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Floods and Household Welfare: Evidence from Southeast Asia

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Floods and Household welfare: evidence from Southeast Asia

Le Thi Ngoc Tu [1]

Abstract:

This research uses a rich panel data set of household surveys and external long-term flood data extracted from satellite images to complete a puzzling picture of the effects of floods on household welfare. Floods bring many negative effects to households; the floods reduce household incomes dependent on natural sources, pushing farmers out of the fields to seek extra income from non-agricultural activities. In addition, the floods increase all expenditure categories. The finding of a lower household subjective wellbeing score reaffirms all these results. Further, this research shows the efforts that rural households are trying to cope with the effects of flooding. They use both formal and informal coping mechanisms; however, only intra-household coping methods show significantly effective.

***Keywords*:** Flood impacts; Welfare impacts; Income impacts; Consumption impacts; Geographic Information Systems (GIS), MODIS images

MSC: 91B76

JEL: I31, Q15, Q51, Q54

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1 Introduction

According to the definition of household welfare measures from the World Bank, household welfare can be measured on the monetary dimensions of wellbeing such as income or consumption. Household welfare also can be based on non-monetary dimensions such as health or education, or subjective wellbeing measures or qualitative measures.

Many researchers around the world contribute findings for this field of study from different contexts, different time periods, different methods of welfare measures as well as using different flood indicators, all depending on the availability of data that researchers can assess. All research findings are necessary to create a global picture of the relationship between floods and household welfare. However, we lack research where the relationship between floods and household welfare is examined in multiple dimensions on the same population over time. This study will contribute such a missing piece to the whole picture of literature. In this research, I examine household welfare viewed through a multi-dimensional lens including income compositions, consumption categories, and health expenditure as an indicator of health impact in household, and household subjective wellbeing.

This research aims to answer two research questions: (1) How do floods impact on households in multi-dimensional concept of welfare?" and (2) "Which channel of insurance mechanism is commonly used and effective in rural households to cope with flood shock?" These questions are addressed by focusing on floods in Vietnam and Thailand using long-time measurement of household welfare, combined with an external flood indicator, which is a measure of local inundation by using satellite floodwater images provided by NASA, the MODIS Near Real Time Global Flood Water (MFW).[1]

The results show that floodwater reduces household incomes dependent on natural sources and pushes farmers out of the fields to seek extra income from non-agricultural activities. On the other hand, floodwater increase all consumption categories, and lays a burden on financial cost for health care on household budgets. Analysis from household subjective wellbeing tells a story of people living in affected villages who are less happy than people living in non-affected villages. I also find that intra-house coping strategies are more commonly used in rural households; however, the scope of the impact of flooding is too large to be coped with at household level.

Measuring household welfare: straight-forward concept, and expanded concept

The World Bank's Living Standards Measurement Study introduces three alternative approaches to the measurement of household welfare. The first approach is the estimation of true indices of welfare; this is conceptually superior in that it relies on a complete set of behavioral equations depicting households' consumption and employment behavior, from which to derive welfare. The second one is the full income approach. And the third approach looks only at household expenditures (Moratti & Natali, 2012).

The true index approach uses observed behavior as ordering references to estimate a measure of welfare. The full income and expenditure use monetary and imputed flows without specific assumptions about preferences. Both methods require deflation of the welfare measure with a price index. Generally, the expenditure method seems to be easier to measure and tends to be less subject to fluctuations than income (Grootaert, 1983).

There are some other components of welfare that have been seen in literature; among those methods, employing an expanded range of human development indices is the most popular approach. These indicators include health, education, nutrition, fertility and infant mortality. However, these methods were not considered much until recent years.

In recent decades, researchers in macro-economic have become aware that GDP does not provide policy-makers with a sufficiently detailed picture of the living conditions that ordinary people experience. Evidence of strong economic growth during the early 2000s, which was amplified by the financial and economic crisis that followed it, is a confirmation that income alone cannot be a good indicator reflecting a true measure of sustainable welfare improvement. A wide range of factors that affect people and their wellbeing is necessary for the credibility and accountability of public policies.

