veng to 16 percent in Banteay Meanchey. Savings were used by 24 percent of the flooded households while 27 percent of flooded households, especially in the three provinces in the Tonle Sap Lake region, relied on additional labor income to cope with the 2011 flood. Despite the variety of strategies

[11] We note that rice fields are typically located in lower land than the residential areas. If the housing areas were flooded, it was very likely that the rice fields were also flooded. Thus, our household flood days captured the (non-linear) intensity of the 2011 flood, especially when the flood levels were high enough to damage housing and household assets.

available, the use of "destructive" strategies, e.g., asset sales and child labor, was common in some provinces.

Overall, the descriptive statistics in Table 1 suggest (1) the significant and varying impacts of the 2011 flood on rice-farming communities in Cambodia; (2) the importance of natural resources as a safety net during the mega flood; (3) the limited role of social and government/NGO assistance during the flood; and (4) the great extent and variety of self-coping mechanisms used by flooded farmers.

[Table 2]

Table 2 reports descriptive statistics of various household- and village-level characteristics (at the time of the survey in April 2014), stratified by their experience to the 2011 flood. Overall, Panels A and B show that most characteristics were similar for flooded and non-flooded villages, and especially for flooded and non-flooded households. These statistics were similar for the non-flooded group. Availability of village infrastructure and public programs also appeared similar across flood groups. Panels A and B of Table 2 also show some characteristics that were significantly different between the flooded and non-flooded villages, namely, gender and primary education of the respondents, household size, and land per capita. If the characteristics we found to be different across flood groups were also correlated with our outcomes variables, there could be biases in our estimation results.

2.3 Outcome Variables: Preferences, Subjective Expectation, and Household Behaviors

In addition to questions in standard household surveys, our questionnaire also includes a series of hypothetical experiment questions to elicit risk, time, and social preferences; subjective expectations of future floods and resulting income loss; and household perceptions of the reliability of various safety net institutions to mitigate the impacts of future floods. Appendix 1 provides a summary of the experiments and associated preference parameters.

First, for risk preference we use a variant of Binswanger (1980) game by asking respondents to choose different rice seed types with different degrees of risk and return. Seed choices thus reflects the respondent's degree of risk aversion. We then construct our risk aversion variable as a scaling indicator ranging from 1 (most risk tolerant) to 5 (most risk averse). For time preference, the experiment consists of a series of seven questions, each asking a respondent to choose between the choice of receiving some amount of money now or receiving a larger amount that keeps increasing as the experiment progresses from questions 1 to 7 if the respondent waits to receive it in the future. The first time when the respondent choose to accept the payment in the future therefore reflects the extent to which he or she discounts the future over the present, i.e., the degree of impatience. We then construct our impatience variable as a scaling indicator ranging from 0 (most patient) to 8 (most impatient).[12] For social preference, we used a dictator game to illicit measures of household's altruism. Each respondent is given some amount of money, all or part of which could then be given to a randomly chosen household in his or her own village. The respondent is also told that the chosen beneficiary would be anonymous and that the respondent's decision would be kept confidential. We repeat this game but change the beneficiary to be a randomly chosen flood-affected household in the village. We then construct our altruism variable for each game from the proportion (0-100 percent) of money the respondent choose to give. Finally, we use a general social science survey to elicit the degrees to which each respondent trusts family, neighbors, businesses, and local governments. These questions allow us to construct a series of binary trust variables.

For the experiments on subjective expectations, we ask each respondent to assign probabilities to future flood events. We used 10 coins as a visual aid to express the probability concept and ask each respondent to place the coins in front of each of three flood events (no flood, mild flood, and severe flood), where the number of the coins the respondent put reflects the subjective likelihood that each event would occur in the following 10 years.[13] Before we begin the exercise, our enumerator first clarifies the definition of mild flood (i.e., a flood event with less than knee-high floodwater and fewer than 10 days of waterlogging in the farm) and the definition of severe flood (i.e., a flood event with more than knee-high floodwater or more than 10 days of waterlogging in the farm). We define no-flood, mild-flood, and severe-flood events as mutually exclusive events by framing the questionnaire to get the response about the extent of the disaster at its peak. We explain the exercise, using several examples (see Appendix 1). We also repeat this exercise to elicit the respondent's expectations of the proportion of rice income loss and the reliability of various safety nets conditional on the occurrence of mild and severe floods in the future. We then construct each subjective expectation variable directly from the number of coins the respondent assigns to each event.

[12] We note that our simple measure of time preference was subject to risk aversion, as preferring to accept lower instantaneous payment to higher future payment may reflect an aversion to future payment that could be perceived as risky, in addition to time impatience.

[13] Visual aids such as ours have been used widely in low-income countries with relatively illiterate subjects who may find direct questions about probability too abstract; see Delavande et al. (2011) for a review.

[Table 3]

The top panel of Table 3 reports descriptive statistics of our measures of preferences, again, at the time of the survey in April 2014. First, the table shows that the sampled households were relatively risk averse with the mean of risk aversion index ranging from 2.9–3.8 (out of 5) in all groups. Our simple comparison shows that the mean risk aversion variables were not significantly different between flooded and non-flooded households. Second, the impatience measure appeared similar between households in flooded versus non-flooded villages. Third, on average, the altruism measure as measured by the amount of money given to a random household in the same village appeared to be significantly larger for flooded households than that for the non-flooded counterparts. The average share of money given to a randomly matched villager was about 0.24-0.26 in the flooded groups as compared to 0.18-0.20 in the non-flooded groups. The numbers were higher for the share of money given to a random flood victim in the village. Fourth, for trust, we find that in all groups almost all (97-100 percent) of our sampled households trusted their family, followed by neighbors (82-98 percent), local governments (71-94 percent), and businesses (31-53 percent).

For subjective expectations, the middle panel of Table 3 shows that our sampled households assigned large probabilities of flood risk in general (0.38-0.41 for mild flood and 0.28-0.45 for severe flood). This was expected given that our sampled households were all from flood-affected communes. Most flooded households, however, assigned significantly higher subjective probabilities to severe flood. Finally, the descriptive statistics of household's perception on safety net institutions also revealed some interesting results. For both mild and severe floods, the largest percentage of households (25-40 percent) in all groups perceived that they could rely on natural resources as a safety net. For severe flood, the perceived ability to rely on governments and social networks was 25-35 percent and 9-22 percent, respectively. For mild flood, however, both perceived ability to rely on governments and social networks appeared to be similar, at only 7-14 percent.

Finally, we are interested in the impacts of the 2011 mega flood on household behaviors over the past year from the survey that could determine household's production and its resilience to future floods. The variables of our interest are (1) whether the household invested in land and irrigation; (2) whether the household had savings; (3) the number of dependable friends (as an indicator of social capital formation); (4) whether the household collected forest products and engaged in fishing; and (5) the household's willingness to pay for commercial flood insurance. The bottom panel of Table 3 reveals that, compared to the non-flooded households, a significantly larger percentage of flooded households had savings and demanded for commercial insurance.

There are two considerations regarding our elicitation of preferences, subjective expectation, and household behaviors. First, the measures of preferences and subjective expectation elicited from the instruments include not only the intrinsic tastes but also other influences like the economic circumstances of the respondents. For example, respondents with similar tastes but different liquidity constraints, wealth, or investment opportunities may make different choices. This is especially important because it is possible that the disaster affected the economics circumstances of people in villages affected by flooding.[14] In this respect, our elicited preferences and subjective expectation used in our analysis should be interpreted as 'observed', rather than 'intrinsic' preferences and expectation.

Second, the measures of preference and subjective expectations in this study were elicited from hypothetical experiments and not from incentivized experiments such as those with real money and there is literature showing that choices could be different when real stakes were used.[15] For example, respondents in the altruism game might give consistently more if it is not their own money (or money they will be paid out in the end). Furthermore, if answers are given in a face-to-face interview, the social desirability bias might also lead to higher amounts of money given to others compared to the real world. We acknowledge that there are likely measurement errors to our elicited variables. But as long as such measurement errors are not correlate with the mega flood exposure, these measurement errors would not create bias to our estimated mega flood impacts.

3. Empirical Strategy

[14] Ingwersen (2014) reviews literature on this issue and discusses potential pathways for changes in attitude toward risk, which include a decrease in wealth and income and an increase in liquidity constraint following natural disasters. However, he also argues that the disasters could be followed by large assistance that may result in an increase in wealth and a decrease in financial constraints. Other channels include changes in perceptions or tastes for risk.

[15] This concern dates back to at least Smith (1962) who shows that unincentivized hypothetical experiments were vulnerable to erratic and unreliable responses. Several subsequent studies have confirmed this conclusion. For example, Smith and Walker (1993) and Camerer and Hogarth (1999) conclude that paying real money does reduce variance and outliers of responses. More recently, Gachter and Renner (2010) find that belief accuracy is significantly higher when beliefs are incentivized. Rosenboim and Shavit (2012) show that financial rewards create a more realistic environment within the lab while Carpenter, Verhoogen, and Burks (2005) argue that subjects consider their decisions more carefully when they have financial incentives. On the other hand, there are also studies arguing that incentives may not be as important as one would expect (see Amir, Rand, and Gal 2012; and a discussion in Camerer 2003) or hypothetical and incentivized decisions may reflect fundamentally different situations (see Frey and Oberholzer-Gee 1997; and Buhren and Kundt 2015).

3.1 Exposure to the Mega Flood

Our sampling strategy and survey data allows us to construct three flood exposure variables. First, village-level flood exposure is a binary variable indicating whether the household was in a flooded village in 2011, where flooded village was defined using satellite data as a village flooded more than 15 days. Employing this *objectively measured* flood variable, our estimation identifies the impacts on households living in severely flooded villages relative to those living in villages that were not severely flooded. Second, household-level flood exposure is another binary variable indicating whether rice fields of the household were completely submerged by floodwater for more than 15 days based on survey data. Employing this household-level flood variable, our estimation identifies the impacts on households directly hit by the 2011 flood. Finally, based on survey data, we use the number of days that household's rice fields were completely submerged by floodwater to capture household-level flood intensity. Our estimation using this flood variable identifies the heterogeneous effect of different levels of flood intensity on flooded households. Altogether, these three variables capture the varying aspects of the 2011 flood experienced by Cambodian rice-farming households.

The official record of flood victims is also used to verify the construction of our flood exposure variables. As shown in Appendix Table C.1, our satellite-based measure of flooded villages are those with an average of 73 percent of households experiencing crop losses according to the official record, comparing to 27 percent in the non-flooded villages. We also find that our self-reporting measure of flooded households is correlated very well with the official record. Only 7 percent of the self-reporting flooded households were not flood victim according to the official record and 11 percent of the self-reporting non-flooded households were flood victims according to the official record. The latter could reflect that our definition of flooded households was relatively more conservative (i.e., rice fields must be completely submerged by floodwater for more than 15 days, implying complete harvest loss).

3.2 Estimation Models

We estimate the impacts of the 2011 mega flood by regressing our preference and behavioral variables on flood exposure, controlling for individual, geographical characteristics, and village fixed effects. Our estimations thus follow a simple specification:

$$y_{iv} = \beta_0 + \beta_1 Flood_{iv} + \beta_2 Flood_{iv} Floodprone_{iv} + \beta_3 X_{iv} + \alpha_v + \varepsilon_{iv}$$

where y_{iv} represents preference, subjective expectation, or behavioral variables of interest. $Flood_{iv}$ is a variable that captures household's exposure to the 2011 flood. Again, in our analysis, we use three different measures of this exposure: (1) an objectively measured village-level binary indicator if a household was in the flooded village, utilizing the exogenous variation of flood experience across villages; (2) a household-level binary indicator if a household was directly affected by flood, utilizing exogenous variations of flood experience across households within each village; and (3) the number of days that household's rice fields were completely submerged by floodwater, capturing the variation in household-level flood intensity. $Floodprone_{iv}$ is a household-level binary indicator variable capturing whether each household was prone to floods since the flood-prone villages/households were likely be flooded. We add this variable and its interaction with flood exposure variable in each regression so our results imply the effects of flood exposure within either flood-prone or non-flood prone group.[16] X_{iv} is a vector of various household-level controls while α_v controls for unobserved heterogeneity at village level.[17] We cluster all specifications at the commune level.[18]

3.3 Possible Biases: Selective Exposure, Changes in Household Composition, Spillovers, and Self-reporting Bias

As argued by Ingwersen (2014), studies of impacts from natural disasters are subject to possible biases. The first one could come from *selective exposure* to disasters. In our context, villages and households in the flood-prone areas could have higher chance of being affected by the 2011 mega flood, relative to those in the non-flood prone areas. Villages and households in these two groups could also be different, especially in flood anticipation, farm elevation, rice variety, and timing of sawing. For flood anticipation, one may argue that if households anticipate floods, they may adjust cropping pattern, hence affecting our measure of flood exposure. Similarly, elevation of rice farm is

[16] Note that flood proneness at the household level is constructed from a self-reported measure. The reported number of floods might depend on household characteristics and households might thus be grouped into flood-prone versus non-flood prone not based on their actual risk of being flooded but on their personal characteristics, leading to possible biases in the estimated effects. Unfortunately, available objective data from the satellite do not have sufficient detailed resolution that would allow us to construct the household flood-proneness at the household level.

[17] For village flood exposure, commune level fixed effects are used.

[18] We cluster standard errors at the commune level because villages in the same commune shared geographic proximity and were also similar in terms of institutions and public goods. We also cluster at the village level for robustness check; overall conclusions are similar.

generally correlated with flood exposure since lower areas are more prone to floods. Rice varieties are also related to flood exposure since different varieties are suitable for and survive under different water depth.[19] Finally, sowing month could also matter. Sowing earlier could be less vulnerable to flood as it allows farmers to harvest early, hence avoiding complete crop damages. Sowing time could also depend on some complex functions of various factors such as rice varieties and the starting of rainfall.

The factors listed above could result in different household behaviors. Simply selecting and comparing outcome variables between the flooded and non-flooded villages or households could leave us with selection biases–leading our estimates to capture impacts of flood risk rather than of the 2011 flood itself. To deal with this issue, we further stratify villages and households by the degree to which they were prone to floods. At the village level, we again use remote sensing maps from WFP to identify communes that were prone to floods, based on 10 years of inundation data.[20] At the household level, we construct a flood-prone variable from the frequency of floods reported by each household, defining a flood-prone household as the one that reported at least two flood experiences in the past five years. When we stratify our sample into flood-prone and non-flood prone groups, Table 4 shows that these factors are not different between the flooded and the non-flooded households *within each stratified group*. In other words, given flood-proneness, exposure to the 2011 mega flood did not depend on these factors. Since we include the flood-prone variable and its interaction with the 2011 flood exposure in all of our regression analyses, our results capture the *within-group* impacts of the 2011 flood on the outcome variables. Finally, note that these findings are not surprising as we define the exposure to 2011 flood conservatively as rice fields being completely submerged for longer than 15 days. Exposure to this severe flood implies complete harvest loss. As mentioned earlier, this severity

[19] There are three rice varieties grown in our study areas. (1) *Medium-duration rice*: Majority (54 percent) of rice grown by our sampled households and the most common variety in the areas are local, traditional/hybrid varieties with shorter crop cycle up to 6 months. These varieties could be less prone to flooding during the flood season if being sowed early in the year. The adoption of these varieties should be correlated with flood prone. *Flooded rice*: Flood rice, accounting for 40 percent of our sample, is widely grown in flood prone Tonle Sab Lake area. This variety relies on floodwater during rainy season and is still in growing stage when floodwater comes. Crop cycle could be up to 9 months and vulnerable to extreme flood like 2011 if it was completely submerge. Again, the adoption of these varieties should be correlated with flood prone. *Long-duration rice*: This variety accounts for 5 percent of our sample. It is a high-yield variety with a long crop cycle. It is grown in relatively less flood-prone and fertile areas in some encouraged villages/communes in these provinces. This variety was also vulnerable to the 2011 flood as it had not yet been harvested during flood period. The adoption of this variety is correlated with flood-proneness and village/commune fixed effects.

