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CHAPTER 4
The Effects of Natural Disasters on Households' Preferences and Behaviours: Evidence from Cambodian Rice Farmers After the 2011 Mega Flood

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This paper studies the impacts of the 2011 mega flood on preferences, subjective expectations, and behavioural choices among Cambodian rice-farming households. We found 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' behavioural choices, some of which could further determine long-term economic development and resilience to future floods. We found flooded households to have lower productive investment, to substitute away social insurance with by increasing

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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.

1. Introduction

Natural disasters often create adverse impacts on the livelihoods of people, especially those living in developing economies where access to safety nets is limited. Disasters not only destroy physical, human, and social capital of households, catastrophic disasters can lead to a change in risk, time, and social preferences.[1] In addition, largely unexpected and rare disasters as well as the success or failure of safety net institutions in coping with disasters may lead to a revision of subjective expectations of future events. Such impacts could induce changes in behavioural choices that could in turn affect long-term economic development and resilience to future floods. Understanding these consequences also has crucial policy implications for the design of incentive-compatible safety nets and development programmes for agricultural households in rural 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 behaviours by studying the consequences of the 2011 mega flood in Cambodia—the country's biggest flood in recent history—on preferences, subjective expectations, and behavioural choices of affected Cambodian rice-farming households. We use the 2011 mega flood as a natural experiment and utilise 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 behavioural choices.

The Cambodian 2011 mega flood was a unique natural disaster event. Although flood is the most common natural disaster in Southeast Asia, most floods occur

[1] Recent studies provide empirical evidence that natural disasters can cause changes in risk, time, and social preferences. For risk preference, see Eckel, *et al.* (2009); Cameron and Shah (2012); Cassar, *et al.* (2011); and Page, *et al.* (2012). For time preference, see Callen (2011). For social preference, see Castillo and Carter (2011); and Cassar, *et al.* (2011).

in Indonesia, the Philippines, and Thailand, while Cambodia has experienced relatively less frequent floods—only 15 occurrences during 1981-2010. However, unlike other countries in Southeast Asian, the death toll per flood event in Cambodia is the highest in the region, averaging nearly 90 casualties, i.e., a death toll nearly twice as high as in Indonesia and Thailand on a per-event basis.[2] The 2011 flood was particularly important since it was the largest and deadliest in recent decades, with a death toll nearly three times as high as the historical average. Heavy rain and overflow of the Mekong River and the Tonle Sap from the second week of August 2011 affected 18 out of 24 provinces in 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 more than 1.7 million people affected. More than 400,000 hectares (ha) of rice crops were affected, 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 USD 625 million worth of losses and damage, with infrastructure damage estimated at USD 376 million. The damage included roads (national, provincial, and rural), irrigation facilities, water supply and sanitation facilities, schools, and health centres. The flooding posed a serious challenge to development and the livelihoods of people, particularly the poor and socially disadvantaged such as women and children.

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 and behaviours. This study focuses particularly on the effects of the flood on rice-farming households because most of the areas directly affected by the flood in Cambodia were farmland, especially for rice cultivation, and these farms were operated by relatively poor households whose access to risk management and risk coping mechanisms was relatively limited. The mega flood therefore had substantial impacts on the livelihoods of many farming households and thus understanding these impacts would provide important insights for policymaking regarding safety nets of poor and vulnerable households.

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[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.

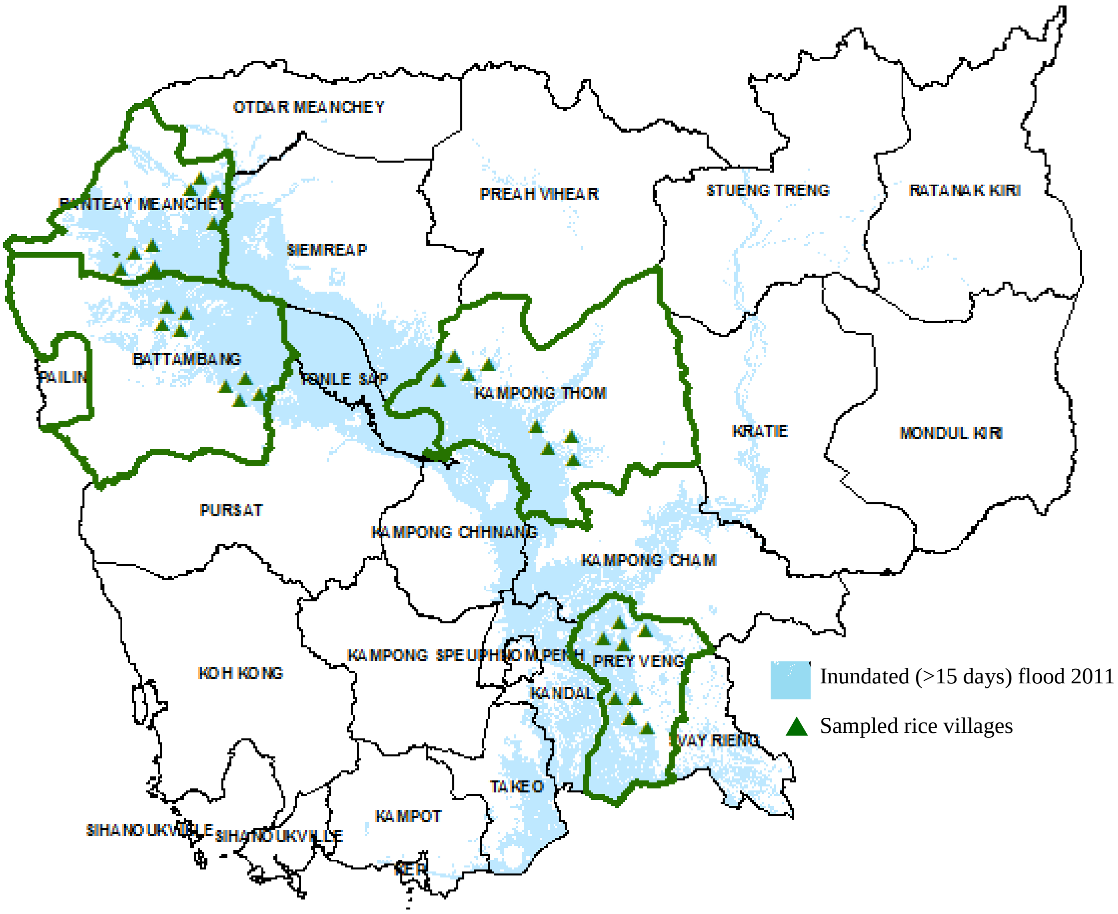
We found that the mega flood seemed to have made the affected Cambodian rice-farming households become more risk averse, and this increase in risk aversion appears greatest among poorer households. The mega flood also reduced impatience and increased altruistic behaviour among the affected households. Surprisingly, the 2011 flood, caused a significant reduction in trust of neighbours and local governments. Flood victims revised upward their subjective expectations of future severe floods and of the 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' behavioural choices. We found the flooded households to have lower productive investment, to substitute away social insurance with an increase in 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.

The paper is organised as follows. Section 2 describes our sampling strategy, our flood exposure variables, and the survey and summary statistics of our 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 in four of Cambodia's key rice-growing provinces: Prey Veng, Kampong Thom, Banteay Meanchey and Battambang. As shown in Figure 4.1, these four provinces were severely affected by the 2011 flood. 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 livelihoods are prone to floods. These variations could potentially contribute to the variations in the nature of the 2011 flood experience, as well as the capacity and strategies of households and communities in coping with and managing floods.

Figure 4.1: Map of studied villages



2.1. Sampling strategy

The survey and experiments cover 256 rice-farming households in 32 rice-growing villages in 16 communes in the four provinces. Four considerations underlie our sampling strategy: First, we confine our study to rice growing areas and households. Second, we utilise the discontinuity generated by the 2011 flood to construct a variation in flood experience. This discontinuity allows us to compare villages and farmers directly hit by the flood with those who did not directly experience the flood. Third, spillover and general-equilibrium effects on the non-flood households were unavoidable. These effects include, but are not limited to, new information about the flood and the management of the flood by the government as perceived by the farmers. 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-flood areas. With household-level flood experience, the effects, however, should bias our results toward finding no difference in preferences and behaviours between the farmers who were directly hit by the flood and those whose farms were not flooded. We also attempted to produce another set of comparable results to capture within-village spillover effects by creating variations in village-level 2011 flood experience.[3]

Finally, since 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 and the two groups could also have different characteristics, which could potentially result in different behavioural outcomes, simply selecting and comparing outcome variables between the flood affected and unaffected villages or households could leave us with a risk of selection problem–leading our estimates to capture impacts of the flood risk rather than of the mega 2011 flood itself. Our sampling strategy, therefore, also involves further stratification by the degree to which households or villages are prone to floods to account for variations in flood risk, so that we can control for this problem outright in our econometric estimations. Overall, our sampling strategy for each province involves two stratifications, at both the village and household levels: (i) whether the village/household was flooded in 2011, and (ii) whether the village/household is generally prone to floods in normal years.

To implement our sampling strategy, we went through the following steps. First, we used 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. We then used remote sensing maps of inundated areas produced by the World Food Program (WFP) to identify (i) communes severely affected by the 2011 mega flood (i.e., areas identified as inundated for more than 15 days) and (ii) communes that are prone to floods (based on 10 years of inundation data) in our four provinces.[4] For each province, we then selected

[3] We note that our strategy thus will not capture the likely spillover effects within the flooded commune, district or even province. But with village-level flood experience, the commune-level spillovers should bias our results toward finding no effect.

[4] 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. Mapping of severely affected areas was done by defining severely affected areas as those (non-permanent water) areas covered with floodwater for more than 15 days (i.e., where we saw water in at least two consecutive inundation maps). The WFP's flood risk mapping utilises 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

four rice-growing communes with extended areas severely affected by the 2011 flood, and two of which are flood-prone. In total, 16 flooded communes were selected, half of which are flood-prone.

Within each commune, there could also be a variation in the flood experience across rice-growing villages, e.g., with respect to the share of areas/households affected. In the second step, we exploited this potential variation by defining flooded villages as villages with a majority of areas severely flooded (i.e., with large areas identified as inundated for more than 15 days). Using GIS village locators and the flood maps, we then selected two rice-growing villages—one severely flooded and another not (severely) flooded in each commune.[5] Chiefs of the chosen communes were consulted to confirm our GIS-based classification and accessibility of the chosen villages. In cases where our chosen villages did not fit our categorisation,[6] we relied on commune chiefs and commune-level data for village selection instead. In particular, a rice-growing village is classified as a flooded village if more than 50 percent of households reported rice production loss following the 2011 flood. In total, 32 rice-growing villages were selected. In sum, the sampling strategy up to this point thus allowed us to ensure the variation in village-level 2011 flood experience (severely flooded versus not [severely] flooded), as well as the variation of flood risk (flood-prone versus not flood-prone) within the flooded and non-flooded village groups.