[1] MODIS Flood Water (MFW), MODIS Surface Water (MSW): Currently these are only distributed as vector products (shapefile and kmz) for standard composites. MSW gives all land-based water (with a buffer into oceans) that was observed in the given product. MFW removes from MSW a reference or expected water layer, such that the remaining water is likely to be floodwater.

A framework for improvements in measuring the wellbeing of people and households has been developed by the OECD.[2] This framework is built on three distinct domains: material conditions, quality of life and sustainability. Each of these domains includes a number of relevant dimensions: material living conditions (income and wealth, jobs and earnings, housing conditions) and quality of life (health status, work-life balance, education and skills, social connections, civic engagement and governance, environmental quality, personal security and subjective wellbeing). Sustainability refers to the future wellbeing that determines wellbeing over time through preserving capitals such as natural and economic, human and social (*OECD Guidelines on Measuring Subjective Well-being*, 2013).

The study, (OECD, 2013) "How's Life? Measuring wellbeing", a report of the progress in measuring wellbeinghas covered a range of areas, such as income and wealth, education, environment and subjective wellbeing. This measure reflects a wide range of people's attributes and circumstances; however, it should not be considered as the single all-encompassing measure of people's wellbeing. In measuring overall human wellbeing, subjective wellbeing should be placed alongside measures of non-subjective outcomes, such as income, health, knowledge and skills, safety, environmental quality and social connections.

Flood impacts on household welfare, and coping strategies

Among all kinds of natural disasters, floods are the most common in both developed and developing countries, accounting for approximately 40% of all natural disasters. Asia is the most flood-affected region, accounting for nearly 50% of flood-related fatalities in the last quarter of the 20th century (Jonkman, 2005). The objectives of this literature review section is to summarize the impacts of flood on household welfare in terms of income, consumption, health, and subjective wellbeing.

(Khandker, 2007) examines the impact of floods on household welfare in Bangladesh during 1998, that study finding that flood intensity actually reduced household welfare both in terms of consumption and household non-land assets. Although the effect of flooding on household welfare is significant, the floods had no lasting impact on consumption and assets. This is explained as either due to the ensuing productive crop, or through other available sources including borrowing from micro-credit and assistance programs after floods. Based on a study conducted on the same population after the 1988 flood, (Emdad Haque & Zaman, 1993) found rather that the majority of the households sold their land, livestock, or belongings to reduce the losses due to the flood, and many moved their housing structures, livestock, and family members to safer places. Another study in Bangladesh (Parvin, Shimi, Shaw, & Biswas, 2016) found that the three major coping strategies adopted during the 1998 flood were reducing expenditure, selling assets, and borrowing, with borrowing being the most important.

(Tran et al., 2008) study flood risk management in Thua Thien Hue, Central Vietnam. They explore the impacts of floods on the economy, environment, and society and try to clarify the rural community's coping mechanism to flood disasters using a mixed methodology. The results show that annual floods bring significant damage to agriculture and aquaculture by destroying crops in the rice field, sweeping away aquaculture products, or ruining fish and shrimp ponds. Despite these negative impacts, the survey revealed that a high percentage of respondents think that floods help to clean the environment. Floods bring alluvium to agricultural land and kill insects and rats. Some respondents even claimed that every 3 years a big flood is needed to refresh the lagoon environment. Many respondents agreed that the production of aquaculture and agriculture increase after a large flood. However, their approach only permitted a subjectively assessment of the effect of floods on agriculture.

Research by (Yasuaki Hijioka, Erda Lin, 2014) indicates that increases in floods and droughts will exacerbate rural poverty in parts of Asia, as a result of negative impacts on the rice crop and resulting increases in food prices. The rising cost of living will in turn have an increasing impact on human health, security, livelihoods, and poverty, with the type and magnitude of impact varying across Asia.

(Bui et al., 2014) use the Vietnam Household Living Standard Survey in 2008 to examine the effect of natural disasters on household income, expenditure, poverty and inequality. The results are estimated at 6.9% and 7.1% declines in household income and expenditure per capita, respectively.