[20] The WFP's flood risk mapping utilizes 10 years of inundation flood maps and produces three flood priority classifications based on the 10-year flood frequency. The first, second, and third priority flood zones consist of areas that experienced at least three, two or one extended flood(s) in the past ten years. We select our flood-prone communes from the group of communes in the WFP's first flood priority.

of flood was rare and the 2011 mega flood was the first one in decades. Although exposure to minor flood could be endogenous (anticipated and pre-emptively prepared), the mega flood was not.[21]

In terms of identification strategy, our paper is closely related to Ingwersen (2014) who studies of the impacts of the 2004 Indian Ocean tsunami on Indonesian households, and Page, Savage, and Torgler (2014) who study of the impacts of the 2011 Australian floods. Both studies analyze the impacts of unexpected natural disasters on *non-disaster prone* households so their studies are equivalent to the subsample of non-flood prone households in our study. However, in addition to the non-disaster prone group, our paper also provides additional findings on the impact of household prone to regular floods, but still not anticipating the 2011 mega flood. Using the terminology from Page et.al. paper, our study also looks at the "impact on localized areas around the flood limit" where "localized areas" in our paper are either flood-prone or non-flood prone. We argue that households on both sides of the localized flood limit were comparable because the mega flood was a rare and unanticipated event.

[Table 4]

There is also a concern as to whether household-level flood experience was exogenous. First, there were factors determining rice growing patterns that could be correlated with flood exposure and damages, e.g., geography, irrigation, and market conditions in the high-demand areas like Battambang. To address this issue, we control for village fixed effects (in addition to the flood-prone indicator) in our analysis. Second, even within the same village, other factors creating the variation in household's experience of the 2011 mega flood such as the choice of rice production cycle (including harvest time), rice varieties (including deep-water varieties of rice), and the damage from the flood, were correlated. However, we argue that the rice production cycle was unlikely endogenous to the 2011 flood. In particular, even advanced farmers found it difficult, if not impossible, to adjust their growing period to reduce flood risk in 2011 since the flood with this extraordinary severity was very

[21] Table B.1 in the Appendix also provides further robustness check when we change definition of 'flood prone'. Specifically, we show that similar results hold when we stratify our sample by flood frequency. Note that to make sure we get large enough sample size, we can only categorize the frequency as: (i) less than 2 floods in 5 years (0 or 1), (ii) 2 floods in 5 years, and (iii) more than 2 floods in 5 years (the latter group is very small and cannot be broken down further). Note also that we cannot break 0 and 1 flood as the data also include the 2011 mega flood and so there would be no flooded group if we considered only those with 0 flood in 5 years. Again, the results confirm that once we stratify by different degrees of flood proneness in our analysis, the variation of flood exposure are no longer significant. Also, one may argue that elevation of farms could be endogenous due to locational choice and self-sorting into communal farms. However, both land and membership of communal farms were inherited and historically determined. As shown in Table 1, the average number of years since households moved into the farmland was 26-27 years so sorting/selection should not be a serious problem for the anticipation of unexpected severe flood that rarely occurred.

much unexpected when it arrived. When we asked whether households had done anything to prepare for the 2011 flood, the majority of households responded that they had not.

The second possible bias was from *changes in household composition*. Migration could generate endogeneity in our flood exposure, especially if many households moved from flooded to non-flooded areas. However, this problem should be minimal for our sampled households since lands in Cambodia were largely inherited. If the household owned land (or relied on community land), mobility was difficult. There was also a problem of changes in household composition between the time of the 2011 flood and the time of the survey in 2014. This problem resulted not only from demographic changes (unlikely due to the short time frame), but also from migration of household members as a consequence of the 2011 flood. This could be problematic since we interviewed only one member per household. If exposure to the disaster was related to the likelihood that household members chose to migrate then there may be a selection bias in the study sample as the remaining household members may have systematically different preferences, subjective expectations, and behaviors than migrating household members. However, we argue that this concern was minimal in our study as Table 2 shows that the share of migration and the characteristics of migrants were similar between the flooded and the non-flooded groups. Also, following the standard household survey, our first choice of the survey respondent for each household was the household head (defined as the person who was in charge of most household's decision makings) and the second choice was the head's spouse. In our sample, 91.7 percent of the respondents were household head and this proportion was not statistically significant across flooded and non-flooded villages and households.[22]

Another possible bias arising from changes in household composition was from selective mortality, which was relevant for post-disaster survey in high-mortality areas. However, this concern was insignificant in our study. Although the mortality from the 2011 mega flood was very high relative to normal floods, the death toll was still at 250 for the whole country. Again, Table 1 shows that member loss was only 1.1 percent in our sample. We do not think that selective mortality would change our overall conclusions.

The third possible bias was that *spillover and general-equilibrium effects* on the non-flooded households were unavoidable. These effects included, but were not limited to, household's new

[22] We also ran regression with a subsample of households that the respondents were household head; the results are similar (which is not surprising, given that the majority of respondents in our sample were household head).

perception about the flood and the disaster management by the government. There were also disruptions to local, regional, and national economic activities that affected prices of goods and services, as well as incomes of many households in the non-flooded areas. However, these effects should bias our results toward finding no difference in preferences and behaviors between the farmers who were directly hit by the flood and those whose farms were not flooded. Note that we also provide the results that capture within-village spillover effects by creating variations in village-level 2011 flood experience.

Finally, the fourth possible bias was the potential endogeneity problem due to self-reporting nature of our household-level flood exposure variables. It is highly possible that self-reported flood exposure measures are likely correlated with some preferences. The recording of past events depends on individual traits and characteristics. As such, more risk averse households are likely to have more salient memories of past floods and might in turn report the flood as being more severe. Similarly, reverse causality might bias the results if people perceive floods as more salient (and thus recall them better) if they did not receive help from others. Results of the regressions relying on self-reported flood measures might thus be biased. We attempt to resolve this potential bias by asking households to describe their flood experience in a more objectively measured fashion, i.e., in term of the number of days that their rice fields submerged by floodwater, of which they had to count by referring to their calendar of event. We then construct a more conservative flood exposure measure defining flooded households as those with rice fields submerged for more than 15 days, which likely implied complete harvest loss. Moreover, our constructed survey-based household flood exposure variable was found to be highly correlated with the list of flood victims in the official records, which could be considered more objective given that local officials were the one collecting the data for administrative purposes. This evidence thus makes our self-reporting household flood variable less prone to this endogeneity problem. For the flood intensity variable, the number of days that household's rice fields submerged by floodwater had been used. However, without objective information on household's actual flood loss, there is no way to verify how accurate this variable is. We admit that our results could be biased due to the correlations between self-reporting intensity and household's characteristics and preferences.[23]

4. Empirical Results

[23] One might expect the result to upwardly bias the flood impacts on risk aversion and subjective expectation of loss, and downwardly bias the impacts on altruism, trust and safety net perceptions.

4.1 How did the 2011 mega flood affect preferences?

Table 5 summarizes the regression results of the 2011 flood on households' risk aversion. Columns (1) to (6) report various ordinary least squares (OLS) regressions of risk aversion on our three measures of flood exposure. Overall, controlling for commune fixed effects, columns (1) and (2) show no significant relationship between living in severely flooded villages and risk aversion even when controlling for flood proneness and other key covariates. Controlling for village fixed effects and whether households were in flood-prone areas, column (3) shows a significant positive effect of the 2011 flood on risk aversion among flooded households in non-flood-prone areas. This result is also robust when we add a full control of other covariates. For flooded households already living in flood-prone areas, however, the 2011 flood did not result in statistically significant change in their risk aversion. Interestingly, the wealth interaction term is significantly negative. Finally, as reported in columns (5) and (6), we find no significant impact of flood on risk aversion when we use flood days as our measure of flood exposure. This is possible since damages from flood were non-linear in flood days. These results are robust when we use ordered probit estimation, as shown in columns (7) to (12). In all specifications, we also find that households living in flood-prone areas tend to have significantly higher risk aversion than those in non-flood-prone areas.[24]

[Table 5]

Our results reveal that the impact of the 2011 mega flood on a household's risk aversion depends on whether the household was living in the flood-prone or the non-flood-prone area prior to the flood. On the one hand, for households in non-flood-prone areas, our result shows that the 2011 flood led to higher risk aversion. Our result also shows that the impact of the 2011 mega flood on risk aversion among those living in non-flood prone areas also declined with wealth. On the other hand, for households that already lived in the flood-prone areas, the 2011 flood did not affect their risk aversion. Our finding for the non-flood prone groups is consistent with several other studies that analyze the impact of disasters on risk aversion. For example, Shah (2012) finds that individuals who recently suffered a flood or an earthquake in Indonesia exhibit higher risk aversion than individuals living in

[24] This finding suggests that risk aversion was not a key determinant of the choice of rice farm locations, especially in the studied areas where most of the lands are largely inherited. The high risk aversion of farmers living in the flood prone areas could also reflect the consequence of flood risk on household's risk aversion.

otherwise like villages. Cassar, Healy, and Kessler (2011) show that the 2004 Indian Ocean tsunami in Thailand resulted in higher risk aversion. In particular, this finding is also consistent with a conclusion reached by Chantarat, Lertamphainont, and Samphantharak (2016) who find that the 2011 mega flood in Thailand had a positive impact on risk aversion of flooded farming households. On the contrary, Page, Savage, and Torgler (2012), analyzing the 2011 Brisbane flood in Australia, find that after a large negative wealth shock, those directly affected became more willing to adopt riskier options in their decision-making process. Likewise, Ingwersen (2014) finds a decrease in observed risk aversion of victims from the Indian Ocean tsunami in Indonesia.[25]

[Table 6]

Table 6 summarizes the regression results for impatience. Columns (1) to (6) report various OLS regressions of impatience on village-flood exposure. Controlling for commune fixed effects, we find no statistically significant relationship between living in severely flooded villages and impatience, even when we control for the degree of flood-prone and other key covariates. Controlling for village fixed effects and whether households were in flood-prone areas, as well as all covariates, column (3) shows that the 2011 flood did not significantly affect impatience among flooded households. However, when we add wealth interaction to the regression, we find instead in column (4) that the 2011 flood significantly reduced impatience among flood-prone households who were hit by the flood, and that this negative impact increased with wealth. We also find weak or no impact of flood on time preference when we use flood days as a measure of flood exposure.

These results are robust when we use ordered probit estimation instead of OLS, as shown in columns (7) to (12). Moreover, in almost all specifications, we find that households living in flood-prone areas were significantly less patient than those in non-flood-prone areas. However, we find no further impact of increasing flood intensity. Our finding adds to the mixed results from various existing impact studies of disasters on time preference. For example, Callen (2011) shows that exposure to the Indian Ocean Earthquake tsunami affected a patience measure in a sample of Sri Lankan wage workers.

[25] Table B.2 in the Appendix presents results from various robustness checks: (1) using a subsample of households whose respondent is head; (2) defining flood prone as household experiencing more than two floods in five years; (3) stratifying regression by flood prone group instead of using interaction terms; and (4) using various binary measures of risk aversion. The overall qualitative conclusion remains the same for all of the robustness specifications.

Chantarat, Lertamphainont, and Samphantharak (2016) find no systematic pattern of the impact on the impatience of farming households in Thailand that were affected by the 2011 mega flood.[26]

[Table 7]

Table 7 summarizes the regression results for altruism. We pool the two altruism dependent variables (the proportion of money given to a random villager and the proportion given to a random flood victim) and use an indicator variable "Given to Flood Victim" to indicate the results for the latter variable. The higher amount of money given to others is interpreted as higher altruism. In the regression, the significantly positive effect of this variable thus reflects the marginal effect of flood on altruistic behavior. OLS estimations in columns (1) and (2) show no significant effect of the 2011 flood on altruism among households living in flooded villages. Controlling for village fixed effects, columns (3) and (4) report that the 2011 flood significantly increased altruistic behavior among flooded households. Using a flood intensity variable, columns (5) and (6) further show a significant positive effect of increasing flood intensity on altruistic behavior. Our findings thus add to existing literature on disasters and social preference. For example, Castillo and Carter (2011) find that a large negative shock from Hurricane Mitch in 1998 affected altruism, trust, and reciprocity in small Honduran communities, while Cassar, Healy, and Kessler (2011) show that the 2004 Indian Ocean tsunami in Thailand resulted in higher altruism. However, Chantarat, Lertamphainont, Samphantharak (2016) find that the 2011 mega flood in Thailand made flooded households become less altruistic.[27]

[Table 8]

Finally, Table 8 summarizes the regression results for trust, using probit estimation. We regress the four binary trust variables (trust family, neighbors, businesses, and local government) on our three measures of flood exposure. The 2011 flood does not affect the trust of family (both for flood-prone and non-flood prone farmers).[28] The flood and the increasing flood intensity, however, significantly reduced trust of neighbors and local government among flooded households. One of the explanations

[26] Table B.3 in the Appendix presents results from various robustness checks; the overall qualitative conclusion remains the same.
[27] Table B.4 in the Appendix presents results from various robustness checks; the overall qualitative conclusion is unchanged.
[28] We note that there is extremely low variation in the trust of family variable with only 3 out of 256 households reporting trust family = 0.

could be that flooded households realized the limited roles of social risk sharing and local government in the presence of aggregate shocks. Alternatively, the mega flood might create some conflicts within flooded communities, e.g., with respect to resources allocation or water management. The flood also resulted in a significant reduction of trust in businesses among flooded households in flood-prone areas.[29]

Overall, the mega flood effects were detected from the household-level flood exposure and intensity variables rather than the satellite-based measured of flooded village. One possible explanation could be that there were still large variation of flood experience (i.e., crop loss) within each flooded village. However, since most of the flood effects were significant even with the binary household flood variable, which was shown earlier to be highly correlated with the objectively-collected list of flood victims from the official record, it is likely that our results provide an overall unbiased conclusion.

4.2 How did the 2011 mega flood affect subjective expectations of future floods, rice income loss, and reliability of various safety nets?

Table 9 summarizes the regression results for subjective expectations of future mild flood, severe floods, and the expected proportion of rice income loss following mild or severe floods. We first pool mild and severe flood events and use an indicator variable "For Mild Flood" to indicate results for the mild flood. Columns (1) and (2) report regression results using village flood exposure; columns (3) and (4) for household flood exposure; and columns (5) and (6) for flood intensity, with relevant fixed effects and full controls. In all specifications, we find that the subjective expectation of mild floods appeared significantly larger than that of severe floods. Households living in flood-prone areas had significantly larger subjective expectations of severe flood than those in non-flood-prone areas. The 2011 flood significantly increased subjective expectations of future severe floods among households living in flooded villages and flooded households. The occurrence of a flood, therefore, may induce them to update their expectations. However, the positive effect was smaller (and almost non-existent in some specifications) if households were already in flood-prone areas and so had already experienced regular floods. According to columns (2), (4), and (6), being in flooded villages did not affect perceptions of rice income loss when future flood occurs. Increasing flood intensity, however, was significantly associated with the expectation of increasing rice income loss from future severe

[29] Table B.5 in the Appendix presents results from various robustness checks; the overall qualitative conclusion is robust.

floods. The effects on the subjective expectation of mild flood, however, were inconclusive across specifications.[30]

[Table 9]

Table 10 summarizes regression results on household's perceptions of the reliability of government, social networks, and natural resources as a safety net during mild and severe floods. According to the findings in columns (1), (4), and (7), the expectation of assistance from the government was significantly lower for mild floods relative to severe floods. This result reveals the well-known fact that emergency assistance tends to respond more to severe disasters. Households living in flood-prone areas also did not have significantly different expectations of government help from those in non-flood-prone areas. The 2011 flood also did not significantly affect household's expectation of government assistance in the event of future floods. One possible explanation is that government assistance has always been minimal and the experience during the 2011 flood did not lead affected households to update their perceptions. Columns (2), (5), and (8) present the flood effect on perception of dependability of social networks. We find a (statistically weak) significant reduction of the perception of social networks as a safety net during future mild floods, especially among flooded households in flood-prone areas. This finding is consistent with the reduction in trust of friends among flooded households that we reported earlier. If the perception could affect social interactions, the mega flood could crowd out social capital formation among the 2011 flood victims in the flood-prone communities. Finally, columns (3), (6), and (9) reveal opposite results for natural resources. Our results for both flood exposure variables show that the 2011 flood caused a significant increase in perceived reliability of natural resources as a safety net during future mild floods among flooded households.[31]

[Table 10]

4.3 How did the 2011 mega flood and (updated) preferences affect household behaviors?

[30] Table B.6 in the Appendix presents results from various robustness checks; the overall qualitative conclusion remain the same.