Within each village, there could also be sources of exogenous variations of the 2011 flood experience across households. Since our sampled households were rice farmers, the variation in the 2011 flood experience could relate closely to the extent that the flood affected rice production—the variation of which then depended largely on the (largely exogenous) correlations between rice production cycle, timing of the flood, and flood severity (flood height and the

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the past ten years. We selected our flood-prone communes from the group of communes in the WFP's first flood priority.

[5] Since the 2011 mega flood was largely covariate, it was not possible to find a completely non-flooded village. Our distinction of the flooded and non-flooded villages is thus the intensity of the 2011 flood extent, observed through share of areas/households affected by flood. Our village level flood impact analysis thus explores marginal variations in the village flood experience.

[6] One of the key reasons is that the resolution of our flood maps could only allow accurate flood identification at commune level.

inundation period).[7] In the third step, we again exploited these potential variations by proceeding to generate variations in the 2011 flood experience at the household level. A household was classified as a flooded household if it reported that its rice fields were submerged by floodwater for longer than 15 days in 2011.[8] In consultation with the village chiefs during subsequent field visits, we finally selected eight rice-growing households in each village applying the following criteria: (i) both flooded (rice fields were flooded) and non-flooded (rice fields were not flooded) households were selected for each village and (ii) the rice fields of the chosen households were geographically dispersed and varied in terms of the size of farm land.

The sample size by province is shown in Panel A of Table 4.1. Note that, although we had originally intended to collect a balanced sample for flooded and non-flooded households, the sample size was largely unbalanced. 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 samples were relatively more balanced in Prey Veng (29 flooded households out of 64 households).

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[7] It is possible that some of these factors could be correlated with household characteristics. For example, some advanced households may study and adjust their rice growing patterns to escape common floods. However, we argued that the majority of these factors were largely exogenous for Cambodian rice farmers. First, a large variation in the rice growing cycle was driven by variation in rice varieties. For example, long-life vs. short-life rice, or flooded vs. non-flooded rice are all common varieties in our studied areas. Second, while some farmers could learn to adjust their growing patterns to be more resilient to climate change, the extent and severity of the 2011 mega flood had been largely unexpected by rice farmers, as discussed in Section 1. In the survey, we also asked farmers if they had done anything to prepare for the 2011 flood; most answered that they had done nothing to prepare.

[8] Using this definition, our estimation results using household-flood experience should capture flood impacts on households that had seen their rice production hit directly by the 2011 flood. A common occurrence were households that did not experience rice production damage even though housing and (bare) agricultural land were flooded, e.g., if they had harvested their rice prior to the flood. Such households we classified as non-flooded households.

Table 4.1: Sampling and Summary Statistics of the 2011 Mega Flood by Studied Province

	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	182		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 (%)	0.68	0.29	0.68	0.36	0.75	0.27	0.58	0.26	0.71	0.26
Consumption lost (%)	0.08	0.14	0.06	0.13	0.08	0.13	0.10	0.15	0.09	0.15
Rice income lost ($)	1,648	6,150	1,459	1,693	1,209	4,425	579	599	3,425	11,050
Asset lost ($)	163	1,054	119	189	104	291	27	53	408	2,063
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

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.

Figure 4.1 shows our survey villages in the four provinces overlaid with the 2011 flood map. 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 flow 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 high-potential 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 Reserve, meaning people there also greatly rely on the forest and natural resources for their livelihoods. Kampong Thom is located on the eastern floodplain of Tonle Sap lake and occupies key core biodiversity areas in the reserve. The province is among the largest in the country, so people have good access to employment and financial services. 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 labour migration opportunities. Battambang is the country's largest rice production province in Cambodia and its rice is predominantly a high-yielding variety. The province also serves as a commercial and tourist hub in the northwestern region, with extended market access and alternative livelihoods, making the province wealthier than the other three.

The 2011 mega flood posed a serious challenge to development and the livelihoods of people in all these four rice-growing provinces. The variations of flood experience across the four provinces are shown in Panel B of Table 4.1. 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 used this information to generate the total number of days that each household experienced the 2011 flood.[9] On average, the mega flood resulted in 26 submerged days, with a maximum of 180 days experienced in Kampong Thom. The mega flood damaged 89 percent of rice fields and resulted in an average of USD 1,648 lost in rice income and USD163 lost in assets in the four provinces, per household. The largest loss

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

was suffered by the relatively wealthy rice farmers in Battambang (averaging USD3,425 rice income loss and USD408 asset loss). Among the key assets lost were livestock and productive farm assets. 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 on child schooling, and 15 percent on health care, with slightly greater impacts in Kampong Thom.

Panel C of Table 4.1 shows the variations of coping strategies the flooded households used during the 2011 mega flood across the four provinces. Strikingly, despite great variations, reliance on natural resources as a safety net was the most salient mechanism in all of the provinces—it was adopted by 39 percent of flooded households. Social mechanisms and reliance on assistance from the government or non-governmental organisations (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 borrowed from informal institutions such as microfinance institutions and saving groups. Use to credit to cope with the flood also varied across provinces, ranging from 45 percent in Prey Veng, 37 percent in Kampong Thom, 20 percent in Battambang, to 16 percent in Banteay Meanchey. Savings were used by some 24 percent of affected households and 27 percent of flooded households, especially in the three provinces in the Tonle Sap region, used additional labour income to cope with the 2011 flood. Despite the variety of strategies available, the use of "destructive" strategies, e.g., asset sales and child labour, were also common in some provinces.

Overall, the above statistics suggest (i) significant and varying impacts of the 2011 flood on rice-farming communities in Cambodia; (ii) the importance of natural resources as a safety net during the mega flood; (iii) a striking limit to social and government/NGOs assistance during the flood; and (iv) the great extent and variety of self-coping mechanisms used by flooded Cambodian farmers during the flood. These varying flood experiences, opportunities and limits to the use of various mechanisms among affected households, therefore, could affect preferences, subjective expectations and behavioural choices.

2.2. The 2011 flood exposures

Our sampling strategy discussed above allows us to construct three flood exposure variables. First, village-level flood exposure is a binary variable indicating whether the household was in a (relatively more severely) flooded village in 2011, where flooded village is defined as a village with a majority of areas flooded for more than 15 days and/or a village with more than 50 percent of households reporting rice production loss due to the flood. Employing this flood variable, our estimations should be able to identify the potential (marginal) impacts on households living in severely flooded villages relative to those living in not so severely flooded villages. Thus, the estimated impacts should generally include overall effects including likely spillover and general equilibrium effects on non-flooded households in these severely flooded villages. We note that our estimates could still suffer from the likely spillover effects within the flooded commune, district, province, or even country. But with village-level flood exposure, spillover effects at the higher levels should bias our results toward finding no effect.

Second, household-level flood exposure is another binary variable indicating whether a household was flooded in 2011 (i.e., when their rice fields were completely submerged by floodwater for more than 15 days). Employing this household-level flood variable, our estimations should be able to identify the potential impacts on households directly hit by the 2011 flood. However, estimated impacts could still suffer from likely spillover effects, which again should bias out results toward finding no effect.

Finally, we also used the number of days that households’ rice fields were completely submerged by floodwater to capture continuous household-level flood intensity. Our estimations using this flood variable should identify the potential heterogeneous effect of different levels of flood intensity on flooded households. Altogether, these three variables should capture the varying aspects of the 2011 flood experienced by Cambodian rice-farming households.

2.3. The Survey

The fieldwork conducted in April 2014 includes a standard household socioeconomic survey with detailed questions on the 2011 flood experience, other risks experienced by households over the past 10 years, risk management strategies, as well as key behavioural choices related to farm investment, saving and other safety net behaviours. The fieldwork also included a series of hypothetical experiment questions to elicit risk, time, social preferences; subjective expectations of future floods and resulting income loss; and household perceptions of the reliability of various safety net institutions to protect against the impacts of future floods. Appendix 1 provides a summary of the experiments and the associated preference parameters.

First, for risk preference, we replicated the simple Binswanger (1980) game by allowing respondents to choose different rice seed types with different degrees of risk and return. Respondents' seed choices could thus reflect their degree of risk aversion. We then constructed our risk aversion variable as a scaling indicator ranging from 1 (least averse) to 5 (most averse).

Second, for time preference, the experiment consisted 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 kept increasing as the experiment progressed from questions 1 to 7) in the future if he or she could wait to receive it. Observing the patterns of answers to these seven questions—specifically the first time when the respondent chose to accept the payment in the future—could reflect the extent to which respondents discount the future over the present, i.e., the degree of impatience. We then construct our impatience variable as a scaling indicator ranging from 0 (not impatient) to 8 (most impatient). [10]

[10] We note that our simple measure of time preference is 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.

Third, for social preference, we used a dictator game to illicit measures of household's altruism. Each respondent was given some amount of money, all or part of which they could give to a randomly chosen household in their village. The respondent was also told that the chosen beneficiary would be anonymous and that the respondent's decision would be kept confidential. We repeated this game but changed the beneficiary to be a randomly chosen flood-affected household in their village. We then constructed our altruism variable for each game from the proportion (0-100 percent) of money respondent chose to give.

Fourth, in our experiments on subjective expectations we asked each respondent to assign probabilities to future flood events. We used 10 coins as visual aids to express the probability concept[11] and asked each respondent to place the coins in front of each of three flood events (no flood, mild flood, and mega flood), where the number of the coins he/she put would reflect the likelihood he/she thought each event would occur in the next 10 years. Before we began the exercise, our enumerator first clarified 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—and explained the exercise, using several examples (see Appendix 1). We repeated this exercise to also elicit the respondents' perceptions of the likely 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 constructed each respondent's subjective expectation variables directly from the number of coins he/she assigned to each event.

Finally, we also used a general social science survey to elicit the degrees to which each respondent trusted family, neighbours, businesses and local governments. These questions allowed us to construct series of binary trust variables.

[11] 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.