(Arouri, Nguyen, Youssef, 2015) use commune fixed-effect regressions to estimate the effect of natural disasters on household welfare and poverty in Bangladesh. They find that all the three disaster types considered in

[2] The OECD work on Measuring Progress and Well-Being (www. oecd.org/measuringprogress) has been addressing these issues in the last few years. These efforts have led to the OECD Better Life Initiative, launched by the OECD Secretary-General on 24 May at the 2011 OECD Forum.

the study including storms, floods and droughts have negative effects on household income and expenditure. Access to micro-credit, internal remittances and social allowances can help households strengthen their resilience to natural disasters.

(López-Marrero and Yarnal, 2010) use a case study of two flood-prone communities in Puerto Rico to determine how everyday risks influence people's perceptions of and capacity to adapt to floods. The study reveals that people perceive floods as one of their risks, but they see them as neither the most important nor the most severe risk in their lives. Instead, they find other concerns - health conditions, family well-being, economic factors, and land tenure - more pressing. The results suggest that studies of floods should address these multiple risks, mainstreaming flood management and adaptation into the wider context of people's general wellbeing.

Regarding the impact of floods on human health, there are three systematic review studies on the line of time: (1) Examination of the epidemiological evidence; systematic review (Ahern et al., 2005), in which 212 studies before 2004 were reviewed; (2) This was followed by another systematic review of the relationship between floods and human health (Alderman, Turner, Tong, 2012). 35 published articles over 2004-2011 were chosen. (3) A few year later, a comprehensive review was undertaken (Du et al. , 2017). All three systematic reviews concluded that the harmful impacts of floods on population include direct mortality and morbidity from infectious diseases, indirect displacement, and widespread damage to crops, infrastructure, and property. Most of the existing epidemiology and economics literature shows that floods will increase the global burden of disease, morbidity, mortality, social and economic disruptions, and will place a continuing stress on health services, especially in low-resource countries. It is in these countries where most major floods occur and where vulnerability is the highest.

Floods are expected to impact households in various ways, ranging from the loss of life, injuries and health effects, to the destruction of assets, and reduced incomes. However, little evidence exists to support the impact of floods on household wellbeing. There has been an overwhelming focus on assessing the physical or tangible impacts of flooding; however, much less is known about the intangible impacts or effects on wellbeing of flooding.

(Hudson et al., 2017) study the long term impacts on individual subjective wellbeing (SWB) of flood experiences, individual subjective flood risk perceptions, and household flood preparedness decisions. They collected data from households in flood-prone areas in France. The results reveal that individual experience of flood has a large negative impact on their subjective wellbeing that is incompletely attenuated over time. Moreover, floods also reduce the SWB of individuals who are not directly affected by floods, but they expect their flood risk to increase by seeing a neighbor being flooded. The decomposition of the monetary impacts of flood experience into tangible losses and intangible effects on SWB shows that intangible effects are about twice as large as the tangible direct monetary flood losses. Investments in flood protection infrastructure may be under funded if the intangible SWB benefits of flood protection are not taken into account.

(Hudson et al., 2018) use survey data from flood-prone households in Hue province in Vietnam to estimate the monetary equivalent of subjective well-being (SWB) losses due to flooding. This monetary estimate is derived from finding the amount of monetary compensation that is needed to offset the wellbeing loss from flooding. They estimate that the initial drop in SWB immediately after a flood event is equivalent to up to 300% of annual income in immediate compensation. This shows that the welfare impact of floods is considerable. While a recovery of SWB occurs over time, they find that even 5 years after a flood, the welfare impact still equals a loss that is the equivalent of 40% to 86% of annual income in long-run compensation. The overall welfare losses are significantly larger for women after this period of time (by about 20 to 29 percentage points), indicating a gender-gap in recovery.

The ultimate impact of a flood on a household depends on the household's vulnerability to its effects. In the literature, the vulnerability is often conceptualized as a function of three components; exposure, sensitivity and adaptive capacity (Adger, W. Neil, 2007).