[31] Table B.7 in the Appendix presents results from various robustness checks; the overall qualitative conclusion remains the same for all of the robustness checks.

We motivate our study from the beginning that one of the key values to understand how the mega flood affected preferences and expectations is that these changes in preferences and expectations could affect household behaviors, and some of these behaviors could in turn affect household's long-term prosperity and resilience to future shocks. We revisit our motivations in this section by first exploring how key household behaviors were generally related to preferences and subjective expectations. We then explore whether, and how, the 2011 flood affected these household behaviors, and more importantly to what extent these flood effects could be mediated through the flood-induced changes in preferences and subjective expectations.

[Table 11]

Table 11 summarizes the results from probit estimation on five behaviors that each household made during the 12 months before the survey was conducted in April 2014: (1) whether the household invested in land and irrigation; (2) whether the household had savings; (3) whether the household collected forest products and engaged in fishing; (4) the number of dependable friends the household had; and (5) whether the household was willing to pay for commercial flood insurance. Behavior (1) is critical for future income generation, while behaviors (2) to (5) reflect self, natural resource, social, and market insurance decisions, which are critical for the resilience of households in developing economies.[32] Most of the results from regressing household behavior variables on preference variables with full controls and fixed effects are very much in line with what predicted by economic theory.

First, columns (2) of Table 11 shows that plot investment decreased significantly with risk aversion and subjective expectations of mild floods; however, it increased significantly with impatience and altruism.[33] Second, columns (5) shows that the decision to save decreased significantly with impatience and trust in neighbor, and increased significantly with altruism and subjective expectations of future mild floods. Third, column (8) shows that the decision to exploit forest products decreased significantly especially with altruism and (relatively less significant) with impatience, while it increased with trust in neighbors. Fourth, columns (11) reports that the number of dependable friends also increased significantly with the level of trust of friends and businesses. Finally, we find

[32] Table B.8 in the Appendix shows the results from OLS estimation with fixed effects; the overall conclusion does not change.

[33] The result for altruism is sensible, especially if our measure of altruism is also an indicator for altruistic preference toward descendants or future generations.

household's demand for commercial insurance decreased significantly with impatience, trust of neighbors, and subjective probability of mild flood as shown in columns (14).[34]

How might the 2011 flood affect household behaviors and to what extent might these effects be induced by the impact of the flood on preferences and expectations? Regressing these behavioral variables on the measures of flood exposure and other controls, column (1) shows that the 2011 flood caused a significant increase in plot investment for flooded households in flood-prone areas. This finding is consistent with what we would deduce from our flood results on increasing risk aversion and increasing subjective expectations of future floods, especially among the flooded households in non-flood prone areas. Column (4) shows that the mega flood also led to a significant increase in savings among flooded households, especially those in non-flood-prone areas. This result is consistent with the precautionary motive of savings and also is in line with our earlier finding that the flood caused a significant increase in subjective expectation of future flood and altruism, and a significant decrease in trust in neighbor, with weaker impacts on impatience among the flooded households in non-flood prone areas.

Column (7) of the table shows that the 2011 flood caused a significant decrease in the collection of forest products among flooded households in non-flood-prone areas. The finding is in line with the resulting increase in altruism among flooded households in the non-flood prone areas and the growing perception of the benefit of saving natural resources as a safety net against adverse years in the future.[35] One possible interpretation of these combined results could be that, as the 2011 flood increased the perception of nature as insurance, households realized that preserving the forest in normal years (and also being induced through an increase in altruism) would allow them to rely on these resources in bad years. Another possible explanation is that the mega flood may have induced affected households to insure themselves through other means (for example, through increasing savings and greater resort to commercial insurance, as discussed below), hence reducing their collection of forest products.[36]

[34] Strikingly, insurance demand was not correlated with risk aversion, as economic theory would predict. One possible explanation is that financial literacy, especially with respect to insurance, could still be low among Cambodian rice farmers in our sample.
[35] We asked in our survey about the type of forest products household collected; the top-three responses were (1) wild animals, (2) logging/wood, and (3) fruits/wild vegetable. These data support our implicit assumption that current resource exploitation decreases the usability of these resources in the future, i.e., a reduction in current resource exploitation helps provide future safety nets.
[36] We also find similar results when we use household flood intensity variables. We do not find significant results, however, when we use village flood exposure.

Column (10) of the table shows that the flood also caused a significant reduction in the number of dependable friends, i.e., social capital among flooded households in the non-flood-prone areas (although the estimate was weakly significant). From our earlier results, this might be driven by flood-induced decreasing trust and decreasing perceived benefit of social insurance in the presence of aggregate shocks. Lastly, Column (13) shows that the flood caused a significant increase in demand for commercial insurance among affected households in the flood-prone region. The finding is in line with our earlier finding of a flood-induced increase in subjective expectations of future floods. One potential explanation is that there could be other salient determinants of insurance demand than risk aversion and expectations that could be induced by the mega flood.[37]

5. Conclusion and Policy Implications

Our empirical findings from Cambodian rice farmers contribute to existing literature on the impacts of natural disasters on households in developing countries. Overall, our findings suggest that the 2011 flood—the country's most severe in decades—did affect certain preferences, subjective expectations and behaviors of households, which could further determine their long-term economic livelihood and resilience to future shocks.

Specifically, on preferences, we find that the mega flood seemed to have made the affected households become more risk averse, with poor households showing the largest increase in risk aversion. The mega flood also reduced impatience and increased altruistic behavior among some affected households. Surprisingly, the 2011 flood caused a significant reduction in trust of neighbors and local government. Affected by this mega flood, flood victims seemed to revise upwards their subjective expectations of the occurrence of future severe floods. Overall, the mega flood effects were detected from the household-level flood exposure and intensity variables rather than the satellite-based measured of flooded village, possibly due to a large variation of flood experience within each flooded village. However, most of the flood effects were significant even with the binary household flood

[37] Another possible explanation is from the supply side. The 2011 mega flood may have led to an increase in the supply of commercial insurance that allowed households to have easier access to insurance contracts provided by the private sector. This relaxed constraint on access to insurance could lead to higher participation in commercial insurance despite the lower risk aversion of the population.

variable, which was shown to be highly correlated with the objectively-collected list of flood victims from the official record.

On safety nets and risk-coping strategies, our findings reveal interesting facts about how Cambodian farmers used and perceived the reliability of government, social networks, and natural resources as safety nets for the 2011 mega flood and future floods. First, we find that reliance on governments, NGOs, as well as social networks appeared to be very small among the rice-farming communities during the 2011 mega flood – though the flood did not affect their perception of help from government and NGOs. The flood also further reduced household's perception of the benefit of social networks as a safety net, especially among flooded households in flood-prone regions. This finding is not surprising, given that community risk sharing is likely ineffective in insuring covariate shocks. We also find a limited role of the government, something quite unique compared with other developing agrarian economies where governments are often viewed as the insurer of last resort among poor farmers (Chantarat et al. 2016). With limited social and public support, we find relatively strong evidence of self-coping and self-insurance mechanisms such as savings. The most salient result is that we find natural resources to be a significant source of safety net among these communities and that the mega flood caused them to revise upward their perceived benefit of nature as a safety net. These findings could reflect the fact that three out of the four severely-flooded provinces in our sample were located in the Tonle Sap Biosphere Reserves, the area where reliance on the forest appeared strong. This evidence may extend well beyond Cambodia, since major biodiversity hotspots also appear to be crucial disaster or climate change hotspots as well.

On household behaviors, we find that the 2011 mega flood affected several behaviors of the households. This result is not surprising, given the impact of the flood on household preferences and expectations. First, we find the flooded households to have lower land and irrigation investment relative to their non-flooded counterparts, possibly driven by increasing risk aversion and increasing subjective expectations of future floods. To the extent that productive investment is critical for long-term economic prosperity, our findings have important implications for potential long-term welfare impacts of extreme or catastrophic disasters in general.

Second, we find that flooded households extracted fewer forest products and engaged less in fishing than non-flooded households. According to our results described above, this could be due to increasing altruism among flooded households, which could lead to decreasing incentives among households to exploit public goods. Reduction in forest extraction now could imply that these households had increasingly perceived public natural resources as insurance against future shocks, making them likely to save these natural resources for bad years. In other words, households viewed natural resources as community savings, with potential future benefits. On the one hand, these results could be seen as positive as the incentives to preserve natural resources might increase. On the other hand, if natural resources have increasingly been used as an insurance device, the increasing frequency and intensity of disasters could jeopardize the sustainability of these resources. This finding also raises other concerns—if the Cambodian households extensively use natural resources as insurance, to what extent might this reliance crowds out other safety net institutions? Does natural resource abundance reduce the demand for formal, market-based insurance contracts? Does natural resource endowment reduce the government's incentive to invest in disaster prevention infrastructure?

Third, we find that flooded households reported fewer dependable friends than non-flooded households. According to our results described above, this could be due to falling trust and decreasing perceived benefits of social insurance following the mega flood. Altogether, our findings thus imply that the 2011 flood may reduce social interactions and hence social capital formation in the affected communities. While local social insurance may not be very effective against covariate shocks, it can be very effective for idiosyncratic risk sharing. Furthermore, social capital itself is essential for the functioning of the economy, especially the rural financial system.

Fourth, we find that flooded households had higher savings and higher demand for commercial insurance as compared to non-flooded households. In addition to the main preferences, we find that these results could be driven by increasing subjective expectations of future floods and decreasing trust of friends. The reduced role of social insurance seemed to be substituted by an increase in incentives for self-insurance. This finding also provides supportinve evidence that the increasingly important role of natural resources has not as yet crowded out private incentives to reduce and manage disaster risks. The problem remains whether Cambodian farming households have full access to effective markets and self-insurance strategies.

Finally, on policy implications, our results can contribute to public policymaking regarding the design of incentive-compatible safety nets and development interventions. The empirical results emphasize that public policies promoting effective risk management institutions among households could increase investment incentives and hence be pro-poor policies. Thus, public assistance and safety nets in the form of investment in flood prevention infrastructure, irrigation systems, or other investments to promote alternative and more resilient livelihood could provide longer-term economic development impacts than simple transfer programs.

With the 2011 mega flood inducing more incentives for self-insurance among the affected population, safety-net policies should aim to improve access to effective strategies, e.g., facilitating access to rice varieties that are more resistant to flood, utilizing technology and weather forecasts to make effective adaptations to rice production, or providing access to diversifying crops or income. Our results show that the mega flood induced the demand for market-based insurance instruments. Therefore, policies should also aim to enhance household's access to savings and insurance products, especially among the population with relatively low financial literacy rates. Furthermore, as incentives for using natural resources as insurance by households increase, policies should aim to encourage conservation and sustainable use of these resources, e.g., through forest zoning and incentivized reforestation programs. Finally, interventions should also be designed to rebuild social interactions and capital, which were degraded by the disaster.

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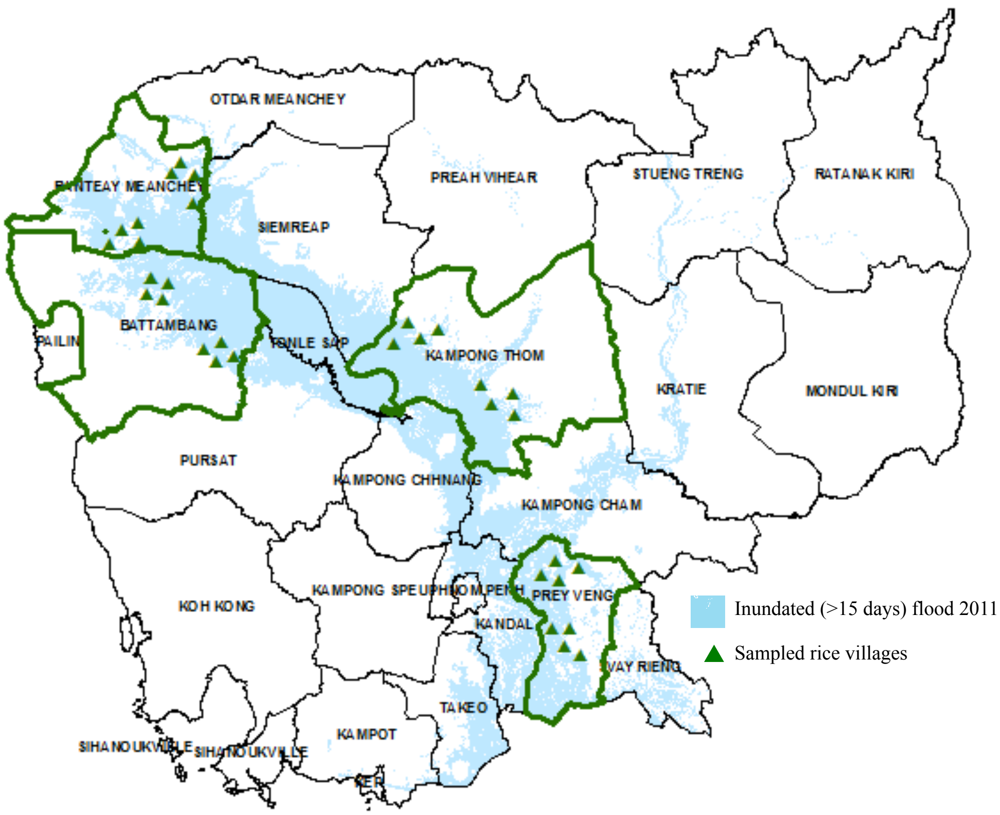
Figure 1 Map of studied villages



Source: Inundated areas are based on the remote sensing map in 2011 produced by the World Food Program (WFP). The studied provinces are outlined by thick borders. The sampled villages are shown by the triangle dots.