2.4. Summary statistics of sampled households

Table 4.2 reports descriptive statistics of the sampled households by village and household-level flood exposure at the time of the survey in April 2014. Overall, household and village characteristics were similar for flooded versus non-flooded villages, and especially for flooded versus non-flooded households. The average household size was about five people. Seventy-eight percent of respondents in the flooded households had primary education, 32 percent had secondary education and these statistics were not significantly different for non-flooded households. Average land owned was 0.53 hectare for flooded households with a mean income per capita of USD701.62 per year, 47 percent of which came from rice production. About 23 percent of flooded households were classified as poor according to the Identification of Poor Household Program (ID Poor) and had faced about 2.3 other shocks over the past 10 years. Again, these statistics were similar for the non-flooded group. Availability of key village infrastructure and public programmes also appeared similar across flood groups.

Table 4.2 also shows some characteristics that were significantly different between the flooded and non-flooded villages—e.g., gender of the respondents, household size and land per capita. We constructed a flood-prone variable from the frequency of floods reported by each household—and so a household was prone to floods if it reported at least two floods experiences in the past five years. Our statistics also shows that flooded households were significantly more flood-prone than non-flooded households, with an average flood frequency of 1.75 in the past five years. If the key characteristics we found to be different across flood groups were also correlated with our behavioural outcomes of interest, this could potentially bias our estimation results. It is important, therefore, that we control for these variables in our empirical analysis.

Table 4.2: Summary Statistics of Sampled Households by Flood Exposure

	Village flood (=1)			Household flood (=1)		
	Flooded	Not flooded	Difference	Flooded	Not flooded	Difference
Household characteristics						
Female (=1)	0.344	0.492	-0.148***	0.436	0.380	0.056
	(0.477)	(0.502)	(0.061)	(0.497)	(0.488)	(0.065)
Age	48.82	50.33	-1.51	48.96	50.82	-1.860
	(12.29)	(13.04)	(1.583)	(12.70)	(12.57)	(1.685)
Have education-primary (=1)	0.844	0.734	0.109**	0.779	0.809	-0.030
	(0.365)	(0.443)	(0.051)	(0.416)	(0.395)	(0.054)
Have education-secondary (=1)	0.359	0.297	0.063	0.319	0.345	-0.025
	(0.482)	(0.459)	(0.059)	(0.467)	(0.478)	(0.062)
Household size	5.383	4.945	0.438**	5.174	5.142	0.032
	(2.238)	(1.652)	(0.245)	(2.070)	(1.777)	(0.263)
Member migrate (%)	0.703	0.570	0.133	0.674	0.559	0.115
	(1.159)	(0.945)	(0.132)	(1.069)	(1.033)	(0.140)
Female member migrate (%)	0.297	0.219	0.078	0.279	0.214	0.065
	(0.656)	(0.485)	(0.072)	(0.605)	(0.516)	(0.076)
Age of migrating members	16.77	15.29	1.48	17.06	13.90	3.160
	(27.97)	(25.52)	(3.347)	(27.24)	(25.67)	(3.560)
Income per capita ($)	689.81	624.79	65.02	701.62	566.53	135.09
	(903.81)	(2060.68)	(198.88)	(1874.43)	(706.81)	(211.67)
Rice income in total income (%)	0.454	0.471	-0.017	0.473	0.522	-0.049
	(0.349)	(0.357)	(0.044)	(0.345)	(0.361)	(0.046)
Land per capita (ha)	0.603	0.479	0.124*	0.532	0.558	-0.026
	(0.774)	(0.506)	(0.081)	(0.684)	(0.595)	(0.087)
Asset per capita ($)	2575.12	2270.55	304.57	2180.40	2466.35	-285.95
	(3700.23)	(2284.54)	(384.23)	(2775.34)	(3625.33)	(410.78)
ID poor household (=1)	0.219	0.250	-0.031	0.232	0.238	-0.006
	(0.415)	(0.434)	(0.053)	(0.423)	(0.428)	(0.056)
Flood prone (=1)	0.539	0.602	-0.063	0.627	0.452	0.175***
	(0.500)	(0.491)	(0.061)	(0.484)	(0.500)	(0.065)
Flood frequency in the past 5 yrs	1.625	1.516	0.109	1.750	1.202	0.548***
	(0.774)	(0.763)	(0.096)	(0.612)	(0.915)	(0.096)
Other shocks in the past 10 yrs	2.461	2.305	0.156	2.373	2.607	-0.234
	(1.674)	(1.829)	(0.219)	(1.651)	(1.932)	(0.232)
Village characteristics						
Have irrigation system (=1)	0.436	0.412	0.024	0.421	0.430	-0.009
	(0.516)	(0.466)	(0.057)	(0.459)	(0.470)	(0.061)
Have electricity (=1)	1.000	1.000	0.000	1.000	1.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
With social land concession (=1)	0.109	0.085	0.024	0.110	0.071	0.039
	(0.313)	(0.281)	(0.037)	(0.314)	(0.259)	(0.039)
With health equity fund (=1)	0.190	0.207	-0.017	0.191	0.177	0.014
	(0.409)	(0.322)	(0.046)	(0.394)	(0.311)	(0.049)

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

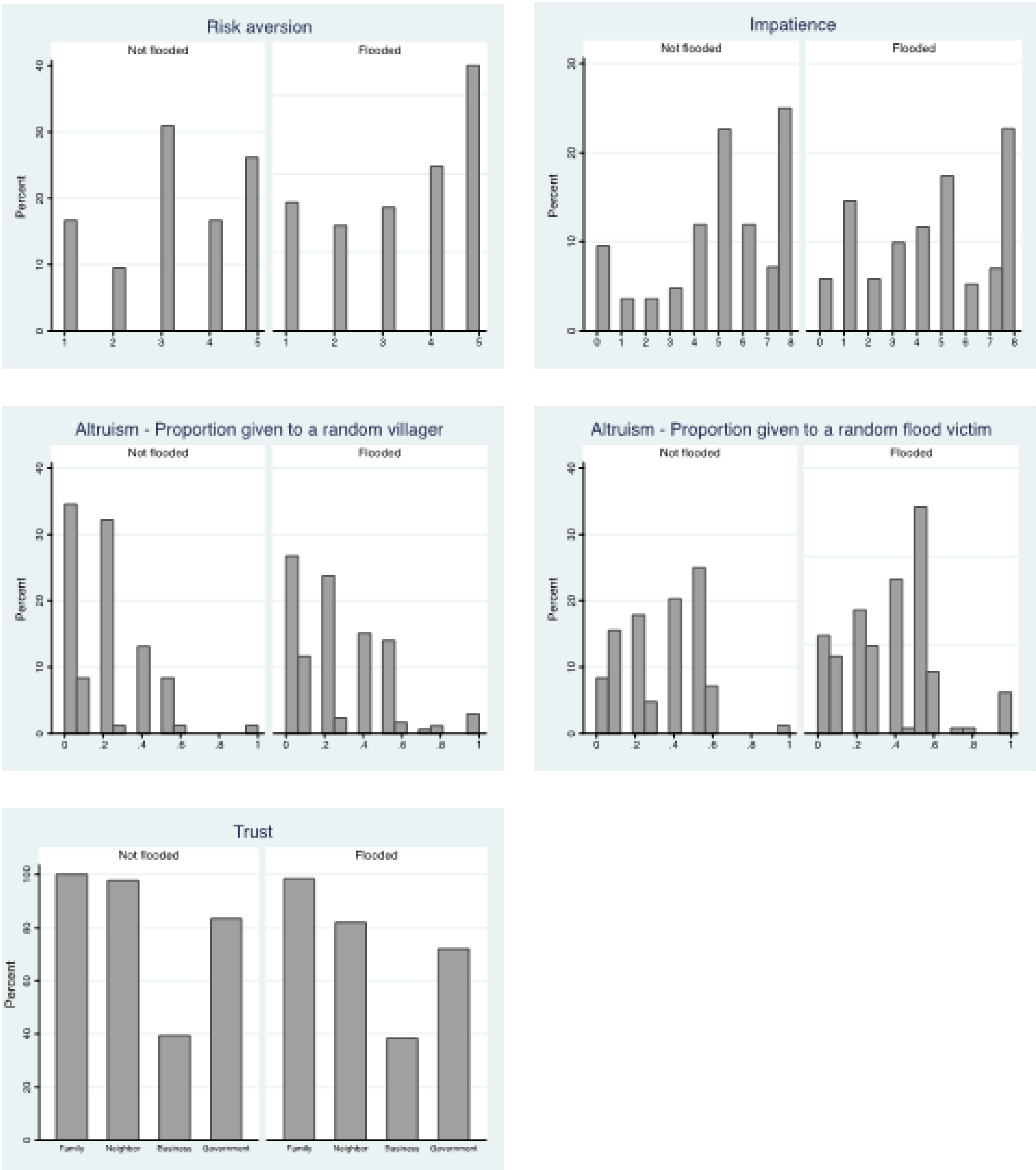
Table 4.3 reports descriptive statistics of our measures of preferences, subjective expectations, and behavioural choices, again, at the time of the survey in April 2014. The table shows that the sampled households were relatively risk averse with both the mean and the median measures of risk aversion ranging from 3.3–3.4 in all groups. Our simple comparison showed that the mean risk aversion variables were not significantly different between flooded and non-flooded villages or households. Figure 4.2 plots distributions of the risk aversion parameter by household flood experience. These plots provide the additional finding that the share of households with extreme risk aversion appeared larger among the flooded households.