Vulnerability, broadly defined as the potential for loss, is an essential concept in hazard research, and is central to the development of hazard mitigation strategies at the local, national and international level (Cutter, 1996). There are subtle yet complex differences in regard to where vulnerability is placed in the conceptual 'chain of events' (James Lewis, 1999), or where authors seem to refer to vulnerability as an outcome (Downing, Olsthoorn, and Tol, 1999): 'the degree of loss resulting from a potentially damaging phenomenon'. While (Neil Adger, 1999) provides a similar definition, 'the exposure of groups or individuals to stress as a result of social and environmental change, where stress refers to unexpected changes and disruption to livelihoods', (Winser et al. , 2005) defines vulnerability as 'characteristics of a person or group in terms of their capacity to anticipate, cope with, resist, and

recover from the impact of natural hazards'. In most papers on vulnerability to floods, which focus on the household or individual level, the most vulnerable groups are low-income peoples, migrants, those without insurance or financial reserves, the elderly, and the infirm (Few, 2003). While some authors show the connection between poverty and vulnerability (Tran et al., 2008), others such as (McElwee et al. , 2017) conclude that poverty alone cannot explain flood vulnerability. (Douglas, 2009) in a study of floods in South Asia shows that the most vulnerable groups in terms of food security during floods under climate change are women, children, and the poor. A systematic review (Rufat et al. , 2015) finds that demographic characteristics are among the most commonly applied social vulnerability indicators and that women and the elderly are often considered among the most vulnerable.

The adaptive capacity to cope is seen as a key component of flood mitigation at the household level. Following the previous studies of coping mechanisms, people experiencing flood risk may take action through physical means to prevent the spread and penetration of floodwaters and to reduce negative effects of flood through actions such as livelihood diversification, relocation of belongings, and sourcing support from the community. (Morrow, 1999) categorizes coping strategies with economic and material resources, human or personal resources (such as education), family and social resources (such as networks of reciprocity), and political resources (such as power and autonomy). The connections between vulnerability and the ownership of a range of assets is highlighted by authors like (Moser, 1998), who state: "The more assets people have, the less vulnerable they are, and the greater the erosion of people's assets, the greater their insecurity." Moser identifies important assets such as labour, housing, social and economic infrastructure, household relations, and social capital. Therefore, when we take an examine of household context, in which it can absorb the impacts of the floods without suffering long-term effects, adaptive capacity reduces sensitivity.

The strengths and limitations of different types of flood data

Measuring the impacts of natural disasters is the subject of a large literature, wherein there are currently four principal types of weather data used: ground station data, gridded data, satellite data, and reanalysis data. The most basic type of data is the ground station data, which directly observes temperature, precipitation, humidity, barometric pressure, as well as wind speed and direction. Another traditional method is respondents' subjective self-reports of what they consider as an adverse weather shock and its degree of intensity. Both methods have their own advantages. While ground data provide a measurement of that exact location's climate, some types of weather data are not available in poor and developing countries, which face more severe constraints to their weather monitoring budget (Burke et al., 2014). Subjective measures have the advantage of being theoretically more precise at the local level than information from spatially aggregated data. However, the subjective measures suffer from both practical and methodological shortcomings (Thomas et al. , 2010). They can hardly assess varying severities of weather shocks precisely while also raising issues of endogeneity, especially when incorporated in the vulnerability of the household in question. While global meteorological databases are available, with the exception of the cyclone databases (UNEP/DEWA/GRID-Europe, n.d.) they typically do not have a high resolution.

When comparing different data sources in measuring floods and their impacts, (Guiteras, Jina, and Mobarak, 2015) compare rainfall data versus flooding data, and self-reports versus satellite images. Their paper makes two key contributions: first, they conclude that objective long-run time series measures of floods will allow us to study human behavioral responses to changes in the distribution of disaster events. Second, they show that rainfall and self-reported exposure are weak proxies for true flood exposure; that measurement error is likely to be correlated with important determinants of socioeconomic outcomes, in particular mean exposure to floods.

To circumvent these weaknesses, we use an external long-run time series measures of floods based on satellite image data. Additionally, as the employed surveys do not refer directly to flood impacts, we avoid endogeneity issues related to the subjective exaggeration of the floods' impacts.