Table 1 Summary statistics of sampling and characteristics of 2011 flood among flooded households

	All		Prey Veng		Kampong Thom		Banteay Meanchey		Battambang	
A. Sampled households										
Total villages	32		8		8		8		8	
Flooded villages	16		4		4		4		4	
Total households	256		64		64		64		64	
Flooded households	172		29		53		46		44	
	All		Prey Veng		Kampong Thom		Banteay Meanchey		Battambang	
B. Characteristics of flood 2011	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Starting month	8.97	0.86	8.79	0.95	8.87	0.92	8.99	0.93	9.22	0.55
Flood height	3.09	0.92	1.98	1.00	3.05	0.86	3.23	0.88	2.95	0.96
Flood days	26.0	16.0	24.8	15.3	29.5	18.9	24.5	14.4	24.3	14.0
Affected rice farm (%)	0.89	0.23	0.82	0.26	0.90	0.23	0.93	0.19	0.88	0.26
Rice income lost ($, median)	994	6,150	1,181	1,693	757	4,425	962	599	1,215	11,050
Rice income lost (% rice income)	0.63	0.29	0.75	0.36	0.48	0.27	0.61	0.26	0.77	0.26
Asset lost ($, median)	50	1,054	76	189	63	291	20	53	53	2,063
Asset lost (% total non-land asset)	0.03	0.17	0.02	0.04	0.02	0.08	0.01	0.03	0.08	0.32
Consumption lost (%)	0.08	0.14	0.06	0.13	0.08	0.13	0.10	0.15	0.09	0.15
With house damage (%)	0.07	0.25	0.00	0.00	0.13	0.34	0.04	0.20	0.07	0.25
With productive asset lost (%)	0.34	0.47	0.42	0.50	0.28	0.45	0.24	0.43	0.43	0.50
With member lost (%)	0.01	0.10	0.00	0.00	0.04	0.19	0.00	0.00	0.00	0.00
With reduced consumption (%)	0.24	0.43	0.24	0.44	0.28	0.45	0.16	0.37	0.28	0.46
With reduced schooling (%)	0.09	0.28	0.09	0.29	0.09	0.29	0.08	0.28	0.09	0.28
With reduced health care (%)	0.15	0.36	0.12	0.33	0.26	0.44	0.10	0.31	0.09	0.28
	All		Prey Veng		Kampong Thom		Banteay Meanchey		Battambang	
C. Coping strategies	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Forest clearance	0.05	0.22	0.06	0.24	0.06	0.23	0.04	0.20	0.04	0.21
Collect forest product/fishing	0.39	0.49	0.36	0.49	0.43	0.50	0.43	0.50	0.33	0.47
Asset sale	0.30	0.46	0.45	0.51	0.37	0.49	0.24	0.43	0.17	0.38
Drawing out saving	0.24	0.43	0.27	0.45	0.26	0.44	0.22	0.42	0.20	0.40
Child labor	0.10	0.30	0.03	0.17	0.07	0.26	0.12	0.33	0.15	0.36
Adult labor	0.27	0.45	0.09	0.29	0.31	0.47	0.33	0.47	0.30	0.47
Borrowing from banks	0.10	0.30	0.15	0.36	0.15	0.36	0.02	0.14	0.09	0.28
Borrowing from MFIs, groups	0.19	0.57	0.30	0.72	0.22	0.62	0.14	0.51	0.11	0.43
Borrowing from friends/relatives	0.06	0.24	0.00	0.00	0.09	0.29	0.08	0.28	0.04	0.21
Borrowing amount ($)	586	836	1,187	1,117	345	489	347	415	609	1,027
Remittances	0.13	0.34	0.03	0.17	0.22	0.42	0.16	0.37	0.07	0.25
Governments	0.15	0.36	0.09	0.29	0.35	0.48	0.04	0.20	0.07	0.25
NGOs	0.19	0.39	0.09	0.29	0.39	0.49	0.06	0.24	0.15	0.36

Note: Flood height = 1 if very little, = 2 if knee high = 3 if chest high = 4 if above chest high. Coping strategies reported as percent of flooded households using the strategies. Flooded villages are villages identified using GIS flood map with more than 50% rice field inundated. Flooded households are households with rice field submerged under floodwater for longer than 15 days.

Table 2 Summary statistics of sampled households by 2011 flood exposures

	Village flood (=1)				Household flood (=1)			
	Flood prone		Less flood prone		Flood prone		Less flood prone	
	Flooded	Not flooded	Flooded	Not flooded	Flooded	Not flooded	Flooded	Not flooded
A. Household characteristics								
Female (=1)	0.349	0.429	0.338	0.451	0.485	0.313	0.369	0.423
	(0.481)	(0.602)	(0.477)	(0.502)	(0.502)	(0.471)	(0.486)	(0.498)
Age (years)	49.63	48.89	48.031	49.95	48.272	50.283	49.904	49.923
	(10.81)	(13.26)	(13.603)	(17.712)	(16.242)	(19.302)	(13.337)	(13.301)
Have education-primary (=1)	0.793	0.735	0.892	0.833	0.758	0.781	0.808	0.826
	(0.408)	(0.444)	(0.812)	(0.646)	(0.431)	(0.422)	(0.396)	(0.382)
Have education-secondary (=1)	0.238	0.294	0.477	0.411	0.273	0.254	0.384	0.403
	(0.429)	(0.459)	(0.503)	(0.562)	(0.447)	(0.439)	(0.489)	(0.495)
Household size	5.523	5.279	5.246	5.133	5.192	4.969	5.152	5.255
	(2.441)	(2.652)	(2.031)	(1.836)	(2.117)	(1.713)	(2.018)	(1.824)
Member migrate (%)	0.667	0.573	0.738	0.567	0.687	0.406	0.657	0.653
	(1.063)	(0.886)	(1.253)	(1.015)	(1.016)	(0.797)	(1.145)	(1.152)
Female member migrate (%)	0.269	0.176	0.323	0.267	0.242	0.156	0.328	0.253
	(0.652)	(0.384)	(0.664)	(0.578)	(0.554)	(0.446)	(0.667)	(0.555)
Age of migrating members	15.746	15.647	17.754	14.883	17.272	10.812	16.789	15.807
	(25.74)	(24.75)	(30.136)	(26.853)	(25.783)	(22.103)	(29.301)	(27.681)
Income per capita ($)	737.51	808.74	643.56	616.32	813.39	654.13	440.051	512.629
	(1062.02)	(2791.68)	(823.83)	(858.91)	(2417.61)	(775.59)	(590.49)	(663.04)
Rice income in total income (%)	0.457	0.460	0.4552	0.484	0.424	0.466	0.447	0.495
	(0.347)	(0.365)	(0.353)	(0.352)	(0.544)	(0.569)	(0.348)	(0.357)
Land per capita (ha)	0.615	0.579	0.591	0.552	0.485	0.593	0.597	0.537
	(0.692)	(0.527)	(0.850)	(0.578)	(0.566)	(0.608)	(0.817)	(0.592)
Asset per capita ($)	1988.62	1522.73	3149.08	2478.08	1634.71	2093.53	2920.47	2695.78
	(2012.35)	(1630.45)	(4748.32)	(2778.94)	(1819.98)	(1854.21)	(3589.17)	(4391.63)
Other shocks in the past 10 yrs	2.016	2.175	1.553	1.558	2.060	2.219	1.616	1.471
	(1.462)	(1.664)	(1.372)	(1.245)	(1.479)	(1.764)	(1.324)	(1.292)
Years since first move to current land	25.861	27.538	26.573	26.956	25.807	29.709	27.180	26.162
	(10.508)	(16.968)	(13.818)	(11.397)	(15.607)	(7,932)	(11.449)	(14.412)
Respondent is head (=1)	0.956	0.937	0.923	0.933	0.918	0.923	0.959	0.885
	(0.215)	(0.341)	(0.268)	(0.251)	(0.328)	(0.359)	(0.119)	(0.322)
B. Village characteristics								
Have irrigation system (=1)	0.496	0.415	0.379	0.409	0.453	0.453	0.377	0.417
	(0.463)	(0.468)	(0.452)	(0.467)	(0.463)	(0.481)	(0.454)	(0.467)
Have electricity (=1)	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
With social land concession (=1)	0.107	0.095	0.092	0.071	0.101	0.094	0.123	0.057
	(0.335)	(0.263)	(0.292)	(0.302)	(0.303)	(0.296)	(0.331)	(0.235)

Note: Household is flood prone if it experienced at least 2 floods in the past 5 years. Standard deviations in parentheses. * p<0.1; ** p<0.05; *** p<0.01.

Table 3 Summary statistics of preference, subjective expectation and behavioral choice variables

	Village flood (=1)				Household flood (=1)			
	Flood prone		Less flood prone		Flood prone		Less flood prone	
	Flooded	Not flooded	Flooded	Not flooded	Flooded	Not flooded	Flooded	Not flooded
Preferences								
Risk aversion (1,2,..,5)	3.492	3.691	3.246	3.017	3.535	3.781	3.273	2.942
	(1.435)	(1.374)	(1.511)	(1.408)	(1.431)	(1.313)	(1.529)	(1.349)
Impatience (0,1,2,..,8)	4.936	4.588	4.507	4.767	4.545	5.406*	4.465	4.865
	(2.361)	(2.389)	2.878)	(2.824)	(2.556)	(1.543)	(2.774)	(2.950)
Altruism - percent money given to randomly matche	0.264	0.200*	0.255	0.202	0.240	0.203	0.264	0.182**
villager (0-1)	(0.229)	(0.221)	(0.241)	(0.183)	(0.223)	(0.231)	(0.251)	(0.162)
Altruism - percent money given to randomly matche	0.420	0.352**	0.361	0.384	0.377	0.409	0.384	0.354
flood victim in the village (0-1)	(0.204)	0.195)	(0.234)	(0.183)	(0.197)	(0.216)	(0.241)	(0.159)
Trust family (=1)	0.998	0.985	0.984	0.983	0.989	1.00	0.972	1.00
	(0.043)	(0.121)	(0.124)	(0.129)	(0.101)	(0.000)	(0.164)	(0.00)
Trust neighbor (=1)	0.857	0.852	0.892	0.883	0.818	0.968**	0.821	0.981***
	(0.353)	(0.356)	(0.312)	(0.323)	(0.387)	(0.176)	(0.385)	(0.138)
Trust business/trader (=1)	0.308	0.460**	0.400	0.383	0.333	0.531**	0.452	0.307**
	(0.465)	0.502)	(0.493)	(0.490)	(0.473)	(0.507)	(0.501)	(0.466)
Trust local government (=1)	0.809	0.751	0.738	0.733	0.727	0.937**	0.712	0.769
	(0.395)	(0.436)	(0.442)	(0.445)	(0.447)	(0.245)	(0.455)	(0.425)
Subjective expectations								
Probability of mild flood (0-1)	0.401	0.410	0.409	0.385	0.412	0.385**	0.411	0.377
	(0.216)	(0.240)	(0.209)	(0.241)	(0.221)	(0.251)	(0.230)	(0.219)
Probability of severe flood (0-1)	0.414	0.447	0.413	0.313**	0.448	0.376***	0.423	0.284***
	(0.242)	(0.279)	(0.283)	(0.225)	90.251)	(0.289)	(0.279)	(0.207)
Probability of loss when mild flood occurs (0-1)	0.326	0.344	0.331	0.263	0.372	0.225	0.348	0.227**
	(0.277)	(0.298)	(0.298)	(0.265)	(0.297)	(0.223)	(0.285)	(0.256)
Probability of loss when severe flood occurs (0-1)	0.738	0.777	0.720	0.705	0.797	0.638	0.758	0.664
	(0.241)	(0.228)	(0.324)	(0.290)	(0.197)	(0.296)	(0.249)	(0.371)
Can rely on govnt. when mild flood (=1)	0.094	0.136	0.163	0.128	0.118	0.109	0.167	0.128
	(0.181)	(0.191)	(0.269)	(0.251)	(0.192)	(0.173)	(0.264)	(0.255)
Can rely on govnt. when severe flood (=1)	0.268	0.351	0.298	0.246	0.296	0.353	0.291	0.248
	(0.315)	(0.319)	(0.307)	(0.270)	(0.303)	(0.366)	(0.287)	(0.295)
Can rely on social network when mild flood (=1)	0.121	0.124	0.133	0.123	0.118	0.185	0.169	0.071
	(0.299)	(0.310)	(0.264)	(0.245)	(0.176)	(0.303)	(0.2920	(0.175)
Can rely on social network when severe flood (=1)	0.149	0.219	0.120	0.125	0.187	0.178	0.145	0.090
	(0.236)	(0.291)	(0.239)	(0.259)	(0.276)	(0.244)	(0.275)	(0.203)
Can rely on natural resource when mild flood (=1)	0.396	0.367	0.341	0.285	0.382	0.378	0.332	0.288
	(0.394)	(0.341)	(0.351)	(0.359)	(0.355)	(0.405)	(0.347)	(0.367)
Can rely on natural resource when severe flood (=1	0.336	0.307	0.303	0.248	0.319	0.328	0.289	0.259
	(0.357)	(0.291)	(0.335)	(0.322)	(0.322)	(0.332)	(0.339)	(0.317)
Behavioral choices								
Investment in land and irrigation (=1)	0.142	0.122	0.138	0.167	0.131	0.031	0.123	0.192
	(0.352)	(0.322)	(0.348)	(0.375)	(0.0339)	(0.173)	(0.331)	(0.397)
Have saving (=1)	0.117	0.079	0.183	0.107	0.188	0.071**	0.151	0.134
	(0.324)	(0.272)	(0.390)	(0.312)	(0.394)	(0.257)	(0.360)	(0.344)
Number of dependable friends	0.525	0.558	0.521	0.623	0.534	0.539	0.517	0.604
	(0.919)	(0.871)	(0.943)	(0.961)	(0.998)	(0.861)	(0.978)	(0.956)
Collect forest products and fishing (=1)	0.112	0.105	0.088	0.134	0.095	0.112	0.087	0.129
	(0.241)	(0.333)	(0.234)	(0.393)	(0.283)	(0.311)	(0.291)	(0.302)
Demand market insurance (=1)	0.121	0.078	0.091	0.083	0.134	0.083	0.087	0.071
	(0.390)	(0.284)	(0.209)	(0.288)	(0.374)	(0.255)	(0.289)	(0.259)

Standard deviations in parentheses. * p<0.1; ** p<0.05; *** p<0.01

Table 4 Exogeneity of household flood exposure controlling for flood prone

By flood prone group	Flood prone (at least 2 in 5 yrs)			Less flood prone (less than 2 in 5 yrs)		
	Flooded	Not flooded	Difference	Flooded	Not flooded	Difference
Have prepared for 2011 flood (=1)	0.203	0.101	0.102	0.137	0.123	0.014
	(0.404)	(0.305)	(0.079)	(0.348)	(0.331)	(0.065)
Elevation (1,2,3,4)	1.038	1.000	0.038	2.680	2.661	0.020
	(0.242)	(0.000)	(0.039)	(0.852)	(0.122)	(0.162)
Grow floating rice (=1)	0.436	0.283	0.153	0.461	0.333	0.128
	(0.487)	(0.444)	(0.098)	(0.484)	(0.456)	(0.091)
Grow long-duration rice (=1)	0.054	0.050	0.004	0.074	0.019	0.056
	(0.212)	(0.190)	(0.043)	(0.228)	(0.136)	(0.036)
Sowing month (1,2,…,12)	5.321	5.509	-0.188	6.585	6.021	0.564
	(1.056)	(1.204)	(0.249)	(2.334)	(2.148)	(0.457)
N	108	38	146	64	46	110

Note: Household flooded (= 1) is used as flood exposure variable. Household is flood prone if it experienced at least 2 floods in the past 5 years. Other household and village characteristics are also tested and not significantly different across flooded and nonflooded group within each flood prone group.