Table 4.3: Summary Statistics of Preference and Behavioral Variables by Flood Exposure

	Village flood (=1)			Household flood (=1)		
	Flooded	Not flooded	Difference	Flooded	Not flooded	Difference
Preferences						
Risk aversion (1,2,..,5)	3.367	3.375	-0.008	3.424	3.261	0.163
	(1.473)	(1.425)	(0.181)	(1.474)	(1.389)	(0.192)
Impatience (0,1,2,..,8)	4.718	4.671	0.047	4.511	5.071	-0.560*
	(2.635)	(2.593)	(0.326)	(2.643)	(2.511)	(0.346)
Altruism - percent money given to randomly matched	0.259	0.201	0.058**	0.252	0.191	0.061**
villager (0-1)	(0.239)	(0.202)	(0.027)	(0.234)	(0.192)	(0.029)
Altruism - percent money given to randomly matched	0.380	0.323	0.057**	0.364	0.326	0.038*
flood victim in the village (0-1)	(0.245)	(0.192)	(0.027)	(0.232)	(0.198)	(0.030)
Trust family (=1)	0.992	0.984	0.008	0.982	1.000	-0.018
	(0.088)	(0.124)	(0.013)	(0.131)	(0.000)	(0.014)
Trust neighbor (=1)	0.875	0.867	0.008	0.819	0.976	-0.156**
	(0.332)	(0.340)	(0.042)	(0.385)	(0.153)	(0.043)
Trust business/trader (=1)	0.429	0.343	0.086*	0.383	0.392	-0.009
	(0.496)	(0.476)	(0.060)	(0.487)	(0.491)	(0.065)
Trust local government (=1)	0.773	0.742	0.031	0.720	0.833	-0.112**
	(0.420)	(0.439)	(0.053)	(0.449)	(0.374)	(0.056)
Subjective expectations						
Probability of mild flood (0-1)	0.393	0.409	-0.016	0.411	0.380	0.031
	(0.228)	(0.225)	(0.028)	(0.224)	(0.230)	(0.030)
Probability of severe flood (0-1)	0.413	0.384	0.029	0.437	0.319	0.118***
	(0.262)	(0.262)	(0.032)	(0.263)	(0.244)	(0.034
Probability of loss when mild flood occurs (0-1)	0.328	0.306	0.022	0.362	0.226	0.135***
	(0.282)	(0.285)	(0.035)	(0.291)	(0.243)	(0.036)
Probability of loss when severe flood occurs (0-1)	0.729	0.743	-0.014	0.776	0.654	0.122
	(0.286)	(0.260)	(0.034)	(0.222)	(0.342)	(0.035)
Can rely on govnt. when mild flood (=1)	0.128	0.137	-0.009	0.138	0.121	0.017
	(0.232)	(0.220)	(0.028)	(0.226)	(0.226)	(0.030)
Can rely on govnt. when severe flood (=1)	0.283	0.301	-0.018	0.294	0.288	0.006
	(0.310)	(0.300)	(0.038)	(0.295)	(0.326)	(0.040)
Can rely on social network when mild flood (=1)	0.127	0.171	-0.045*	0.179	0.089	0.090***
	(0.260)	(0.272)	(0.033)	(0.297)	(0.176)	(0.035)
Can rely on social network when severe flood (=1)	0.134	0.175	-0.041*	0.170	0.123	0.046*
	(0.237)	(0.280)	(0.032)	(0.275)	(0.222)	(0.034)
Can rely on natural resource when mild flood (=1)	0.368	0.328	0.04	0.361	0.322	0.039
	(0.372)	(0.350)	(0.045)	(0.351)	(0.382)	(0.048)
Can rely on natural resource when severe flood (=1)	0.319	0.279	0.04	0.306	0.285	0.021
	(0.345)	(0.306)	(0.040)	(0.328)	(0.322)	(0.043)
Behavioral choices						
Investment in land and irrigation (=1)	0.140	0.117	0.023	0.122	0.142	-0.020
	(0.349)	(0.322)	(0.042)	(0.328)	(0.352)	(0.044)
Have saving (=1)	0.188	0.188	0.000	0.244	0.071	0.173***
	(0.392)	(0.392)	(0.049)	(0.433)	(0.259)	(0.051)
Number of dependable friends	0.625	0.508	0.117	0.529	0.643	-0.114
	(1.049)	(0.822)	(0.118)	(0.933)	(0.965)	(0.126)
Collect forest products and fishing (=1)	0.086	0.109	-0.023	0.076	0.143	-0.067**
	(0.281)	(0.313)	(0.037)	(0.265)	(0.352)	(0.394)
Demand market insurance (=1)	0.094	0.086	0.007	0.110	0.048	0.063**
	(0.293)	(0.281)	(0.035)	(0.314)	(0.214)	(0.038)

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

Figure 4.2: Risk Aversion, Impatience, Altruism and Trust by Household Flood Exposure



The impatience variable appeared similar between households in flooded versus non-flooded villages. Our simple comparison, however, shows that flooded households seemed to be significantly less impatient than non-flooded households. Figure 4.2 further shows that the share of households with extreme impatience appeared smaller among flooded households than among the non-flooded group.

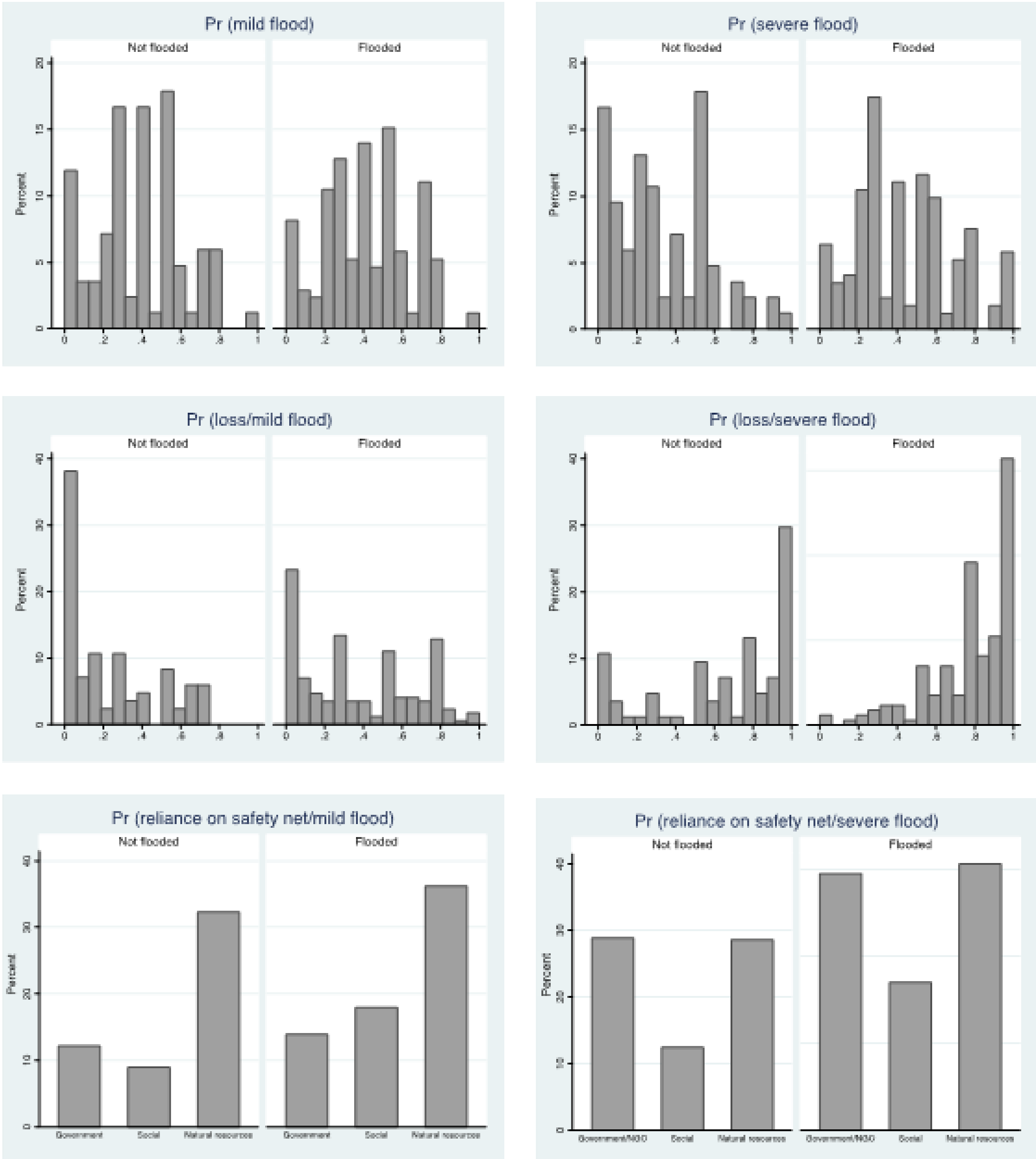
On average, there appeared to be significantly larger altruism variables for flooded households and households in flooded villages than for non-flooded groups. The average share of money given to a randomly matched villager was about 0.25 in the flooded group. As shown in Figure 4.2, a smaller share of households gave nothing but a larger share of households gave a large amount to a random villager in the flooded group than that of the non-flooded group. And in all groups, the proportion given to a random villager was smaller than that given to a flood victim.

For trust, we found that in all groups almost all (99 percent) of our sampled households trusted family, followed by trusting neighbours (82-98 percent), trusting local governments (72-83 percent) and trusting businesses (34-43 percent). The share of households that trusts family and businesses appears similar across flood groups, whereas the share of those trusting neighbours and local government appears significantly smaller in the flooded group.

For subjective expectations, our sampled households assigned large probabilities of flood risk in general (0.38-0.41 for mild flood and 0.32-0.44 for severe flood). This was to be expected given that our samples are all from flood-affected communes. The flooded households, however, assigned significantly higher subjective probabilities to severe flood, and also a significantly higher perceived proportion of rice income loss in the event of a mild flood.

Finally, the descriptive statistics of households' perceptions on safety net institutions also revealed some interesting results among our sampled rice-farming households. For both mild and severe floods, the largest percentage of households (27-37 percent) in all groups perceived that they could rely on natural resources as a safety net. These were followed by a perceived ability to rely on governments (28-30 percent) and social networks (12-17 percent) when a severe flood occurs. For mild flood, however, both perceived ability to rely on governments and social networks appeared to be similar, at only 12-13 percent. Statistically, these safety net perceptions were not significantly different across flood groups, except for the perceived ability to rely on social networks. Similar findings are depicted in Figure 4.3.