2 Methodology

This research uses a household dataset collected by the "DFG-FOR 756: Vulnerability to Poverty in Southeast Asia" project. This data source is enriched by flood indicators retrieved from daily satellite MODIS Flood Water images (MFW). These satellite images were provided by NASA product version 4.9. The flood areas were constructed using Geographical Information Systems (GIS) and Google Earth to draw neighborhoods of villages. Linking these data sources with a panel dataset of rural households in Thailand and Vietnam allows us to estimate the impact of varying flooding intensities on an array of household welfare outcomes in a panel regression setup. The following sections will describe our data sources and estimation approach in more detail.

2.1 Household data

The panel data consists of 4,400 rural households interviewed in 2007, 2008, 2010 and 2013, in six peripheral provinces of Thailand and Vietnam. These include three provinces in Northeast Thailand, namely Buri Ram, Ubon Ratchathani and Nakhon Phanom, and three provinces from the northern central coast and western highlands in Vietnam, namely Ha Tinh, Thua Thien Hue and Dac Lac (see the map of study area in Appendix Figure B.1). These six provinces were chosen because they offer excellent conditions to undertake such research on vulnerability. Although they have experience with high rates of economic growth and success in poverty reduction, they have also suffered from various types of shocks. Among those, weather shocks are considered as a factor that keeps many households in these areas below the poverty line. A majority of the households in all six provinces are engaging in agriculture activities, informal self-employment, and off-farm employment.

In line with the overall objective of the project "Vulnerability to Poverty in Southeast Asia", the target population were rural households, which are poor or vulnerable to poverty. The sampling procedure applied was a three-stage cluster sampling with explicit strata for agro-ecological zones in Vietnam and implicit stratification in Thailand.[3] As the attrition rate over the four-waves panel lay at a relatively low 5%, we are able to include around 4000 households in the main specification sample. In the main specifications, we work with a total sample of about 4000 households. As a rich dataset, it contains information about demographic composition, health, educational achievements, economic activities, agricultural activities, shocks and risks, employment, financial activities, assets and housing conditions, network and subjective assessment of wellbeing of the sampled households. The survey also includes a section for village heads, which provides fundamental information of the villages. A full list of the relevant variables as well as their definitions may be found in Appendix Table A1.

For study how flood shocks impact on household welfare in multi-dimensions, we use all the above-listed information from sections for individuals, household heads, and village heads provided in household surveys. Further, we use available data to create household income compositions, household consumption categories, and measures of subjective assessment of wellbeing of households. In the survey, there are questions asking about household subjective life satisfaction based on the evaluation of their own wellbeing as a whole, the expectation of minimum net monthly income for their household, and the subjective comparison with other households in their community or in their country. The answers are categorized in an ordinal scale from 1 to 5. We use that variety of questions combined with households' actual income to create a subjective wellbeing variable (SWB), which is a measure of overall household's subjective wellbeing. The outcome is measured in an ordinal scale from 1 to 5, where (1) denotes very dissatisfied (2) dissatisfied (3) neither satisfied nor dissatisfied (4) satisfied, (5) very satisfied. The variable SWB is alternatively measured in both the short term and long term. In the short term, the reference time is from the previous year of the survey year to the next year. In the long term, the reference time is five year ago to the next five years.

As a rich dataset, we have sufficient information for control variables at two levels: household and village. At the household level, we control *Social-demographic* factors such as shares of age groups, gender of household head, marital status of household head, family type, household size, ethnic/ religion identification; the surveys are conducted in rural areas therefore the classification of urban/rural is not necessary in this study. We also control *Material condition* such as household wealth, fluctuation of income, housing quality. Further, we control the *Quality of life* such as employment in household, health status in household, education of household members and household head, social connections. At the village level, we control for village infrastructure, village joint agricultural program, the assess to sanitation and public waste disposal in village, epidemic in the village, and security in living community.