Table 5 Flood and risk aversion

	OLS						Ordered Probit					
	Village flood (=1)		Household flood (=1)		Flood days		Village flood (=1)		Household flood (=1)		Flood days	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Flood	0.274	0.236	0.386*	0.476**	0.006	0.011	0.243	0.280	0.278	0.324*	0.007	0.009*
	(0.271)	(0.262)	(0.201)	(0.208)	(0.007)	(0.009)	(0.200)	(0.194)	(0.182)	(0.194)	(0.005)	(0.005)
Flood*Flood prone	-0.283	-0.211	-0.662*	-0.505	-0.012	-0.008	-0.258	-0.327	-0.531*	-0.484*	-0.011	-0.009
	(0.348)	(0.359)	(0.334)	(0.333)	(0.010)	(0.011)	(0.268)	(0.265)	(0.301)	(0.294)	(0.007)	(0.007)
Flood*Land per capita		0.102		-0.188		-0.015		-0.104		-0.113		-0.007
		(0.270)		(0.164)		(0.009)		(0.197)		(0.200)		(0.008)
Flood*Land per capita		-0.172		-0.425**		-0.012		0.171		-0.123		-0.004
*Flood prone		(0.216)		(0.153)		(0.008)		(0.140)		(0.164)		(0.007)
Flood prone	0.470	0.466	0.726***	0.705**	0.552**	0.551*	0.514**	0.514**	0.727***	0.722***	0.600***	0.613***
	(0.297)	(0.296)	(0.236)	(0.240)	(0.251)	(0.266)	(0.224)	(0.224)	(0.254)	(0.255)	(0.215)	(0.220)
Female	0.293	0.291	0.312	0.297	0.279	0.268	0.134	0.138	0.141	0.128	0.109	0.092
	(0.209)	(0.206)	(0.221)	(0.223)	(0.217)	(0.218)	(0.151)	(0.153)	(0.140)	(0.144)	(0.144)	(0.149)
Age	0.001	0.002	0.002	0.003	0.002	0.003	-0.002	-0.002	-0.003	-0.002	-0.003	-0.002
	(0.010)	(0.010)	(0.010)	(0.009)	(0.010)	(0.010)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Education-primary	-0.176	-0.166	-0.090	-0.085	-0.105	-0.108	-0.175	-0.183	-0.161	-0.155	-0.169	-0.170
	(0.204)	(0.206)	(0.206)	(0.205)	(0.201)	(0.200)	(0.173)	(0.178)	(0.158)	(0.157)	(0.158)	(0.160)
Education-secondary	0.157	0.149	0.089	0.087	0.077	0.076	0.092	0.101	0.125	0.123	0.116	0.113
	(0.168)	(0.165)	(0.149)	(0.135)	(0.151)	(0.135)	(0.126)	(0.123)	(0.139)	(0.130)	(0.139)	(0.131)
Household size	0.032	0.029	0.021	0.014	0.015	0.004	-0.003	-0.001	0.000	-0.002	-0.005	-0.008
	(0.038)	(0.040)	(0.041)	(0.042)	(0.042)	(0.045)	(0.035)	(0.036)	(0.032)	(0.031)	(0.033)	(0.033)
Ln asset per capita	-0.104	-0.101	-0.111	-0.120	-0.109	-0.124	-0.120*	-0.122*	-0.130*	-0.136**	-0.124*	-0.132*
	(0.083)	(0.082)	(0.087)	(0.086)	(0.087)	(0.086)	(0.069)	(0.069)	(0.070)	(0.069)	(0.070)	(0.069)
Land per capita	-0.289**	-0.308	-0.336***	-0.046	-0.341***	0.076	-0.214**	-0.204	-0.204**	-0.076	-0.205**	-0.027
	(0.124)	(0.259)	(0.108)	(0.181)	(0.111)	(0.172)	(0.106)	(0.196)	(0.096)	(0.199)	(0.101)	(0.166)
Number of shocks	-0.041	-0.039	-0.032	-0.028	-0.036	-0.029	-0.017	-0.018	-0.020	-0.018	-0.021	-0.020
in the past 10 years	(0.043)	(0.043)	(0.043)	(0.045)	(0.042)	(0.044)	(0.043)	(0.043)	(0.044)	(0.045)	(0.044)	(0.045)
FE	commune	commune	village	village	village	village	-	-	-	-	-	-
N	229	229	229	229	229	229	229	229	229	229	229	229
F - Joint signt. of all flood vars	0.51	0.39	2.60	4.23	0.75	7.83	1.49	3.11	3.49	4.98	2.46	6.27

Dependent variable is risk aversion. Robust standard errors in parentheses clustered at commune level. * p<0.1; ** p<0.05; *** p<0.01. Constants included but omited. Sample size reduced due to exclusion of 27 households choosing inconsistent risk aversion game choice.

Table 6 Flood and impatience

	OLS						Ordered Probit					
	Village flood (=1)		Household flood (=1)		Flood days		Village flood (=1)		Household flood (=1)		Flood days	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Flood	-0.333	-0.253	0.322	1.015	0.007	0.025*	-0.175	-0.187	-0.057	0.120	-0.001	0.003
	(0.494)	(0.522)	(0.594)	(0.589)	(0.015)	(0.013)	(0.179)	(0.175)	(0.186)	(0.218)	(0.004)	(0.004)
Flood*Flood prone	0.701	0.633	-0.732	-0.988*	0.011	0.003	0.313	0.356	-0.231	-0.300	0.005	0.004
	(0.748)	(0.754)	(0.556)	(0.548)	(0.018)	(0.017)	(0.278)	(0.274)	(0.163)	(0.185)	(0.006)	(0.006)
Flood*Land per capita		-0.246		-1.810***		-0.067		0.025		-0.509**		-0.018
		(0.930)		(0.547)		(0.039)		(0.351)		(0.228)		(0.014)
Flood*Land per capita		0.176		0.725		0.033		-0.103		0.219		0.010
*Flood prone		(0.716)		(0.437)		(0.031)		(0.271)		(0.164)		(0.010)
Flood prone	0.209	0.209	1.153***	1.187***	0.377	0.361	-0.073	-0.074	0.266	0.262	-0.033	-0.047
	(0.326)	(0.325)	(0.377)	(0.365)	(0.450)	(0.452)	(0.139)	(0.139)	(0.198)	(0.196)	(0.186)	(0.187)
Female	0.124	0.132	0.298	0.196	0.324	0.234	0.018	0.017	0.022	0.006	0.021	0.001
	(0.419)	(0.410)	(0.448)	(0.466)	(0.446)	(0.478)	(0.164)	(0.160)	(0.159)	(0.163)	(0.162)	(0.168)
Age	-0.001	-0.001	-0.002	0.001	-0.001	0.000	0.004	0.004	0.004	0.005	0.005	0.005
	(0.014)	(0.014)	(0.015)	(0.016)	(0.015)	(0.015)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Education-primary	0.458	0.458	0.438	0.408	0.420	0.373	0.344**	0.353**	0.333**	0.340**	0.345**	0.336**
	(0.373)	(0.395)	(0.360)	(0.338)	(0.376)	(0.353)	(0.160)	(0.165)	(0.145)	(0.141)	(0.151)	(0.148)
Education-secondary	0.028	0.039	0.004	0.064	0.034	0.063	-0.019	-0.025	-0.032	-0.012	-0.038	-0.026
	(0.389)	(0.373)	(0.407)	(0.370)	(0.426)	(0.402)	(0.161)	(0.159)	(0.155)	(0.149)	(0.155)	(0.150)
Household size	-0.130	-0.125	-0.152	-0.134	-0.162	-0.161	-0.056	-0.057*	-0.051	-0.046	-0.054	-0.051
	(0.092)	(0.081)	(0.103)	(0.097)	(0.098)	(0.094)	(0.036)	(0.033)	(0.036)	(0.034)	(0.036)	(0.034)
Ln asset per capita	-0.070	-0.074	-0.077	-0.127	-0.058	-0.098	-0.031	-0.029	-0.033	-0.044	-0.024	-0.032
	(0.166)	(0.161)	(0.176)	(0.176)	(0.170)	(0.163)	(0.057)	(0.055)	(0.058)	(0.056)	(0.059)	(0.055)
Land per capita	0.262	0.385	0.297	1.354**	0.284	1.166*	0.080	0.096	0.082	0.377	0.079	0.313
	(0.387)	(0.505)	(0.426)	(0.541)	(0.411)	(0.583)	(0.129)	(0.190)	(0.135)	(0.237)	(0.131)	(0.221)
Number of shocks	-0.082	-0.082	-0.075	-0.063	-0.047	-0.045	-0.055	-0.054	-0.061	-0.059	-0.054	-0.055
in the past 10 years	(0.108)	(0.110)	(0.106)	(0.109)	(0.116)	(0.117)	(0.042)	(0.042)	(0.043)	(0.042)	(0.044)	(0.044)
FE	commune	commune	village	village	village	village	-	-	-	-	-	-
N	256	256	256	256	256	256	256	256	256	256	256	256
F - Joint signt. of all flood vars	0.44	0.22	0.97	3.71	1.90	2.42	1.29	1.75	3.75	12.06	1.30	2.56

Dependent variable is risk aversion. Robust standard errors in parentheses clustered at commune level. * p<0.1; ** p<0.05; *** p<0.01. Constants included but omited.

Table 7 Flood and altruism

	Village flood (=1)		Household flood (=1)		Flood days	
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	OLS	OLS	OLS	OLS	OLS
Flood	0.013	0.005	0.097**	0.116**	-0.001	0.000
	(0.036)	(0.042)	(0.043)	(0.045)	(0.001)	(0.001)
Flood*Given to flood victim	-0.002	-0.002	-0.022	-0.022	0.001*	0.001*
	(0.032)	(0.032)	(0.026)	(0.026)	(0.001)	(0.001)
Flood*Flood prone	0.050	0.053	-0.065	-0.045	-0.001	-0.001
	(0.043)	(0.049)	(0.057)	(0.047)	(0.001)	(0.001)
Flood*Land per capita		0.026		-0.042		-0.002
		(0.036)		(0.042)		(0.003)
Flood*Land per capita		-0.009		-0.054		-0.001
*Flood prone		(0.056)		(0.052)		(0.002)
Given to flood victim	0.123***	0.123***	0.136***	0.136***	0.096***	0.096***
	(0.023)	(0.023)	(0.019)	(0.019)	(0.021)	(0.021)
Flood prone	-0.013	-0.012	0.054	0.052	0.038	0.038
	(0.037)	(0.037)	(0.038)	(0.036)	(0.029)	(0.028)
Female	-0.062***	-0.063**	-0.065**	-0.068**	-0.066***	-0.068**
	(0.021)	(0.021)	(0.023)	(0.024)	(0.022)	(0.023)
Age	-0.002**	-0.002**	-0.002*	-0.001*	-0.002**	-0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Education-primary	-0.020	-0.020	-0.021	-0.020	-0.019	-0.020
	(0.029)	(0.027)	(0.033)	(0.036)	(0.032)	(0.034)
Education-secondary	-0.032	-0.033	-0.031	-0.031	-0.034	-0.034
	(0.026)	(0.026)	(0.028)	(0.028)	(0.028)	(0.028)
Household size	0.004	0.004	0.004	0.004	0.003	0.002
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Ln asset per capita	0.012	0.012	0.010	0.009	0.009	0.007
	(0.019)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
Land per capita	0.050**	0.034	0.054***	0.103***	0.052**	0.102**
	(0.017)	(0.026)	(0.018)	(0.032)	(0.018)	(0.038)
Number of shocks	0.009	0.009	0.012	0.012	0.011	0.011
in the past 10 years	(0.007)	(0.007)	(0.008)	(0.007)	(0.008)	(0.008)
FE	commune	commune	village	village	village	village
N	512	512	512	512	512	512
F - Joint significant	2.02	5.99	1.71	3.46	2.10	1.55

Dependent variable is altruism measured by percentage of money given to randomly matched villager or flood victim in the village. Robust standard errors in parentheses clustered at commune level. * p<0.1; ** p<0.05; *** p<0.01.

Table 8 Flood and trust

	Village flood (=1)				Household flood (=1)				Flood days			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Family	Neighbor	Business	Local Govt.	Family	Neighbor	Business	Local Govt.	Family	Neighbor	Business	Local Govt.
	Probit	Probit	Probit	Probit	Probit	Probit	Probit	Probit	Probit	Probit	Probit	Probit
Flood	0.868	0.142	-0.028	0.035	0.000	-1.222***	0.255	-0.455**	-2.757	-0.019***	0.010	-0.017***
	(0.809)	(0.333)	(0.255)	(0.220)	(0.000)	(0.433)	(0.182)	(0.207)	(0.000)	(0.007)	(0.007)	(0.006)
Flood*Flood prone	0.000	-0.250	0.545	0.272	0.790	0.246	-0.542*	0.107	-3.246	0.011	-0.015**	0.014
	(0.000)	(0.413)	(0.356)	(0.294)	(0.770)	(0.557)	(0.282)	(0.276)	(0.000)	(0.010)	(0.007)	(0.009)
Flood prone	0.595	0.269	-0.301	0.073	0.000	0.048	0.332	0.198	137.165	-0.095	0.296	-0.047
	(0.799)	(0.214)	(0.226)	(0.222)	(0.000)	(0.524)	(0.209)	(0.231)	(0.000)	(0.345)	(0.192)	(0.238)
Female	0.000	0.141	-0.338**	-0.015	0.000	0.156	-0.374***	-0.037	0.000	0.161	-0.410***	-0.030
	(0.000)	(0.274)	(0.143)	(0.150)	(0.000)	(0.281)	(0.134)	(0.152)	(0.000)	(0.291)	(0.136)	(0.153)
Age	0.071***	0.032***	-0.004	0.001	0.051**	0.029**	-0.005	-0.000	4.053	0.030***	-0.004	-0.001
	(0.025)	(0.011)	(0.007)	(0.005)	(0.024)	(0.012)	(0.007)	(0.005)	(0.000)	(0.011)	(0.007)	(0.006)
Education-primary	0.218	0.775**	-0.585***	-0.008	0.352	0.773**	-0.572***	0.001	11.065	0.842**	-0.588***	0.025
	(0.635)	(0.317)	(0.165)	(0.215)	(0.683)	(0.331)	(0.181)	(0.217)	(0.000)	(0.332)	(0.178)	(0.217)
Education-secondary	0.000	-0.107	-0.189	-0.243	0.000	-0.168	-0.212	-0.265	0.000	-0.190	-0.210	-0.287
	(0.000)	(0.281)	(0.212)	(0.188)	(0.000)	(0.303)	(0.218)	(0.214)	(0.000)	(0.287)	(0.212)	(0.216)
Household size	0.476***	0.057	-0.032	0.012	0.430***	0.040	-0.017	0.021	19.501	0.063	-0.023	0.030
	(0.098)	(0.054)	(0.042)	(0.050)	(0.130)	(0.054)	(0.041)	(0.048)	(0.000)	(0.054)	(0.042)	(0.048)
Ln asset per capita	0.374**	0.240***	0.179	-0.075	0.205	0.264***	0.186	-0.067	10.035	0.258***	0.195*	-0.056
	(0.160)	(0.091)	(0.123)	(0.083)	(0.213)	(0.099)	(0.121)	(0.087)	(0.000)	(0.087)	(0.117)	(0.085)
Land per capita	-0.542*	0.471**	-0.223	-0.098	-0.318	0.430**	-0.197	-0.100	-65.276	0.494**	-0.200	-0.102
	(0.298)	(0.205)	(0.145)	(0.187)	(0.388)	(0.196)	(0.142)	(0.175)	(0.000)	(0.216)	(0.142)	(0.177)
Number of shocks	0.710*	-0.045	0.059	0.077	0.602*	-0.060	0.046	0.077	39.229	-0.049	0.041	0.080
in the past 10 years	(0.386)	(0.095)	(0.047)	(0.048)	(0.325)	(0.100)	(0.046)	(0.050)	(0.000)	(0.097)	(0.044)	(0.053)
N	256	256	256	256	256	256	256	256	256	256	256	256
F - Joint significant	-	0.39	9.16	5.68	-	10.26	3.76	6.41	-	11.87	4.27	11.96

Dependent variables are binary variable whether respondent trusts the above institutions, hence a probit model is used. OLS FE was also estimated and reported with qualitatively similar results in Appendix table. Robust standard errors in parentheses clustered at commune level. * $p<0.1$; ** $p<0.05$; *** $p<0.01$. Constants included but omited. There is not enough variation in trust family variable (with only 3 out of 253 reporting trust family = 0).