Figure 4.3: Subjective Expectations by Household Flood Exposure

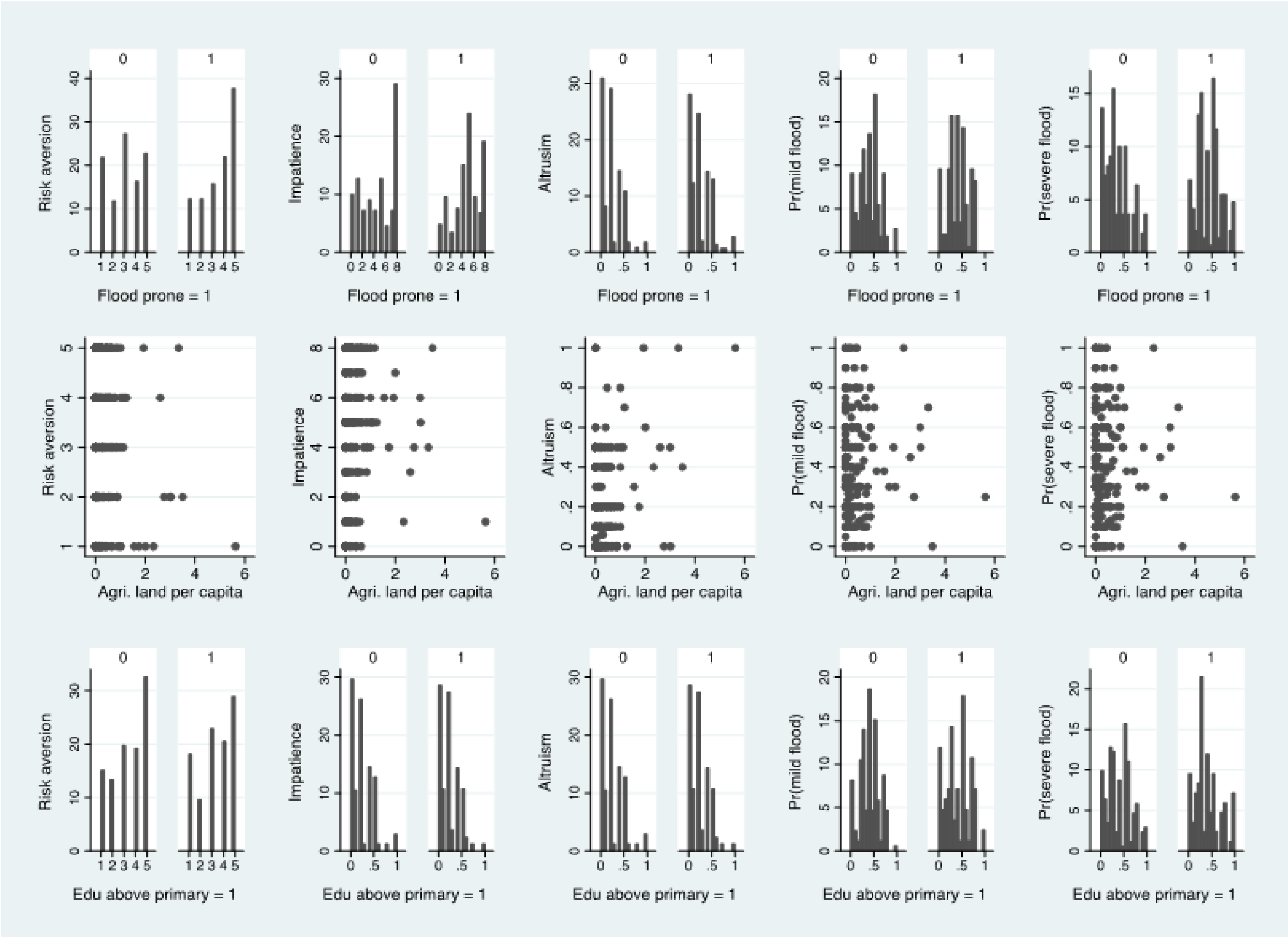


We are also interested in the potential impacts of the 2011 mega flood on some key behavioural choices that could potentially determine households' economic growth and their resilience to future floods. The variables of our interest are (i) whether a household invested in land and irrigation; (ii) whether a household had savings; (iii) the number of dependable friends a household had (as an indicator of social capital formation); (iv) whether a household collected forest products and engaged in fishing; and (v) a household's willingness to pay for commercial flood insurance. Interestingly, Table 4.3

reveals that a significantly larger percentage of households had savings and demand for commercial insurance, and a significantly smaller percentage of households collected forest products among flooded households than among non-flooded households.

These bivariate relationships in Table 4.3, however, should be interpreted with some caution. To what extent might these relationships be driven by other observed and/or unobserved variables that were correlated with both 2011 flood exposure and our outcome variables? Figure 4.4 depicts some bivariate relationships between our preference and expectation variables and (i) whether a household was flood-prone; (ii) land ownership; and (iii) education—the key covariate theoretically known to affect these behavioural variables. As expected, these figures suggest that risk aversion was positively associated with the degree of flood risk and negatively associated with wealth and education. Altruism also appeared to increase with flood risk and wealth. And the subjective probabilities of future floods were also positively associated with the degree of flood risk. Since some of these key variables were also correlated with flood exposure (e.g., flood-prone and land ownership), we will control for these variables in our estimations in the next section.

Figure 4.4: Relationships between Preferences and Key Characteristics



3. Empirical Strategy

We estimate the potential impacts of the 2011 mega flood by regressing our preference and behavioural 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 other behavioural choice variables of interest. $Flood_{iv}$ is a variable that captures households' exposure to the 2011 flood. In our analysis, we use three different measures of this flood exposure: (i) a village-level indicator if a household was in the flooded village, utilising the exogenous variation of flood experience across villages; (ii) a household-level indicator if a household was directly affected by flood, utilising exogenous variations of flood experience across households within each village; and (iii) the number of days that a household's rice fields were completely submerged by floodwater, capturing the continuous household-level flood intensity. $Floodprone_{iv}$ is a household-level indicator variable controlling for the potential lurking effect of the degree to which each household was prone to floods.[12] X_{iv} are various household-level controls while α_v controls for unobserved heterogeneity at village level.[13] We also clustered all specifications at the commune level.

Various potential sources of selection bias are worth discussing. First, one would wonder if the variations of village-level flood experience were exogenous. Since the flood-prone villages were likely be flooded, the flood-prone variable would be correlated with some key behavioural variables. To address this concern, we stratify our sample by their vulnerability to flood, captured by the flood-prone variable, and control for this in the estimation. Another potential problem is migration, which could generate an endogeneity in flood exposure, especially if many households moved from flooded to non-flooded areas. However, this problem should be minimal for our sampled

[12] Again, flood-prone equals one if household had experienced at least two floods over the past five years.

[13] For village flood exposure, commune level fixed effect was used.

households—their lands were largely inherited if they owned and/or relied on community land, making mobility difficult. There is 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 seasonal migration of household members as a consequence of the 2011 flood. Again, this problem should be negligible as Table 4.2 shows that the share of migration and the characteristics of migrants were similar between the two village groups. Likewise, Table 4.2 shows no significantly different characteristics of both households and villages between the flooded and non-flooded groups.

Moreover, there is a concern as to whether the variation of household-level flood experience was exogenous. First, there are factors determining growing patters that are correlated with flood exposure and damages, e.g, geography, irrigation, and market demand in the high demand zone like Battambang. To address this issue, we will control for village fixed effects (in addition to 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 to be 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 severity was very much unexpected when it arrived. When we asked whether households had done anything to prepare for this 2011 flood, the majority of households responding they had not. Finally, although we would expect that farmers in the flood-prone areas are more likely to adopt the flood-resistant varieties and hence less likely to be affected by the 2011 mega flood, this endogeneity should bias our results toward finding no effect of the 2011 mega flood on the flooded households.

4. Empirical Results

4.1 How did the 2011 mega flood affect preferences?

Table 4.4 summarises the regression results of the 2011 flood on households' risk aversion. Columns (1) to (3) report various ordinary least squares (OLS) regressions of risk aversion on village-flood exposure. Overall, controlling for commune fixed effect, we found no significant relationship between living in severely flooded villages and risk aversion even when controlling for the degree of flood-prone and other key covariates. Columns (4) to (7) report various OLS regressions of risk aversion on household-level flood exposure. Controlling for village fixed effects and whether a household was in a flood-prone area, column (5) shows a significant positive effect of the 2011 flood on risk aversion among flooded households in non-flood-prone areas. This result was also robust when we added a full control of other covariates. Specifically, column (6) shows that being affected by the 2011 flood resulted in a 0.39 percentage point increase in risk aversion. For flooded households already living in flood-prone areas, however, the 2011 flood did not result in statistically significant change in their risk aversion. To capture the heterogeneous impacts across wealth groups, column (7) added land per capita and flood interaction terms in the OLS regression. Interestingly, the wealth interaction term was significantly negative. These results were also robust when we performed an ordered probit regression in column (8) and when flood intensity was used in column (9). In all specifications, we also found that households living in flood-prone areas tend to have significantly higher risk aversion—0.72 percentage points higher—than those in non-flood-prone areas.[14]

[14] This finding suggests that risk aversion was not a key determinant of the choice of rice farm locations, as we would expect risk-averse farmers to choose the locations that were less prone to flood.

Table 4.4: The Mega Flood and Risk Aversion

	Village flood (=1)			Household flood (=1)					Flood days
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	OLS	OLS	OLS	OLS	OLS	OLS	OLS	Oprobit	OLS
Flood	-0.008	0.185	0.274	0.133	0.422**	0.386*	0.551**	0.346*	0.013
	(0.151)	(0.280)	(0.271)	(0.220)	(0.191)	(0.201)	(0.207)	(0.202)	(0.009)
Flood*Flood prone		-0.299	-0.283		-0.634	-0.662*	-0.660*	-0.525*	-0.011
		(0.386)	(0.348)		(0.368)	(0.334)	(0.340)	(0.303)	(0.010)
Flood*Land per capita							-0.413*	-0.188	-0.026***
							(0.214)	(0.216)	(0.006)
Flood prone		0.515*	0.470		0.752***	0.726***	0.725***	0.723***	0.547*
		(0.286)	(0.297)		(0.233)	(0.236)	(0.241)	(0.255)	(0.271)
Female			0.293			0.312	0.288	0.129	0.250
			(0.209)			(0.221)	(0.224)	(0.143)	(0.216)
Age			0.001			0.002	0.002	-0.002	0.003
			(0.010)			(0.010)	(0.010)	(0.007)	(0.010)
Education-primary			-0.176			-0.090	-0.095	-0.156	-0.118
			(0.204)			(0.206)	(0.206)	(0.157)	(0.202)
Education-secondary			0.157			0.089	0.100	0.127	0.083
			(0.168)			(0.149)	(0.136)	(0.133)	(0.132)
Household size			0.032			0.021	0.022	-0.000	0.008
			(0.038)			(0.041)	(0.042)	(0.032)	(0.044)
Ln asset per capita			-0.104			-0.111	-0.124	-0.136**	-0.129
			(0.083)			(0.087)	(0.088)	(0.069)	(0.088)
Land per capita			-0.289**			-0.336***	-0.035	-0.075	0.149
			(0.124)			(0.108)	(0.181)	(0.199)	(0.140)
Number of shocks			-0.041			-0.032	-0.028	-0.019	-0.031
in the past 10 years			(0.043)			(0.043)	(0.045)	(0.045)	(0.044)
Constant	3.375***	3.065***	4.557***	3.282***	2.926***	4.606**	4.623**		4.890***
	(0.076)	(0.190)	(1.486)	(0.148)	(0.107)	(1.621)	(1.606)		(1.580)
FE	commune	commune	commune	village	village	village	village	village	village
N	256	256	256	256	256	256	256	256	256
F - Joint signt. of all flood vars		0.30	0.51		2.69	2.60	3.96	4.79	7.35

Dependent variable is risk aversion. Flood variables are indicators if household is in flooded village (1)-(3), if household was flooded (4)-(8) and number of flood days household experienced (9). Robust standard errors in parentheses clustered at commune level. * p<0.1; ** p<0.05; *** p<0.01.