To capture both direct and indirect effects, and illuminate the implicit costs associated with some of the coping strategies, in this study we investigate whether the vulnerability to flooding depends on the economic status of a household by testing through interactions with some coping strategies such as assets (present value), off-farm income (incomes from waged employed activities), insurance mechanism, and social networks. We also examine the role of health insurance in coping with flood-related health expenditure. In addition, households were asked what were the

[3] Secondary data for sampling on Thailand was available down to the village level; population density and agro-ecological conditions were assumed to be sufficiently homogeneous; sample design for Thailand is kept simple and aimed at obtaining a self-weighting sample. The provinces in Vietnam were purposively selected for the survey and are geographically more diverse than those in Thailand. While Dak Lak province is part of the landlocked Central Highland, Thua Thien-Hue, and Ha Tinh provinces extend from the coast to the mountainous border to Laos. In order to take into account this heterogeneity, strata for the first stages were defined as agro-ecological zones within the three provinces

three major shocks that affected their household in the last year, and their coping activities to deal with the shock events. This information indicates if a household in reality took some ex-post action to cope with shock events.

2.2 Flood data

The main flood indicator used in this research is a direct measure of the inundated area of the villages in the study areas. We calculate the proportion of a village area that is covered by floodwater over one year. To calculate the flood indicators, we use the daily satellite MODIS Flood Water images (MFW) provided by NASA, product version 4.9, which produces daily surface and floodwater maps at approximately 250m resolution, in 10x10 degree tiles for South Indochina (see the map in Appendix Figure B.2). This area includes all six provinces in the study. MFW images are used for the period between 2003 and 2013.

To obtain the measure of floods in one year, we join all daily MFW into monthly images, after which all monthly images are unified into yearly products. Each composited yearly image gives an estimate of surface floodwater during the time period, which contains information on the proportion of areas inundated. Figure 3.1 is an example of a flooding map for Hue province from May 2012 to April 2013. To calculate flood indicators at the village level, we needed village administrative maps. However, currently there is no available administrative boundary of villages in rural Vietnam and Thailand. The smallest unit that the Global Administrative data provides is at the sub-district level. Thus, Google Earth was used to draw village boundaries. Drawing was based on the coordinates of one point that belongs to the village,[4] and also referred to the boundary of its commune, and an image of the village which can be viewed on Google Earth (see an example in Appendix Figure B.3). Lastly, we take the inundated area in one year and divide it by the village's area to obtain the proportion of the village area that has been inundated during the year; the value of this indicator lies between 0 and 1. This measure is the main indicator for analysis.

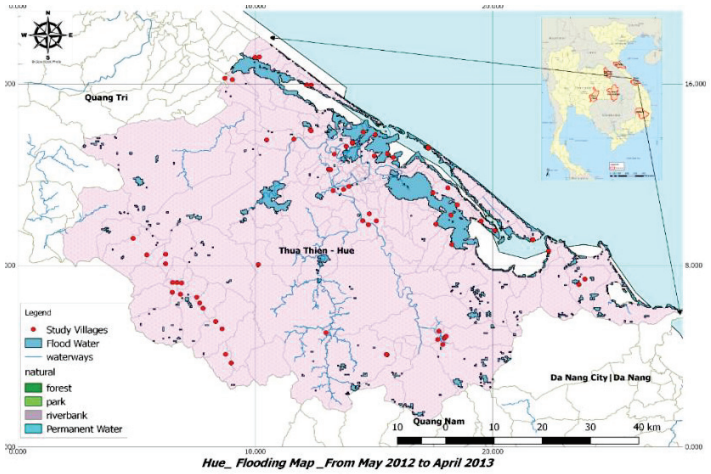
This study follows the definition of flood from the Centre for Research on the Epidemiology of Disasters (CRED). It states that flooding is the "presence of water in areas that are usually dry". Within this definition we choose to regard the most important source of destruction attributable to a flood event as that part of local inundation which is visible in satellite images. A limitation of using satellite images to discern floodwater is missing data.[5] Cloud cover is a significant challenge, as it is not uncommon for atmospheric conditions to obstruct quality observations for days to weeks during the monsoon season. Though compositing routines are used to limit the effects of clouds, there are no guarantees that cloud cover will break during any MODIS overpass (Ahamed and Bolten, 2017).