Table 9 Flood and subjective expectation

	Village flood (=1)		Household flood (=1)		Flood days	
	(1)	(2)	(3)	(4)	(5)	(6)
	Pr(flood)	Pr(loss/flood)	Pr(flood)	Pr(loss/flood)	Pr(flood)	Pr(loss/flood)
	OLS	OLS	OLS	OLS	OLS	OLS
Flood	0.123***	0.026	0.162***	0.044	0.004***	0.003*
	(0.029)	(0.074)	(0.032)	(0.067)	(0.001)	(0.002)
Flood*For mild flood	-0.157***	0.039	-0.134**	0.049	-0.003	-0.002
	(0.053)	(0.089)	(0.056)	(0.082)	(0.002)	(0.002)
Flood*Flood prone	-0.146***	-0.057	-0.124*	0.088	-0.004***	-0.001
	(0.035)	(0.081)	(0.065)	(0.078)	(0.001)	(0.002)
Flood*Flood prone*For mild flood	0.184**	-0.000	0.115	-0.071	0.003	-0.001
	(0.077)	(0.094)	(0.106)	(0.079)	(0.002)	(0.002)
For mild flood	0.128**	-0.440***	0.122**	-0.448***	0.102**	-0.388***
	(0.045)	(0.050)	(0.047)	(0.049)	(0.035)	(0.043)
Flood prone	0.135**	0.020	0.128**	-0.082	0.138***	0.000
	(0.047)	(0.056)	(0.048)	(0.056)	(0.039)	(0.033)
Flood prone*For mild flood	-0.168**	0.003	-0.134	0.045	-0.130*	0.038
	(0.076)	(0.060)	(0.078)	(0.047)	(0.065)	(0.042)
Female	0.006	0.025	-0.002	0.017	-0.006	0.018
	(0.018)	(0.032)	(0.017)	(0.032)	(0.017)	(0.035)
Age	-0.000	0.000	-0.000	0.000	-0.000	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Education-primary	-0.032	-0.050*	-0.048**	-0.049	-0.050**	-0.049
	(0.021)	(0.025)	(0.020)	(0.029)	(0.020)	(0.030)
Education-secondary	0.025	0.050	0.032	0.045	0.035	0.051
	(0.024)	(0.031)	(0.023)	(0.033)	(0.023)	(0.035)
Household size	0.005	0.014*	0.007**	0.015*	0.005	0.013
	(0.004)	(0.007)	(0.003)	(0.008)	(0.003)	(0.008)
Ln asset per capita	-0.012	-0.023*	-0.006	-0.023	-0.008	-0.026*
	(0.007)	(0.012)	(0.007)	(0.014)	(0.007)	(0.013)
Land per capita	-0.014	-0.021	-0.011	-0.008	-0.011	-0.007
	(0.017)	(0.020)	(0.018)	(0.021)	(0.018)	(0.022)
Number of shocks	0.009*	0.020**	0.008	0.020**	0.008	0.020**
in the past 10 years	(0.005)	(0.009)	(0.005)	(0.008)	(0.005)	(0.008)
Constant	0.467***	0.985***	0.364***	0.957***	0.407***	0.975***
	(0.111)	(0.222)	(0.101)	(0.263)	(0.100)	(0.236)
FE	commune	commune	village	village	village	village
N	512	512	512	512	512	512
F - Joint significant	6.77	1.09	7.54	7.02	12.97	2.10

Dependent variable are subjective expectations of probability of severe and mild flood in (1), (3), (5) and probability of loss conditional on occurrence of severe or mild flood. For mild flood is a binary variable =1 if mild flood and = 0 if severe flood. Robust standard errors in parenthesesclustered at commune level. * p<0.1; ** p<0.05; *** p<0.01.

Table 10 Flood and safety net perceptions

	Village flood (=1)			Household flood (=1)			Flood days		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Can rely on govemt when flood	Can rely on social when flood	Can rely on natural when flood	Can rely on govemt when flood	Can rely on social when flood	Can rely on natural when flood	Can rely on govemt when flood	Can rely on social when flood	Can rely on natural when flood
	Probit	Probit	Probit	Probit	Probit	Probit	Probit	Probit	Probit
Flood	0.238	0.138	0.043	0.374	0.228	-0.052	0.004	0.001	0.001
	(0.298)	(0.237)	(0.316)	(0.259)	(0.292)	(0.265)	(0.009)	(0.007)	(0.007)
Flood*For mild flood	0.017	-0.131	0.107	-0.131	0.219	0.334***	-0.003	0.006	0.019*
	(0.166)	(0.186)	(0.124)	(0.219)	(0.222)	(0.123)	(0.009)	(0.010)	(0.010)
Flood*Flood prone	-0.352	-0.457	-0.296	-0.479	-0.066	-0.034	-0.004	0.001	0.003
	(0.309)	(0.317)	(0.385)	(0.387)	(0.306)	(0.362)	(0.009)	(0.007)	(0.010)
Flood*Flood prone*For mild flood	-0.222	-0.057	-0.024	0.328	-0.486*	-0.103	-0.001	-0.001	-0.017*
	(0.305)	(0.275)	(0.148)	(0.394)	(0.291)	(0.183)	(0.012)	(0.008)	(0.010)
For mild flood	-0.806***	0.126	0.057	-0.743***	-0.083	-0.069	-0.750***	-0.068	-0.217
	(0.126)	(0.083)	(0.134)	(0.175)	(0.140)	(0.115)	(0.212)	(0.175)	(0.171)
Flood prone	0.084	0.405*	0.320	0.187	0.193	0.241	-0.021	0.156	0.130
	(0.269)	(0.242)	(0.239)	(0.272)	(0.319)	(0.317)	(0.237)	(0.273)	(0.283)
Flood prone*For mild flood	0.141	-0.308*	-0.017	-0.170	0.018	-0.014	0.084	-0.318	0.272
	(0.181)	(0.178)	(0.133)	(0.264)	(0.237)	(0.136)	(0.299)	(0.228)	(0.166)
Female	-0.197	0.022	-0.125	-0.125	0.057	-0.109	-0.129	0.060	-0.109
	(0.172)	(0.173)	(0.188)	(0.164)	(0.168)	(0.207)	(0.164)	(0.177)	(0.208)
Age	-0.005	-0.016*	-0.039***	-0.006	-0.017**	-0.042***	-0.006	-0.016**	-0.041***
	(0.005)	(0.008)	(0.006)	(0.004)	(0.008)	(0.006)	(0.005)	(0.008)	(0.006)
Education-primary	-0.000	-0.486***	0.064	0.042	-0.500***	0.057	0.043	-0.496***	0.053
	(0.165)	(0.169)	(0.262)	(0.173)	(0.178)	(0.266)	(0.178)	(0.181)	(0.269)
Education-secondary	-0.094	-0.213	-0.412**	-0.093	-0.198	-0.399**	-0.102	-0.197	-0.382**
	(0.155)	(0.170)	(0.185)	(0.148)	(0.176)	(0.194)	(0.154)	(0.178)	(0.188)
Household size	-0.014	0.022	0.112***	-0.017	0.015	0.104**	-0.020	0.008	0.098**
	(0.028)	(0.033)	(0.040)	(0.029)	(0.032)	(0.041)	(0.029)	(0.031)	(0.040)
Ln asset per capita	-0.134*	0.021	0.110	-0.139*	0.019	0.098	-0.140*	0.019	0.097
	(0.074)	(0.122)	(0.088)	(0.080)	(0.121)	(0.094)	(0.083)	(0.123)	(0.096)
Land per capita	-0.222	-0.251	-0.135	-0.209	-0.244	-0.119	-0.218	-0.257	-0.115
	(0.155)	(0.170)	(0.154)	(0.149)	(0.166)	(0.153)	(0.150)	(0.167)	(0.150)
Number of shocks	0.159**	0.091*	0.109*	0.160**	0.098*	0.118*	0.157**	0.102*	0.124*
in the past 10 years	(0.072)	(0.052)	(0.066)	(0.075)	(0.052)	(0.067)	(0.076)	(0.052)	(0.068)
N	512	512	512	512	512	512	512	512	512
F - Joint significant	4.24	5.32	2.05	2.53	5.54	16.98	1.33	3.22	7.84

Dependent variable is binary variable representing subjective expectations whether or not household can rely on government (1),(4),(7), on social insurance (2),(5),(8) or on natural resources (3),(6),(9) when severe or mild flood occurs. Hence, a probit model is used. OLS FE was also estimated and reported with qualitatively similar results in Appendix table. For mild flood is a binary variable =1 if mild flood and = 0 if severe flood. Robust standard errors in parentheses clustered at commune level. * p<0.1; ** p<0.05; *** p<0.01.

Table 11 Flood and behavioral choices

	Investment in land and irrigation			Have saving			Collect forest products and fishing			Number of dependable friends			Demand for market insurance		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
	Probit	Probit	Probit	Probit	Probit	Probit	Probit	Probit	Probit	OLS	OLS	OLS	Probit	Probit	Probit
Flood	-0.483**		-0.710***	0.835***		0.891***	-1.332***		-1.244***	-0.298*		-0.299*	-0.053		-0.011
	(0.201)		(0.259)	(0.323)		(0.285)	(0.360)		(0.371)	(0.159)		(0.159)	(0.370)		(0.366)
Flood*Flood prone	1.476***		2.284***	-0.029		-0.224	1.365***		1.355**	0.168		0.285	4.976***		5.674***
	(0.530)		(0.549)	(0.471)		(0.446)	(0.525)		(0.544)	(0.253)		(0.235)	(0.535)		(0.798)
Risk aversion		-0.227**	-0.204**		-0.012	-0.011		0.008	0.039		0.022	0.024		-0.059	-0.032
		(0.111)	(0.098)		(0.068)	(0.069)		(0.075)	(0.077)		(0.041)	(0.041)		(0.091)	(0.103)
Impatience		0.085**	0.094**		-0.077**	-0.074**		-0.081*	-0.085*		0.002	0.005		-0.090**	-0.079**
		(0.033)	(0.044)		(0.038)	(0.036)		(0.045)	(0.045)		(0.021)	(0.021)		(0.039)	(0.039)
Altruism		1.169**	1.347**		1.277***	1.157***		-1.465***	-1.463***		-0.417	-0.366		0.278	0.238
		(0.580)	(0.603)		(0.383)	(0.385)		(0.478)	(0.486)		(0.305)	(0.309)		(0.493)	(0.519)
Trust family		0.000	0.000		0.000	0.000		0.000	0.000		0.293	0.285		0.000	0.000
		(0.000)	(0.000)		(0.000)	(0.000)		(0.000)	(0.000)		(0.211)	(0.186)		(0.000)	(0.000)
Trust neighbor		-0.331	-0.444		-0.357***	-0.211		0.874***	0.798**		0.417***	0.378***		-0.979***	-0.976***
		(0.397)	(0.496)		(0.123)	(0.175)		(0.312)	(0.337)		(0.088)	(0.081)		(0.302)	(0.228)
Trust business/trader		0.163	0.270		0.031	0.077		0.047	0.093		0.396***	0.404***		-0.187	-0.086
		(0.245)	(0.243)		(0.163)	(0.148)		(0.268)	(0.288)		(0.110)	(0.112)		(0.338)	(0.355)
Trust local governments		0.527**	0.663*		0.244	0.364		0.056	0.062		0.028	0.020		0.191	0.323
		(0.268)	(0.347)		(0.275)	(0.284)		(0.217)	(0.221)		(0.146)	(0.142)		(0.271)	(0.285)
Sjt. prob of severe flood		0.080	0.420		-0.017	-0.332		-0.891	-0.697		0.341	0.430		-0.572	-0.701
		(0.388)	(0.463)		(0.619)	(0.681)		(0.583)	(0.621)		(0.377)	(0.353)		(0.481)	(0.560)
Sjt. prob of mild flood		-1.273**	-1.331***		1.632***	1.387***		0.311	0.507		0.323	0.412		-1.402**	-1.753**
		(0.512)	(0.512)		(0.510)	(0.518)		(0.529)	(0.545)		(0.287)	(0.271)		(0.635)	(0.796)
Flood prone	-1.391**	-0.265	-2.002***	-0.034	-0.040	0.067	-0.262	0.358	-0.155	0.017	0.037	-0.142	-4.954***	-0.089	-5.574***
	(0.548)	(0.235)	(0.366)	(0.487)	(0.172)	(0.445)	(0.358)	(0.231)	(0.406)	(0.263)	(0.159)	(0.264)	(0.531)	(0.294)	(0.686)
Other controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
FE	-	-	-	-	-	-	-	-	-	village	village	village	-	-	-
N	229	229	229	229	229	229	229	229	229	229	229	229	229	229	229

Dependent variable are binary variables representing behavioral choices observed in the household data, except for number of dependable friends which is a continuous variable. Hence a probit model is used for binary variables (OLS FE model was also estimatedand reported with qualitatively similar results in the Appendix. Flood variable is whether household experienced floood in 2011. Results for flood days are qualitatively similar, so omited. Robust standard errors in parentheses clustered at commune level. * p<0.1; ** p<0.05; *** p<0.01. Same set of control variables were used, results not reported here. Sample size reduced due to exclusion of 27 households choosing inconsistent risk aversion game choice.

Appendix

A. Summary of experiments and constructed preference parameters

A.1 Risk aversion

We use a coin toss game similar to Binswanger (1980) with the payoffs, corresponding risk aversion coefficients, risk classes, and our simple ordinal risk aversion index (1,2, … , 5), as presented in Table A.1.

[Table A.1]

A.2 Impatience

We use the following hypothetical questions to elicit time preference. *Suppose we will give you US$50 tomorrow. You have two options. Option A: we will give you US$50 tomorrow. Option B, if you are willing to wait another 15 days, we will give you an amount higher than US$50. In each situation below, will you choose Option A or Option B?*

[Table A.2]

Impatience index (1,2, …, 8) is calculated based on the situation that subject first switch from A to B. If subject does not switch (and so chooses A in all situations), the impatience index is equal to 8, which represents a very high impatience level.

A.3 Altruism

Parameters ranging from 0 to 1 reflect the share of money give to a randomly matched villager or to flood victims according to the following questions:

Suppose you will be paired with another villager in the same village. Your partner will be chosen randomly. You and other people will never know who your partner is. Your partner will never know who you are. Also, your answer to this question will be strictly confidential.

Suppose we give you 10 US$5 notes and you will have an opportunity to give a part of your US$50 to your partner. After this transfer, the arrangement will end. If you give 10 notes to your partner, you will receive nothing at the end of the game. If you give 0 notes to your partner, you will receive 10 notes at the end of the game. How many notes will you give to your partner?

Now suppose you will be paired with those who lost their home during the 2013 flood. Your partner will be chosen randomly from the victims. The amount you send to a victim will be delivered as a donation to the World Food Program. How much will you give to your partner?

A.4 Trust

We base our binary trust parameters on a general social science question: how much you trust different groups of people. How much do you feel you can trust the people in each of the following groups? (1) People in your family, (2) People in your village/neighborhood, (3) Business owner/traders you buy things from or do business with, and (4) Village/local government. For each, choose between the following choices: 1 = They can be trusted, 2 = They cannot be trusted, 3 = No idea. Binary trust variables are then created accordingly.

A.5 Subjective probability of flood

We calculate perceived probability of flood from the experiment question: *I would like to ask your opinion about the likelihood of flood events occurring in the next 10 years. We will give you 10 coins. You will be asked to assign them to situations to reflect your view on what are the chances these events will occur. The situation with largest number of coins assigned to it is the situation you think is most likely to occur over the next 10 years. Example: What is the likelihood, in your view, that different flood events will occur over the next 10 years? Explain. (Show Figure A.1)*

[Figure A.1]

Case A could be someone who foresees severe floods occurring at a frequency of once every five years in the future and foresees a mild flood occurring once every other year. Case B might think that his/her farm is quite prone to flooding in the future.

A.6 Perceptions of loss and safety net when flood occurs

We use the above coin exercise for the series of questions below described in Figure A.2.

[Figure A.2]

B. Robustness Checks and Extensions

Tables B.1-B.8 show various robustness checks and extensions of the analyses.

[Tables B.1-B.8]

C. Checking Self-reporting Flood Exposure Variables

Table C.1 show comparison between flooded villages and flooded households defined based on survey data with those in the official record.