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 for the Cambodian sample 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.[15]

In theory, changes in risk preference could affect household behaviours in various ways, some of which could affect economic development. For example, an increase in risk aversion could induce households to invest in more conservative projects, while an increase in risk loving behaviour may induce a higher demand for gambling and other risky behaviours, or more aggressive investment in risky ventures. Furthermore, an increase in risk aversion may generate higher demand for safety nets, through self-insurance (savings and consumption reallocation, as well as diversification of household income), market-based strategies (credit and insurance contracts), community assistance (informal assistance among family members and friends), and public assistance from the government and non-governmental organisations (NGOs). In this sense, our findings have important policy implications. For example, the resulting flood-induced reduction in risk aversion could potentially crowd in productive-yet-risky investment ventures among risk-prone flood victims. The mega flood consequently could reduce investment incentives for flood victims in the non-flood-prone region, who could become more risk averse. This adverse effect was greatest for poor flood-affected households, probably inducing them to focus on conservative investment projects with lower average returns.

Table 4.5 summarises the regression results for impatience. Columns (1) to (3) report various OLS regressions of impatience on village-flood exposure. Controlling for the commune fixed effects, we found no statistically significant relationship between living in severely flooded villages and impatience, even when we controlled for the degree of flood-prone and other key covariates. Columns (4) to (7) report OLS regressions of impatience on household-level flood exposure. Controlling for village fixed effects and whether a household

[15] Existing literature finds inconclusive results on the impact of disasters on risk aversion. On the one hand, Cameron and Shah (2012) found that individuals who recently suffered a flood or earthquake in Indonesia exhibit higher risk aversion than individuals living in otherwise like villages. Cassar, *et al.* (2011) showed that the 2004 Indian Ocean tsunami in Thailand resulted in higher risk aversion. In particular, this finding is also consistent with the conclusions reached by Samphantharak and Chantarat (2014) who found that the 2011 mega flood in Thailand had a positive impact on risk aversion of flooded farming households. On the other hand, Page, *et al.* (2012), analysing the 2011 Brisbane flood in Australia, found that after a large negative wealth shock, those directly affected became more willing to adopt riskier options in their decision-making process.

was in a flood-prone area, as well as all covariates, column (5) to (6) show that the 2011 flood did not significantly affect impatience among flooded households. But when we added wealth interaction to the current OLS regression, we found instead in column (7) that the 2011 flood significantly reduced impatience among flooded households, and that this negative impact increased with wealth. This result was also robust when we performed an ordered probit estimation in column (8). Moreover, in almost all specifications, we found households living in flood-prone areas to have significantly higher impatience than those in non-flood-prone areas. But we found no further impact of increasing flood intensity.[16] Again, our findings have relevant policy implications. In theory, a change in time preference could affect intertemporal decisions of households such as savings. The significant increase in impatience among the flooded households could potentially affect savings, investment, and growth as households increase their current consumption at the expense of future growth through saving and investing. This effect could be especially salient among the (highly impatient) risk-prone low-wealth households, which might currently have low savings to start with.

[16] The impact of disasters on time preference in the existing literature is mixed at best. Callen (2011) showed that exposure to the Indian Ocean Earthquake tsunami affected a patience measure in a sample of Sri Lankan wage workers. Samphantharak and Chantarat (2014) found no systematic pattern of the impact on the impatience of farming households in Thailand that were affected by the 2011 mega flood.

Table 4.5: The Mega Flood and Impatience

	Village flood (=1)			Household flood (=1)					Flood days
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	OLS	OLS	OLS	OLS	OLS	OLS	OLS	Oprobit	OLS
Flood	0.047	-0.242	-0.333	0.090	0.391	0.322	0.888	0.082	0.018
	(0.282)	(0.449)	(0.494)	(0.444)	(0.595)	(0.594)	(0.583)	(0.215)	(0.013)
Flood*Flood prone		0.565	0.701		-0.744	-0.732	-0.724	-0.221	0.012
		(0.715)	(0.748)		(0.505)	(0.556)	(0.546)	(0.167)	(0.017)
Flood*Land per capita							-1.425**	-0.396*	-0.036
							(0.533)	(0.227)	(0.021)
Flood prone		0.256	0.209		1.147***	1.153***	1.152***	0.257	0.371
		(0.329)	(0.326)		(0.338)	(0.377)	(0.379)	(0.196)	(0.437)
Female			0.124			0.298	0.213	0.002	0.285
			(0.419)			(0.448)	(0.454)	(0.163)	(0.449)
Age			-0.001			-0.002	0.001	0.005	0.001
			(0.014)			(0.015)	(0.016)	(0.005)	(0.016)
Education-primary			0.458			0.438	0.424	0.342**	0.402
			(0.373)			(0.360)	(0.333)	(0.139)	(0.354)
Education-secondary			0.028			0.004	0.042	-0.020	0.043
			(0.389)			(0.407)	(0.378)	(0.150)	(0.415)
Household size			-0.130			-0.152	-0.148	-0.051	-0.172
			(0.092)			(0.103)	(0.103)	(0.036)	(0.100)
Ln asset per capita			-0.070			-0.077	-0.119	-0.044	-0.085
			(0.166)			(0.176)	(0.174)	(0.056)	(0.168)
Land per capita			0.262			0.297	1.335**	0.375	0.955
			(0.387)			(0.426)	(0.543)	(0.236)	(0.607)
Number of shocks			-0.082			-0.075	-0.062	-0.058	-0.040
in the past 10 years			(0.108)			(0.106)	(0.107)	(0.042)	(0.115)
Constant	4.672***	4.518***	5.999**	4.635***	4.093***	5.779*	5.837*		5.667**
	(0.141)	(0.235)	(2.523)	(0.298)	(0.369)	(2.928)	(3.027)		(2.641)
FE	commune	commune	commune	village	village	village	village	village	village
N	256	256	256	256	256	256	256	256	256
F - Joint significant		0.32	0.44		1.23	0.97	3.65	10.78	2.88

Dependent variable is impatience. Flood variables are indicators if household is in flooded village in (1)-(3), if household was flooded (4)-(8) and number of flood days household experiened in (9). Robust standard errors in parentheses clustered at commune level. * p<0.1; ** p<0.05; *** p<0.01

Table 4.6 summarises the regression results for altruism. We pooled the two altruism variables (proportion of money given to a random villager and to a random flood victim) and used an indicator variable "Given to flood victim" to indicate the results for the latter variable. Columns (1) to (3) report OLS regressions of altruism on village flood exposure. With full control, we found no significant effect of the 2011 flood on altruism among households living in flooded villages. Columns (4) to (7) show various OLS regression results of altruism on the household-level flood exposure variable. Controlling for village fixed effects, we found that the 2011 flood significantly increased altruistic behaviour among flooded households. Using a flood intensity variable, column (8) further shows a significantly positive effect of increasing flood intensity on the amount given to flood victims among flooded households in non-flood-prone regions.[17] Economic theory predicts that an increase in altruism may lead to a reduction in public goods exploitation and a rise in social capital. The resulting increase in altruism among Cambodian flooded households discussed above could crowd in better communities and social capital formation among flooded communities.

[17] As for studies of disasters and social preference, Castillo and Carter (2011) found that a large negative shock from Hurricane Mitch in 1998 affected altruism, trust, and reciprocity in small Honduran communities, while Cassar, *et al.* (2011) showed that the 2004 Indian Ocean tsunami in Thailand also resulted in higher altruism. However, Samphantharak and Chantarat (2014) found that the 2011 mega flood in Thailand made flooded households become less altruistic.

Table 4.6: The Mega Flood and Altruism

	Village flood (=1)			Household flood (=1)				Flood days
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
Flood	0.058**	0.026	0.013	0.057	0.093**	0.097**	0.125**	0.000
	(0.022)	(0.028)	(0.036)	(0.038)	(0.042)	(0.043)	(0.045)	(0.001)
Flood*Given to flood victim	-0.001	-0.001	-0.002	-0.022	-0.022	-0.022	-0.022	0.001*
	(0.032)	(0.032)	(0.032)	(0.026)	(0.026)	(0.026)	(0.026)	(0.001)
Flood*Flood prone		0.057	0.050		-0.070	-0.065	-0.070	-0.001
		(0.036)	(0.043)		(0.057)	(0.057)	(0.052)	(0.001)
Flood*Land per capita							-0.064	-0.003
							(0.053)	(0.002)
Given to flood victim	0.122***	0.122***	0.123***	0.136***	0.136***	0.136***	0.136***	0.096***
	(0.022)	(0.022)	(0.023)	(0.018)	(0.018)	(0.019)	(0.019)	(0.021)
Flood prone		-0.018	-0.013		0.058	0.054	0.054	0.037
		(0.031)	(0.037)		(0.041)	(0.038)	(0.037)	(0.028)
Female			-0.062***			-0.065**	-0.069**	-0.070**
			(0.021)			(0.023)	(0.024)	(0.024)
Age			-0.002**			-0.002*	-0.001	-0.002**
			(0.001)			(0.001)	(0.001)	(0.001)
Education-primary			-0.020			-0.021	-0.021	-0.021
			(0.029)			(0.033)	(0.034)	(0.034)
Education-secondary			-0.032			-0.031	-0.029	-0.033
			(0.026)			(0.028)	(0.027)	(0.028)
Household size			0.004			0.004	0.005	0.002
			(0.006)			(0.006)	(0.006)	(0.006)
Ln asset per capita			0.012			0.010	0.008	0.006
			(0.019)			(0.020)	(0.020)	(0.020)
Land per capita			0.050**			0.054***	0.105***	0.108***
			(0.017)			(0.018)	(0.032)	(0.034)
Number of shocks			0.009			0.012	0.012	0.011
in the past 10 years			(0.007)			(0.008)	(0.007)	(0.007)
Constant	0.201***	0.212***	0.126	0.192***	0.165***	0.076	0.079	0.203
	(0.014)	(0.018)	(0.308)	(0.023)	(0.029)	(0.340)	(0.336)	(0.329)
FE	commune	commune	commune	village	village	village	village	village
N	512	512	512	512	512	512	512	512
F - Joint significant	4.31	4.25	2.02	1.20	1.66	1.71	2.27	1.92

Dependent variable is altruism measured by percentage of money given to randomly matched villager or flood victim in the village. Flood variables are indicators if household is in flooded village in (1)-(3), if household was flooded (4)-(7) and number of flood days household experienced in (8). Tobit regressions with random effects are qualitatively similar. Robust standard errors in parentheses clustered at commune level. * p<0.1; ** p<0.05; *** p<0.01.

Finally, Table 4.7 summarises the regression results for trust. We first regressed the four trust variables (trust family, neighbours, businesses, and local government) on household flood exposure in columns (1) to (4) and on flood intensity in columns (5) to (8), controlling for village fixed effects and all covariates. Similar results were found in both household flood variables.[18] The 2011 flood does not affect trust of family and businesses. The flood and the increasing flood intensity, however, significantly reduced trust of neighbours and local government among flooded households. One of the reasons could be that flooded households realised the limitation of the role of local government and social risk sharing in the presence of aggregate shocks. Or 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, which, without flood, trusted this sector significantly more. To the extent that trust could determine social interactions and thus formation of social capital in the community, the resulting reduction in trust of friends among flooded households could obscure social capital formation in the affected communities. The resulting reduction in trust of social networks and local government could also provide a greater incentive for households to become more self reliant in terms of risk coping and managing, including entering into insurance contracts provided by the private sector. Note that this result is not contradictory with the earlier finding that the flood led to higher altruism. While the 2011 mega flood resulted in lower trust of friends and local government, the failures of local community and government during the mega flood could in fact induce the flooded households to recognize the importance of community assistance during the time of catastrophe, hence resulting in their higher altruism.

[18] We found similar results for households living in flooded villages (i.e., when we used village-level flood exposure in the regressions).

Table 4.7: The Mega Flood and Trust

	Household flood (=1)				Flood days			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Family	Neighbor	Business	Local Govt.	Family	Neighbor	Business	Local Govt.
	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
Flood	-0.022	-0.147***	0.101	-0.287***	-0.001	-0.003	0.003	-0.008***
	(0.014)	(0.047)	(0.067)	(0.094)	(0.001)	(0.002)	(0.003)	(0.002)
Flood*Flood prone	0.031	0.033	-0.226*	0.088	0.001	0.002	-0.006**	0.006*
	(0.021)	(0.055)	(0.113)	(0.113)	(0.001)	(0.002)	(0.003)	(0.003)
Flood prone	-0.003	0.017	0.225***	0.019	0.004	-0.011	0.195***	-0.069
	(0.007)	(0.049)	(0.074)	(0.108)	(0.027)	(0.061)	(0.064)	(0.109)
Female	-0.011	0.008	-0.132**	0.037	-0.010	0.008	-0.147**	0.042
	(0.012)	(0.059)	(0.055)	(0.066)	(0.011)	(0.061)	(0.054)	(0.066)
Age	0.001*	0.007***	-0.003	0.001	0.001*	0.007***	-0.003	0.001
	(0.000)	(0.002)	(0.003)	(0.003)	(0.000)	(0.002)	(0.003)	(0.003)
Education-primary	-0.006	0.145**	-0.291***	0.047	-0.004	0.146**	-0.299***	0.052
	(0.023)	(0.064)	(0.081)	(0.083)	(0.022)	(0.065)	(0.077)	(0.087)
Education-secondary	0.016	0.011	-0.034	-0.121	0.014	0.005	-0.037	-0.135
	(0.015)	(0.049)	(0.087)	(0.081)	(0.013)	(0.047)	(0.085)	(0.084)
Household size	0.005	0.019*	-0.020	-0.002	0.005	0.022**	-0.022	0.005
	(0.005)	(0.009)	(0.015)	(0.024)	(0.005)	(0.009)	(0.015)	(0.024)
Ln asset per capita	0.025	0.052***	0.051	-0.032	0.025	0.056***	0.052	-0.026
	(0.022)	(0.016)	(0.046)	(0.038)	(0.022)	(0.016)	(0.046)	(0.036)
Land per capita	-0.013	0.029	-0.073	-0.053	-0.013	0.030	-0.073	-0.053
	(0.010)	(0.024)	(0.050)	(0.064)	(0.010)	(0.024)	(0.049)	(0.070)
Number of shocks	0.010**	-0.013	0.027	0.038*	0.010**	-0.014	0.025	0.037*
in the past 10 years	(0.005)	(0.022)	(0.020)	(0.020)	(0.004)	(0.022)	(0.021)	(0.021)
Constant	0.525	-0.411	0.011	1.019	0.532	-0.508	0.004	0.884
	(0.361)	(0.272)	(0.708)	(0.679)	(0.388)	(0.308)	(0.743)	(0.635)
FE	village	village	village	village	village	village	village	village
N	256	256	256	256	256	256	256	256
F - Joint significant	1.27	6.11	2.01	5.07	0.48	2.02	2.71	6.45

Dependent variables are binary variable whether respondent trusts the above institutions. Flood variables are indicators if household was flooded (1)-(4) and number of flood days household experience in (5)-(8). Regressions with village level flood are qualitatively similar so as probit regressions with random effects. Robust standard errors in parentheses clustered at commune level. * p<0.1; ** p<0.05; *** p<0.01.

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

Table 4.8 summarises 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 pooled mild and severe flood events and used an indicator variable “For mild flood” to indicate results for the mild flood. Columns (1) and (2) report simple OLS regressions using village flood exposure; columns (3) and (4) for household flood exposure, and columns (5) and (6) for flood intensity, with fixed effects and full controls. In all specifications, we found that the subjective expectation of mild floods (proportion of rice income loss when mild floods occur) appeared significantly larger (smaller) than that of severe floods. And households living in flood-prone areas had significantly larger subjective expectations of severe flood than those in non-flood-prone areas. The effects on mild floods, however, were inconclusive across specifications. 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. But 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 floods. Overall, if subjective expectations of future floods and loss could induce investment incentives regarding flood risk management as theories predict, our positive results might imply that the 2011 mega flood experience could potentially crowd in actions that might improve resilience to future floods among affected households and communities.

Table 4.8: The Mega Flood and Subjective Expectation of Future Flood

	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. Flood variables are indicators if household is in flooded village in (1)-(2), if household was flooded (3)-(4) and number of flood days household experienced in (5)-(6). Tobit regressions with random effects are qualitatively similar. Robust standard errors in parenthesesclustered at commune level. * p<0.1; ** p<0.05; *** p<0.01.

Table 4.9 summarises regression results on households' perceptions of the reliability of government, social networks, and natural resources as safety net during mild and severe floods. We regressed household perceptions on household flood exposure in columns (1) to (3) and on flood intensity in columns (4) to (6). With both flood variables in columns (1) and (4), we first found that the expectation of government help 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. With both flood variables, the 2011 flood also did not significantly affect households' expectation of government assistance in the event of a future flood. One possible reason could be 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) and (5) present the flood effect on households' perceptions of social networks. We found a significant reduction of households' perceptions 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 had already found. Again, if perceptions could affect social interactions, the mega flood could potentially crowd out social capital formation among the 2011 flood victims in the flood-prone communities. Finally, columns (3) and (6) 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.[19]

[19] Again, the flood effects on households living in flooded villages are qualitatively similar, so they are not reported.

Table 4.9: The Mega Flood and Safety Net Perceptions

	Household flood (=1)			Flood days		
	(1)	(2)	(3)	(4)	(5)	(6)
	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
	Probit	Probit	Probit	Probit	Probit	Probit
Flood	0.374	0.228	-0.052	0.004	0.001	0.001
	(0.259)	(0.292)	(0.265)	(0.009)	(0.007)	(0.007)
Flood*For mild flood	-0.131	0.219	0.334***	-0.003	0.006	0.019*
	(0.219)	(0.222)	(0.123)	(0.009)	(0.010)	(0.010)
Flood*Flood prone	-0.479	-0.066	-0.034	-0.004	0.001	0.003
	(0.387)	(0.306)	(0.362)	(0.009)	(0.007)	(0.010)
Flood*Flood prone*For mild flood	0.328	-0.486*	-0.103	-0.001	-0.001	-0.017*
	(0.394)	(0.291)	(0.183)	(0.012)	(0.008)	(0.010)
For mild flood	-0.743***	-0.083	-0.069	-0.750***	-0.068	-0.217
	(0.175)	(0.140)	(0.115)	(0.212)	(0.175)	(0.171)
Flood prone	0.187	0.193	0.241	-0.021	0.156	0.130
	(0.272)	(0.319)	(0.317)	(0.237)	(0.273)	(0.283)
Flood prone*For mild flood	-0.170	0.018	-0.014	0.084	-0.318	0.272
	(0.264)	(0.237)	(0.136)	(0.299)	(0.228)	(0.166)
Female	-0.125	0.057	-0.109	-0.129	0.060	-0.109
	(0.164)	(0.168)	(0.207)	(0.164)	(0.177)	(0.208)
Age	-0.006	-0.017**	-0.042***	-0.006	-0.016**	-0.041***
	(0.004)	(0.008)	(0.006)	(0.005)	(0.008)	(0.006)
Education-primary	0.042	-0.500***	0.057	0.043	-0.496***	0.053
	(0.173)	(0.178)	(0.266)	(0.178)	(0.181)	(0.269)
Education-secondary	-0.093	-0.198	-0.399**	-0.102	-0.197	-0.382**
	(0.148)	(0.176)	(0.194)	(0.154)	(0.178)	(0.188)
Household size	-0.017	0.015	0.104**	-0.020	0.008	0.098**
	(0.029)	(0.032)	(0.041)	(0.029)	(0.031)	(0.040)
Ln asset per capita	-0.139*	0.019	0.098	-0.140*	0.019	0.097
	(0.080)	(0.121)	(0.094)	(0.083)	(0.123)	(0.096)
Land per capita	-0.209	-0.244	-0.119	-0.218	-0.257	-0.115
	(0.149)	(0.166)	(0.153)	(0.150)	(0.167)	(0.150)
Number of shocks	0.160**	0.098*	0.118*	0.157**	0.102*	0.124*
in the past 10 years	(0.075)	(0.052)	(0.067)	(0.076)	(0.052)	(0.068)
FE	village	village	village	village	village	village
N	512	512	512	512	512	512
F - Joint significant	2.53	5.54	16.98	1.33	3.22	7.84

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. Flood variables are indicators if household was flooded (1)-(3) and number of flood days household experienced (4)-(6). Village flood regressions are qualitatively similar, so omited. OLS regressions with fixed effects are also qualitatively similar. Robust standard errors in parentheses clustered at commune level. * p<0.1; ** p<0.05; *** p<0.01.