[Table C.1]

Figure A.1 Subjective probability of flood

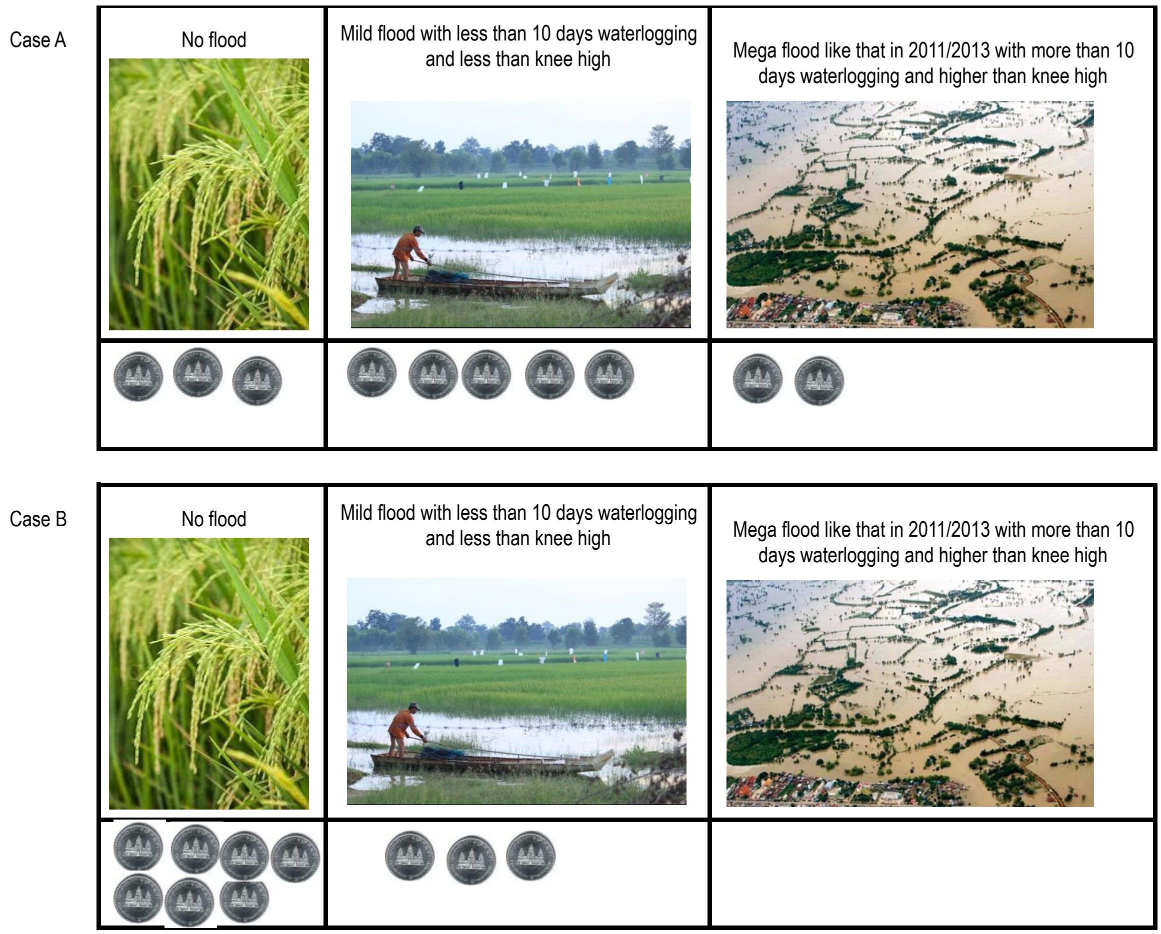


Figure A.2 Perceptions of loss and safety net when flood occurs

	Please assign the coins to the events based on your opinion about the likelihood that the they will occur in the next 10 years future					
What's the likelihood	If the mild flood with less than 10 days waterlogging and less than knee high occurs, 			If the mega flood like that in 2011/2013 with more than 10 days waterlogging and higher than knee high occurs, 		
that flood will affect your rice income?	No loss (coins)	Partial loss (1-50% loss) (coins)	Total loss (100% loss) (coins)	No loss (coins)	Partial loss (1-50% loss) (coins)	Total loss (100% loss) (coins)
that your household will get disaster relief/assistance from governmen/NGOs?		Do not get gov. assistance (coins)	Get gov. assistance (coins)		Do not get gov. assistance (coins)	Get gov. assistance (coins)
that your household can rely on social network, e.g., relatives, friends in your community for help?		Do not get others's assistance (coins)	Get others' assistance (coins)		Do not get others's assistance (coins)	Get others' assistance (coins)
that your household can rely on natural resources (forest product, fishing, forest land) to help smooth consumption?		Cannot rely on nature (coins)	Can rely on nature (coins)		Cannot rely on nature (coins)	Can rely on nature (coins)
that your household will get debt relief/forgiveness?	None (coins)	Some debt forgiven (1-50%) (coins)	All debt forgiven (100%) (coins)	None (coins)	Some debt forgiven (1-50%) (coins)	All debt forgiven (100%) (coins)

Table A.1 Summary of risk aversion parameter based on Binswanger (1980)

Option	Low Payoff (Pr = 0.5)	High Payoff (Pr=0.5)	Expected Payoff	S.D. Payoff	CRRA interval	Geometric mean	Risk class	Our risk aversion parameters
1	1000	1000	1000	0	R>7.5	7.5*	extreme	5
2	900	1900	1400	707	1.74<R<7.5	3.61	severe	4
3	800	2400	1600	1131	0.81<R<1.74	1.19	intermediate	3
4	600	3000	1800	1697	0.31<R<0.81	0.50	moderate	2
5	400	3200	1800	1980	Inconsistent	Inconsistent	Inconsistent	-
6	200	3800	2000	2546	0<R<0.31	0.15**	slightly-to-neutral	1

*Assume the lower bound of extreme risk aversion, ** Arithmatic mean was used

Table A.2 Impatience index

Situation	Option A	Option B	Impatience index if first switch to B in
1	We give you $50 tomorrow	We give you $50 in 15 days	0
2	We give you $50 tomorrow	We give you $50.5 in 15 days	1
3	We give you $50 tomorrow	We give you $51 in 15 days	2
4	We give you $50 tomorrow	We give you $52.5 in 15 days	3
5	We give you $50 tomorrow	We give you $55 in 15 days	4
6	We give you $50 tomorrow	We give you $70 in 15 days	5
7	We give you $50 tomorrow	We give you $85 in 15 days	6
8	We give you $50 tomorrow	We give you $100 in 15 days	7

Table B.1 Exogeneity of household flood exposure controlling for flood frequency

By flood frequency group (in the past 5 yrs)	More than 2 in 5 yrs			2 in 5 yrs			0-1 in 5 yrs		
	Flooded	Not flooded	Difference	Flooded	Not flooded	Difference	Flooded	Not flooded	Difference
Have prepared for 2011 flood (=1)	0.000	0.125	-0.125	0.217	0.125	0.092	0.137	0.123	0.014
	(0.000)	(0.354)	(0.111)	(0.414)	(0.338)	(0.091)	(0.348)	(0.331)	(0.065)
Elevation (1,2,3,4)	1.010	1.000	0.010	1.041	1.000	0.041	2.680	2.661	0.020
	(0.190)	(0.000)	(0.174)	(0.181)	(0.000)	(0.051)	(0.852)	(0.122)	(0.162)
Grow floating rice (=1)	0.583	0.166	0.417	0.419	0.313	0.106	0.461	0.333	0.128
	(0.514)	(0.408)	(0.242)	(0.483)	(0.456)	(0.108)	(0.484)	(0.456)	(0.091)
Grow long-duration rice (=1)	0.042	0.000	0.042	0.055	0.063	-0.007)	0.074	0.019	0.056
	(0.144)	(0.000)	(0.060)	(0.219)	(0.212)	(0.049)	(0.228)	(0.136)	(0.036)
Sowing month (1,2,…,12)	5.200	5.636	-0.436	5.348	5.495	-0.147	6.585	6.021	0.564
	(0.490)	(1.362)	(0.696)	(1.071)	(1.191)	(0.271)	(2.334)	(2.148)	(0.457)
N	39	13	52	69	25	94	64	46	110

Table B.2 Flood and risk aversion (Robustness check for Table 5)

	OLS with FE			Ordered Probit		
	Village flood (=1)	Household flood (=1)	Flood days	Village flood (=1)	Household flood (=1)	Flood days
Subsample only if respondent is head						
Flood	0.206	0.540**	0.010	0.262	0.324*	0.008
	(0.264)	(0.224)	(0.009)	(0.192)	(0.196)	(0.005)
Flood*Flood prone	-0.140	-0.664*	-0.008	-0.281	-0.514*	-0.009
	(0.370)	(0.345)	(0.011)	(0.269)	(0.303)	(0.007)
Flood prone defined as HH with > 2 floods in 5 yrs						
Flood	0.268	0.471**	0.014	0.292	0.311*	0.010*
	(0.245)	(0.185)	(0.008)	(0.183)	(0.178)	(0.005)
Flood*Flood prone	-0.292	-0.528**	-0.013	-0.365	-0.467**	-0.011
	(0.344)	(0.207)	(0.011)	(0.241)	(0.201)	(0.007)
Stratified regression by flood prone group						
Less flood prone (< 2 floods in 5 yrs)						
Flood	0.621**	0.408	0.017	0.561***	0.369*	0.011*
	(0.257)	(0.312)	(0.011)	(0.188)	(0.196)	(0.006)
Flood prone (at least 2 floods in 5 yrs)						
Flood	-0.021	0.032	0.004	-0.124	-0.180	-0.000
	(0.250)	(0.401)	(0.005)	(0.188)	(0.326)	(0.005)
	Probit					
Binary measure of risk aversion						
	Risk aversion (5 vs. <5)			Risk aversion (4-5 vs. <4)		
Flood	0.408*	0.687**	0.017**	0.676***	0.593***	0.015**
	(0.239)	(0.335)	(0.009)	(0.256)	(0.225)	(0.006)
Flood*Flood prone	-0.549*	-0.827*	-0.024**	-0.696**	-0.613	-0.008
	(0.291)	(0.434)	(0.010)	(0.343)	(0.461)	(0.010)
	Risk aversion (3-5 vs. <3)			Risk aversion (2-5 vs. 1)		
Flood	0.007	0.045	-0.003	0.074	0.044	0.005
	(0.240)	(0.265)	(0.006)	(0.273)	(0.252)	(0.006)
Flood*Flood prone	-0.057	-0.561*	0.003	-0.036	-0.252	-0.006
	(0.348)	(0.338)	(0.009)	(0.433)	(0.290)	(0.006)

Full model is run in each regression. Robust standard errors in parentheses clustered at commune level. * p<0.1; ** p<0.05; *** p<0.01. Constants included but omited.

Table B.3 Flood and impatience (Robustness check for Table 6)

	OLS with FE			Ordered Probit		
	Village flood (=1)	Household flood (=1)	Flood days	Village flood (=1)	Household flood (=1)	Flood days
Subsample only if respondent is head						
Flood	-0.234	0.910	0.026*	-0.155	0.127	0.004
	(0.521)	(0.592)	(0.014)	(0.175)	(0.208)	(0.005)
Flood*Flood prone	0.560	-0.847	0.001	0.305	-0.289*	0.002
	(0.744)	(0.572)	(0.018)	(0.272)	(0.160)	(0.006)
Flood prone defined as HH with > 2 floods in 5 yrs						
Flood	-0.109	0.855	0.028**	-0.100	0.107	0.005
	(0.490)	(0.576)	(0.012)	(0.162)	(0.224)	(0.004)
Flood*Flood prone	0.414	-0.758	-0.001	0.212	-0.292	-0.000
	(0.645)	(0.530)	(0.014)	(0.234)	(0.188)	(0.005)
Stratified regression by flood prone group						
Less flood prone (< 2 floods in 5 yrs)						
Flood	0.082	1.450*	0.047**	-0.142	0.458*	0.011
	(0.674)	(0.712)	(0.017)	(0.220)	(0.250)	(0.007)
Flood prone (at least 2 floods in 5 yrs)						
Flood	0.444	-0.894*	0.026*	0.224	-0.417*	0.004
	(0.537)	(0.497)	(0.014)	(0.233)	(0.231)	(0.005)
			Probit			
Binary measure of impatience						
	Impatience (7 vs. <7)			Impatience (6-7 vs. <6)		
Flood	-0.048	0.575*	0.019*	0.108	0.064	0.005
	(0.438)	(0.325)	(0.010)	(0.316)	(0.237)	(0.009)
Flood*Flood prone	0.933***	-0.776***	-0.028**	0.309	-0.784**	-0.035***
	(0.342)	(0.298)	(0.011)	(0.301)	(0.349)	(0.008)
	Impatience (5-7 vs. <5)			Impatience (4-7 vs. <4)		
Flood	0.453	0.023	0.007	0.150	0.101	0.008
	(0.277)	(0.362)	(0.009)	(0.251)	(0.372)	(0.010)
Flood*Flood prone	-0.414	-0.836*	-0.031**	-0.248	-0.942**	-0.033***
	(0.399)	(0.442)	(0.013)	(0.329)	(0.406)	(0.010)
	Impatience (3-7 vs. <3)			Impatience (2-7 vs. <2)		
Flood	0.154	0.215	0.009	0.205	0.311	0.012
	(0.278)	(0.378)	(0.011)	(0.216)	(0.315)	(0.011)
Flood*Flood prone	-0.062	-1.070**	-0.034**	-0.350	-1.198***	-0.033***
	(0.348)	(0.422)	(0.013)	(0.333)	(0.392)	(0.012)
	Impatience (1-7 vs. 0)					
Flood	0.493***	0.506*	0.024*			
	(0.186)	(0.298)	(0.013)			
Flood*Flood prone	-0.478*	-1.139**	-0.037***			
	(0.261)	(0.444)	(0.013)			

Full model is run in each regression. Robust standard errors in parentheses clustered at commune level. * p<0.1; ** p<0.05; *** p<0.01. Constants included but omited.

Table B.4 Flood and altruism (Robustness check for Table 7)

	OLS with FE		
	Village flood (=1)	Household flood (=1)	Flood days
Subsample only if respondent is head			
Flood	0.007	0.102**	-0.000
	(0.042)	(0.043)	(0.001)
Flood*Given to flood victim	-0.005	-0.019	0.001**
	(0.034)	(0.026)	(0.001)
Flood*Flood prone	0.066	-0.040	-0.000
	(0.043)	(0.049)	(0.001)
Flood prone defined as HH with > 2 floods in 5 yrs			
Flood	-0.052	0.035	-0.002
	(0.034)	(0.039)	(0.001)
Flood*Given to flood victim	0.121***	0.115***	0.004***
	(0.020)	(0.018)	(0.001)
Flood*Flood prone	0.051	-0.021	-0.000
	(0.044)	(0.034)	(0.001)
Stratified regression by flood prone group			
Less flood prone (< 2 floods in 5 yrs)			
Flood	0.060	0.091*	-0.001
	(0.054)	(0.044)	(0.001)
Flood*Given to flood victim	-0.061	-0.023	0.002***
	(0.045)	(0.037)	(0.000)
Flood prone (at least 2 floods in 5 yrs)			
Flood	0.040	0.104**	-0.001
	(0.041)	(0.043)	(0.001)
Flood*Given to flood victim	0.044	-0.029	0.002***
	(0.041)	(0.038)	(0.000)

Full model is run in each regression. Robust standard errors in parentheses clustered at commune level. * p<0.1; ** p<0.05; *** p<0.01. Constants included but omited.