In conclusion, on the one hand we found that the 2011 flood led to an increase in altruism, which theoretically should reduce incentives for exploitation of public goods and therefore natural resources. On the other hand, the 2011 flood also caused flooded households to upgrade their perceived reliability of natural resources as their safety net. However, these two apparently contradictory finding could be reconciled. Reduction in forest extraction now could imply that these households had increasingly used public natural resources as insurance against bad years. In this sense, households effectively view natural resources as community savings, with potential future benefits.

4.3 How did the 2011 mega flood and (updated) preferences affect households' behavioural choices?

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 households' behavioural choices, and some of these behaviour choices could in turn affect households' long-term economic development and resilience to future shocks. We revisit our motivations in this section by analysing whether and how the 2011 flood affected households' key behavioural choices. We then explore if and how these behavioural choices were related to preferences and subjective expectations. Combining these two analyses with our earlier results, we hope to provide some insights relevant to policymakers.

Table 4.10 summarises regression results on five behavioural choices that households made during 12 months before the survey was conducted in April 2014: (i) whether households invested in land and irrigation; (ii) whether household had savings; (iii) the number of dependable friends household had; (iv) whether household collected forest products and engaged in fishing; and (v) whether households were willing to pay for commercial flood insurance. Behavioural choice (i) is critical for economic development, while behaviours (ii) to (v) reflect self, natural resource, social, and market insurance decisions, which are critical for the resilience of households in developing economies.

Table 4.10: The Mega 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)
	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS
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.

Regressing these behavioural choices on household-level flood exposure and other controls, column (1) that the 2011 flood caused a significant decrease (increase) in households' plot investments for flooded households in non-flood-prone (flood-prone) areas. These findings are consistent with what we would deduce from our flood results on risk aversion and increasing subjective expectations of future floods. Column (4) shows that the mega flood also led to a significant increase in savings among flooded households. Again, this result is very much in line with our earlier result that the flood caused a significant decrease in impatience among flooded households.

Column (7) of the table shows that the 2011 flood caused a significant reduction in the collection of forest products among flooded households. The finding is in line with the resulting increase in altruism among flooded households and growing households' perceptions of the benefit of saving natural resources as a safety net against adverse years in the future. One interpretation of these combined results could be that, as the 2011 flood increased households' perception of nature as insurance, they would realise that preserving the forest in normal years (and part of this could also be induced through increases in altruism) will allow them to depend 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, to be discussed in the next paragraph), hence reducing their collection of forest products. [20]

Table 4.10 also shows that the flood also caused a significant reduction in the number of dependable friends (i.e., social capital) among flooded households, as shown in column (10). From our earlier results, this might be driven by flood-induced decreasing trust and decreasing perceived benefit of social insurance. 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 could be that there could be other more salient determinants of insurance

[20] We also found similar results when we used household flood intensity variables. We did not find significant results, however, when we use village flood exposure.

demand than risk aversion and expectations of risk that could be induced by the mega flood.[21]

Finally, our last research question is whether these behavioural results discussed in previous paragraphs were induced by the impact of the flood on preferences and expectations? By regressing households' behavioural choices on preference variables with full controls and village fixed effects, we obtained some key results, most of which are very much in line with economic theory. First, columns (2) and (3) show that plot investment decreased significantly with risk aversion and subjective expectations of mild floods, while it increased significantly with impatience and altruism. Second, columns (5) and (6) show that decisions to save increased significantly with altruism, trust in family and subjective expectations of future mild floods. Third, columns (8) and (9) show that the decision to exploit forest products decreased significantly with altruism. Fourth, columns (11) and (12) show that the number of dependable friends also increased significantly with the level of trust of friends and businesses. Finally, we found households' demand for commercial insurance decreased significantly with growing impatience and decreasing trust of neighbours, as shown in columns (14) and (15). Strikingly, savings decisions were not significantly associated with impatience, and insurance demand was not correlated with risk aversion, as economic theory tends to predict. One potential explanation could be that financial literacy, especially with respect to savings and insurance, could still be low among Cambodian rice farmers in our sample. This last result, however, would not jeopardise our key findings: these behavioural impacts of the 2011 floods could (at least partially) be driven by the changes in preferences and expectations induced by the flood.[22]

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[21] 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.

[22] The flood-induced changes in saving decisions were likely (though partially) the result of increasing altruism and subjective expectation induced by the flood. And the flood-induced changes in insurance decision were also likely the result of decreasing impatience and trust induced by the flood.

5. Conclusions and Policy Implications

We hope our empirical findings contribute to existing literature on the impacts of natural disasters that mediate specifically through behavioural changes. Overall, our key empirical findings on Cambodian rice-farming households suggest that the 2011 flood—the country's biggest flood in the past decade—did affect certain key preferences, subjective expectations and key behavioural choices of households, which could further determine long-term economic livelihoods and resilience to future shocks among affected households.

Specifically, we found that the mega flood seemed to have made affected Cambodian rice-farming households more risk averse, with poor households showing the largest increase in risk aversion. The mega flood also reduced impatience and increased altruistic behaviour among affected households. Surprisingly, the 2011 flood caused a significant reduction in trust of neighbours and local government. Affected by this mega flood, flood victims were found to have further revised upwards their subjective expectations of the occurrence of future severe floods.

Our findings also 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 found that reliance on governments, NGOs, as well as social networks appeared to be very small among these Cambodian rice-farming communities during the 2011 mega flood. The flood also further reduced households' perceptions of the benefit of social networks as a safety net, especially among flooded households in flood-prone regions. While the finding on the marginal roles of social insurance could become more relevant—as community risk sharing is likely ineffective in insuring covariate shocks—the limited role of and perceived reliance on the government appeared quite unique compared with other developing agrarian economies, where governments would often be viewed as the insurer of last resort among poor farmers. With limited social and public support, we thus found relatively strong evidence of self-coping and self-insurance mechanisms in Cambodian rice-farming communities, such as through savings and labour allocations. The most salient result is that we found natural resources to be the most significant sources of safety net among these communities and that the mega flood caused them to further revise upward their perceived benefit of nature as a source of safety net. These findings could reflect the fact that three out of the four severely flooded provinces we studied are located in the Tonle Sap Biosphere Reserve, where reliance on the forest appeared strong. This evidence could extend well beyond Cambodia with increasing evidence that the key biodiversity hotspots also appear to be the key disaster/climate change hotspots as well.

The 2011 mega flood also affected households' behavioural choices. We hypothesise that some of these flood effects should be mediated through their effect on deep parameters of preferences and expectations since we found significant evidence that these preferences and expectations shaped households' behavioural choices, as predicted by economic theory. First, we found the flooded households to have lower land and irrigation investment relative to their non-flooded counterparts, which could potentially be driven by increasing risk aversion and subjective expectations of future floods following the mega flood. To the extent that productive investment is critical for long-term economic growth, our findings have important implications for the potential long-term welfare impact of extreme floods (or catastrophic disasters in general).

We found that flooded households extracted fewer forest products and engage 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 have led to decreasing incentives among households to exploit public goods. Reduction in forest extraction now could also imply that these households had increasingly used public natural resources as insurance, and as they increasingly perceive the benefit of nature as insurance against future shocks, they are likely to save these natural resources for bad years. In this sense, households view natural resources as community savings, with potential future benefits. On the one hand, these results could be seen as positive as disaster-affected households' incentives to preserve natural resources might increase. But on the other hand, if natural resources have increasingly been used as insurance, the widely observed increasing frequency and intensity of disasters could jeopardise the sustainability of these resources. This finding raises some concerns—if the Cambodian households extensively use natural resources as insurance, to what extent might this crowd out other safety net institutions? Does natural resource abundance inhibit the development of the financial system? Does natural resource endowment reduce the government's incentive to invest in disaster prevention infrastructure?

We found flooded households to have fewer dependable friends than non-flooded households. According to our results described above, this could be due to falling trust and the perceived benefit of social insurance following the mega flood. Altogether, our findings thus imply that the 2011 flood could potentially crowd out social interactions and thus social capital formation in the affected communities. While social insurance might not be very effective against covariate shocks, it can be very effective in terms of idiosyncratic risk sharing. And social capital itself is critical for the functioning of the economy, society and even the rural financial system. We found that flooded households have more savings and higher demand for commercial insurance than non-flooded households. In addition to the main preferences, we found these could be driven by increasing subjective expectations of future floods and decreasing trust of friends. The reduced role of social insurance seems to crowd in increasing incentives for needy self-insurance. This could also provide some evidence that the increasingly important role of natural resources has not as yet crowded out private incentives to reduce and manage disaster risks. But do Cambodian farming households have full access to effective markets and self-insurance strategies?

It is hoped our results can contribute to public policymaking regarding the design of incentive-compatible safety nets and development interventions. The empirical results emphasise that public policies promoting effective flood risk management institutions among households could crowd in investment incentives and so really be pro-poor. 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 livelihoods would provide longer-term economic development impacts than simple transfer programmes.

With the 2011 mega flood already renewing inducing increase incentives for self-insurance among the affected population, safety-net policies should aim to help households help themselves. This can be achieved by improving access to effective strategies, e.g., facilitate access to rice varieties that are more resistant to flood, utilisation of technology and weather forecasts to make effective adaptations to rice production, or facilitate access to various ways of diversifying crops and/or income. Our results also show that the mega flood provided a boost to households' incentives to use the market. Policies should aim, therefore, to enhance supply of and access to saving and insurance products, and to ensure effective demand among a population with relatively low financial literacy rates. As households' valuation and incentives for using natural resources as insurance increase, policies should aim to encourage conservation and sustainable use of these resources, e.g., through forest zoning and incentivised reforestation programmes. Finally, all interventions should also be designed to rebuild social interactions and capital, which were degraded by the mega flood.

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