Table B.5 Flood and trust (Robustness check for Table 8)

	Village flood (=1)				Household flood (=1)				Flood days			
	Family	Neighbor	Business	Local Govt.	Family	Neighbor	Business	Local Govt.	Family	Neighbor	Business	Local Govt.
						OLS with FE						
Flood	-0.004	0.014	-0.000	0.005	-0.022	-0.147***	0.101	-0.287***	-0.001	-0.003	0.003	-0.008***
	(0.025)	(0.063)	(0.098)	(0.085)	(0.014)	(0.047)	(0.067)	(0.094)	(0.001)	(0.002)	(0.003)	(0.002)
Flood*Flood prone	0.013	-0.046	0.199	0.123	0.031	0.033	-0.226*	0.088	0.001	0.002	-0.006**	0.006*
	(0.023)	(0.079)	(0.137)	(0.115)	(0.021)	(0.055)	(0.113)	(0.113)	(0.001)	(0.002)	(0.003)	(0.003)
						Probit						
Subsample only if respondent is head												
Flood	0.952	0.185	-0.021	0.031	0.000	-1.192***	0.225	-0.403*	-2.850	-0.019***	0.009	-0.015***
	(0.892)	(0.320)	(0.255)	(0.229)	(0.000)	(0.430)	(0.197)	(0.225)	(0.000)	(0.007)	(0.007)	(0.006)
Flood*Flood prone	0.000	-0.401	0.566	0.304	0.597	0.239	-0.492*	0.089	-2.367	0.011	-0.014*	0.013
	(0.000)	(0.396)	(0.366)	(0.317)	(0.801)	(0.557)	(0.289)	(0.283)	(0.000)	(0.010)	(0.007)	(0.009)
Flood prone defined as HH with > 2 floods in 5 yrs												
Flood	1.306	0.211	0.178	-0.081	0.000	-0.989***	0.265*	-0.618***	-2.374	-0.014**	0.008	-0.020***
	(1.765)	(0.314)	(0.230)	(0.213)	(0.000)	(0.320)	(0.160)	(0.210)	(0.000)	(0.006)	(0.006)	(0.005)
Flood*Flood prone	0.000	-0.393	0.198	0.517*	-5.223	-0.266	-0.623***	0.471*	-2.983	0.004	-0.014**	0.020**
	(0.000)	(0.392)	(0.349)	(0.302)	(8.191)	(0.385)	(0.231)	(0.250)	(0.000)	(0.009)	(0.006)	(0.008)
Stratified regression by flood prone group												
Less flood prone (< 2 floods in 5 yrs)												
Flood	-2.138	0.075	-0.025	0.038	0.000	-1.535***	0.224	-0.468**	-0.189	-0.020***	0.009	-0.018***
	(0.000)	(0.385)	(0.271)	(0.199)	(0.000)	(0.412)	(0.196)	(0.200)	(0.000)	(0.007)	(0.006)	(0.006)
Flood prone (at least 2 floods in 5 yrs)												
Flood	-	-0.089	0.532***	0.301**	-	-1.204***	-0.293	-0.354*	-	-0.009	-0.005	-0.003
	-	(0.218)	(0.189)	(0.148)	-	(0.419)	(0.220)	(0.209)	-	(0.006)	(0.007)	(0.005)

Dependent variables are binary variable whether respondent trusts the above institutions, hence a probit model is used. Robust standard errors in parentheses clustered at commune level. * p<0.1; ** p<0.05; *** p<0.01. Constants included but omited. There is not enough variation in trust family variable (with only 3 out of 253 reporting trust family = 0 and all reporting trust family = 1 if flood prone group.

Table B.6 Flood and subjective expectation (Robustness check for Table 9)

	OLS with FE					
	Village flood (=1)		Household flood (=1)		Flood days	
	Pr(flood)	Pr(loss/flood)	Pr(flood)	Pr(loss/flood)	Pr(flood)	Pr(loss/flood)
Subsample only if respondent is head						
Flood	0.127***	0.035	0.160***	0.025	0.004***	0.003
	(0.030)	(0.065)	(0.032)	(0.068)	(0.001)	(0.002)
Flood*For mild flood	-0.165***	0.035	-0.133**	0.063	-0.003	-0.001
	(0.055)	(0.086)	(0.054)	(0.082)	(0.002)	(0.002)
Flood*Flood prone	-0.162***	-0.082	-0.121*	0.109	-0.004***	-0.001
	(0.037)	(0.071)	(0.066)	(0.086)	(0.001)	(0.002)
Flood*Flood prone*For mild flood	0.203**	0.009	0.119	-0.088	0.003	-0.002
	(0.079)	(0.094)	(0.106)	(0.080)	(0.002)	(0.002)
Flood prone defined as HH with > 2 floods in 5 yrs						
Flood	0.103***	-0.012	0.132***	0.054	0.003**	0.003
	(0.035)	(0.061)	(0.035)	(0.062)	(0.001)	(0.002)
Flood*For mild flood	-0.126**	0.059	-0.106*	0.038	-0.002	-0.002
	(0.051)	(0.069)	(0.058)	(0.071)	(0.002)	(0.002)
Flood*Flood prone	-0.121**	0.010	-0.075	0.075	-0.003**	-0.000
	(0.044)	(0.065)	(0.049)	(0.069)	(0.001)	(0.002)
Flood*Flood prone*For mild flood	0.142*	-0.041	0.065	-0.054	0.002	-0.001
	(0.070)	(0.065)	(0.083)	(0.075)	(0.002)	(0.002)
Stratified regression by flood prone group						
Less flood prone (< 2 floods in 5 yrs)						
Flood	0.136***	0.021	0.152***	0.041	0.004***	0.003
	(0.034)	(0.073)	(0.035)	(0.073)	(0.001)	(0.002)
Flood*For mild flood	-0.157**	0.039	-0.134**	0.049	-0.003	-0.002
	(0.053)	(0.090)	(0.056)	(0.083)	(0.002)	(0.002)
Flood prone (at least 2 floods in 5 yrs)						
Flood	-0.023	-0.025	0.053	0.133*	0.000	0.002**
	(0.037)	(0.034)	(0.057)	(0.063)	(0.001)	(0.001)
Flood*For mild flood	0.027	0.038	-0.020	-0.023	0.000	-0.003**
	(0.059)	(0.035)	(0.096)	(0.070)	(0.002)	(0.001)

Dependent variable are subjective expectations of probability of severe and mild flood in (1), (3), (5) and probability of loss conditional on occurrence of severe or mild flood. For mild flood is a binary variable =1 if mild flood and = 0 if severe flood. Robust standard errors in parenthesesclustered at commune level. * p<0.1; ** p<0.05; *** p<0.01.

Table B.7 Flood and safety net perceptions (Robustness check for Table 10)

	Village flood (=1)			Household flood (=1)			Flood days		
	Can rely on governt when flood	Can rely on social when flood	Can rely on natural when flood	Can rely on governt when flood	Can rely on social when flood	Can rely on natural when flood	Can rely on governt when flood	Can rely on social when flood	Can rely on natural when flood
					OLS with FE				
Flood	0.054	-0.006	-0.031	-0.022	0.015	-0.003	0.000	-0.001	0.001
	(0.058)	(0.054)	(0.074)	(0.066)	(0.054)	(0.066)	(0.002)	(0.002)	(0.002)
Flood*For mild flood	-0.026	0.001	0.019	-0.021	0.035	0.038	-0.003	0.001	0.004*
	(0.039)	(0.044)	(0.032)	(0.055)	(0.036)	(0.043)	(0.002)	(0.002)	(0.002)
Flood*Flood prone	-0.115	-0.049	0.088	-0.060	-0.053	-0.013	-0.000	0.001	-0.000
	(0.076)	(0.071)	(0.086)	(0.091)	(0.066)	(0.105)	(0.002)	(0.002)	(0.002)
Flood*Flood prone*For mild flood	0.056	-0.016	-0.024	0.081	0.036	-0.046	0.002	0.001	-0.004*
	(0.067)	(0.060)	(0.053)	(0.081)	(0.048)	(0.071)	(0.003)	(0.001)	(0.002)
					Probit				
Subsample only if respondent is head									
Flood	0.283	0.125	0.042	0.354	0.184	-0.107	0.004	-0.001	-0.000
	(0.314)	(0.227)	(0.322)	(0.272)	(0.300)	(0.280)	(0.009)	(0.007)	(0.007)
Flood*For mild flood	-0.036	-0.131	0.109	-0.167	0.222	0.344**	-0.004	0.006	0.019*
	(0.180)	(0.187)	(0.124)	(0.223)	(0.224)	(0.138)	(0.009)	(0.010)	(0.011)
Flood*Flood prone	-0.333	-0.388	-0.270	-0.443	-0.022	0.067	-0.004	0.002	0.006
	(0.320)	(0.299)	(0.365)	(0.408)	(0.318)	(0.399)	(0.010)	(0.007)	(0.011)
Flood*Flood prone*For mild flood	-0.180	-0.060	-0.023	0.338	-0.500*	-0.107	-0.001	-0.001	-0.018
	(0.303)	(0.278)	(0.150)	(0.416)	(0.292)	(0.194)	(0.013)	(0.008)	(0.011)

Table B.7 Flood and safety net perceptions (Continued)

	Village flood (=1)			Household flood (=1)			Flood days		
	Can rely on governt when flood	Can rely on social when flood	Can rely on natural when flood	Can rely on governt when flood	Can rely on social when flood	Can rely on natural when flood	Can rely on governt when flood	Can rely on social when flood	Can rely on natural when flood
	OLS with FE								
Flood prone defined as HH with > 2 floods in 5 yrs									
Flood	0.188	0.005	-0.005	0.311	0.140	-0.154	0.006	-0.003	-0.002
	(0.277)	(0.194)	(0.265)	(0.200)	(0.244)	(0.219)	(0.007)	(0.006)	(0.006)
Flood*For mild flood	-0.023	-0.166	0.080	0.041	0.027	0.275***	-0.001	0.004	0.013*
	(0.157)	(0.174)	(0.106)	(0.215)	(0.178)	(0.103)	(0.007)	(0.008)	(0.008)
Flood*Flood prone	-0.288	-0.248	-0.234	-0.411	0.102	0.180	-0.008	0.006	0.009
	(0.313)	(0.261)	(0.309)	(0.296)	(0.285)	(0.288)	(0.007)	(0.005)	(0.008)
Flood*Flood prone*For mild flood	-0.162	0.018	0.025	-0.008	-0.129	0.010	-0.006	0.003	-0.009
	(0.279)	(0.295)	(0.124)	(0.290)	(0.258)	(0.152)	(0.010)	(0.007)	(0.007)
Stratified regression by flood prone group									
Less flood prone (< 2 floods in 5 yrs)									
Flood	0.242	0.235	0.048	0.246	0.279	-0.246	0.000	0.000	0.000
	(0.352)	(0.268)	(0.317)	(0.274)	(0.319)	(0.324)	(0.009)	(0.007)	(0.008)
Flood*For mild flood	0.026	-0.141	0.099	-0.106	0.212	0.431***	-0.003	0.006	0.022**
	(0.168)	(0.195)	(0.118)	(0.234)	(0.224)	(0.121)	(0.009)	(0.010)	(0.010)
Flood prone (at least 2 floods in 5 yrs)									
Flood	-0.190	-0.309	-0.239	-0.087	0.261	-0.035	0.001	0.002	0.008
	(0.269)	(0.213)	(0.274)	(0.265)	(0.305)	(0.252)	(0.004)	(0.006)	(0.007)
Flood*For mild flood	-0.208	-0.189	0.095	0.235	-0.283	0.250**	-0.005	0.006	0.002
	(0.255)	(0.204)	(0.116)	(0.351)	(0.196)	(0.120)	(0.007)	(0.006)	(0.003)

Dependent variable are subjective expectations whether or not household can rely on government (1),(4),(7), on social insurance (2),(5),(8) or on natural resources (3),(6),(9) when severe or mild flood occurs. For mild flood is a binary variable =1 if mild flood and = 0 if severe flood. Robust standard errors in parentheses clustered at commune level. * p<0.1; ** p<0.05; *** p<0.01.

Table B.8 Flood and behavioral choices (Robustness check for Table 11)

	OLS with FE														
	Investment in land and irrigation			Have saving			Collect forest products and fishing			Number of dependable friends			Demand for market insurance		
Flood	-0.157*		-0.176**	0.129*		0.091	-0.181***		-0.148**	-0.298*		-0.299*	-0.017		-0.014
	(0.080)		(0.080)	(0.061)		(0.077)	(0.055)		(0.052)	(0.159)		(0.159)	(0.071)		(0.067)
Flood*Flood prone	0.300***		0.329***	0.026		0.026	0.145		0.116	0.168		0.285	0.158**		0.120*
	(0.099)		(0.097)	(0.085)		(0.087)	(0.099)		(0.099)	(0.253)		(0.235)	(0.070)		(0.067)
Risk aversion		-0.033*	-0.032*		-0.017	-0.016		-0.002	-0.001		0.022	0.024		-0.010	-0.008
		(0.017)	(0.017)		(0.017)	(0.017)		(0.013)	(0.012)		(0.041)	(0.041)		(0.017)	(0.017)
Impatience		0.016**	0.015		-0.011	-0.011		-0.003	-0.002		0.002	0.005		-0.017**	-0.017**
		(0.008)	(0.010)		(0.010)	(0.009)		(0.010)	(0.009)		(0.021)	(0.021)		(0.007)	(0.007)
Altruism		0.338***	0.338***		0.354***	0.327***		-0.178***	-0.150**		-0.417	-0.366		0.048	0.040
		(0.099)	(0.092)		(0.080)	(0.082)		(0.058)	(0.063)		(0.305)	(0.309)		(0.094)	(0.105)
Trust family		0.047	0.005		0.410**	0.395**		0.044	0.044		0.293	0.285		0.251	0.234
		(0.087)	(0.078)		(0.176)	(0.179)		(0.100)	(0.099)		(0.211)	(0.186)		(0.152)	(0.147)
Trust neighbor		-0.030	-0.038		-0.071	-0.051		0.053	0.032		0.417***	0.378***		-0.210**	-0.204**
		(0.096)	(0.095)		(0.066)	(0.074)		(0.051)	(0.046)		(0.088)	(0.081)		(0.094)	(0.085)
Trust business/trader		0.030	0.041		-0.002	0.003		0.027	0.029		0.396***	0.404***		-0.048	-0.041
		(0.044)	(0.045)		(0.045)	(0.042)		(0.047)	(0.048)		(0.110)	(0.112)		(0.045)	(0.047)
Trust local governments		0.024	0.050		0.018	0.035		0.013	0.006		0.028	0.020		-0.008	0.005
		(0.038)	(0.037)		(0.065)	(0.068)		(0.023)	(0.025)		(0.146)	(0.142)		(0.041)	(0.043)
Sjt. prob of severe flood		-0.084	-0.015		-0.011	-0.046		-0.185	-0.139		0.341	0.430		-0.039	-0.042
		(0.099)	(0.095)		(0.087)	(0.090)		(0.125)	(0.128)		(0.377)	(0.353)		(0.106)	(0.098)
Sjt. prob of mild flood		-0.186**	-0.180**		0.374***	0.331***		0.019	0.067		0.323	0.412		-0.171	-0.181*
		(0.082)	(0.070)		(0.111)	(0.101)		(0.123)	(0.125)		(0.287)	(0.271)		(0.100)	(0.093)
Flood prone	-0.256***	-0.061	-0.269***	-0.055	-0.031	-0.059	-0.051	0.030	-0.040	0.017	0.037	-0.142	-0.110*	0.026	-0.060
	(0.072)	(0.045)	(0.070)	(0.065)	(0.044)	(0.055)	(0.090)	(0.044)	(0.094)	(0.263)	(0.159)	(0.264)	(0.056)	(0.043)	(0.057)
Other controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
FE	village	village	village	village	village	village	village	village	village	village	village	village	village	village	village
N	256	256	256	256	256	256	256	256	256	256	256	256	256	256	256

Dependent variable are behavioral choices observed in the household data. Flood variable is whether household experienced floood in 2011. Results for flood days are qualitatively similar, so omited. Robust standard errors in parenthesesclustered at commune level. * p<0.1; ** p<0.05; *** p<0.01. Same set of control variables were used, results not reported here.

Table C.1 Comparison of the constructed flood exposure variables with official flood victim record

	Official record: % flooded victim from official record			
I. Flooded villages (based on satellite data)	*Mean*	*SD*	*Min*	*Max*
Flooded village	73%	11%	67%	93%
Non-flooded village	27%	21%	9%	37%
	Official record: % in offical record			
II. Flooded household (based on survey data)	*In*	*Not in*	*Total*	
Flooded household	93%	7%	100%	
Non-flooded household	11%	89%	100%	