In this research, we use 3-day composite product MFW, which is considered best to limit cloud-shadow issues. According to (Nigro et al. , 2014) MODIS product is rated as almost perfect (five starts) for flood detecting in South Indochina. Two alternative flood indicators were created to check robustness. The first is the 'flooding days' variable that counts the number of days in one year that a village has floodwater. The second variable, 'floodwater variation", is a measure of the deviation of floodwater area in the current year with the average floodwater area during the last five years.

[4] For each village, the interviewers recorded one coordinate during the village interviews. The coordinates were recorded in decimal degrees (latitude, longitude). For example, the geographical coordinates of the village Yang, sub-district Kham Duan, distric Krasang, province Buriam, Thai land is (15.0773638888889, 103.401458333333)

[5] Another limitation of using satellite images is that satellite images of floodwater can only capture the surface of water, but cannot measure the depth of water.

Figure 1: Flooding Map of Hue Province, from May 2012 to April 2013



Source: Author's calculation

2.3 Descriptive statistics of the sample

Table 1 below provides summary statistics of the main variables used in the analysis. The sample is pooled across all four waves. On average, the households in the survey have four people in each house. Men function as head of the majority of the households, with only 23% of households being headed by a woman. As the surveys are conducted in poor rural areas, poor households account for 29% of the sample. Overall, approximately 14% of the heads of households have completed their secondary school, in the sample of study individuals who completed secondary education are few, it is possible that low education is a factor making households more vulnerable to poverty. However, we can see a brighter picture when looking at the share of household members who are still studying, which at 28% suggests that the number of household members pursuing secondary education is rising compared with the existing level of education in the adult generation.

Table 1: Household characteristics

	Mean	SD	Min	Max
Household size	4.09	1.75	0	19
Female head (1/0)	0.23	0.42	0	1
Poor household (1/0)	0.29	0.45	0	1
Education of head	0.14	0.34	0	1
Dependency ratio	0.66	0.70	0	6
Share household members are in school	0.28	0.25	0	1
Household produce crops (1/0)	0.88	0.32	0	1
Share household members as non-agricultural employment	0.40	0.30	0	1
Saving in household (1/0)	0.64	0.48	0	1
Household has free Health Card (1/0)	0.80	0.40	0	1
Household member has health insurance (%)	0.09	0.22	0	1
Observations	15976			

Note: Consumption and income variables have been converted to 2005 USD.

Source: Sample of panel household data 2007, 2008, 2010, 2013; author's calculation.

The dependency ratio[6] in the sample is quite high; this phenomenon demonstrates a fact in households in rural southeast Asia that "grandparents in the villages take care of the grandchildren while their own children work outside and often far from the village" (Hardeweg & Waibel, 2009). It is obvious that agriculture plays a major role in rural areas with 88% of households producing crops. However, they often have a second job which is mostly outside agriculture: the average share of household members work as non-agricultural employment is 40%. Although poor people spend most of their income on foods, they do have a habit of saving money for necessary time, there are about 64% of household has at least one saving in house. The percentage of households has a free health card is 80%, while only 9% of the sample are using private health insurance.

Table 2: Household income composition

Income Source	Full Sample	Thailand	Vietnam
Total household annual income	7096	7610	6053
Household income from off-farm employment	1804	2147	1252
Household income from self-employment	1659	2010	1064
Remittance receive from household members or relatives	1033	1256	632
Household income from all crops	1432	1336	1468
Household income from livestock	299	228	484
Household income from hunting and aquaculture	420	155	109
Other incomes	499	478	1044
N (households)	*15971*	*7979*	*7992*

Note: Consumption and income variables have been converted to 2005 USD.

Source: Sample of panel household data 2007, 2008, 2010, 2013; author's calculation.

Table 2 show mean of income composition in the full sample and for Thailand and Vietnam in particular. On average, the annual household income is approximately 7096 USD, Thailand consistently having a higher annual household income than Vietnam except for incomes from crop and livestock. Although agriculture is the major work activity in the rural areas, the incomes from agriculture contribute around 30% to the total income; the remaining 70% of income come from non-agricultural activities, remittances and other sources.

Table 3: Household consumption categories

Consumption categories	Full Sample	Thailand	Vietnam
Total annual income per capita	1935	2109	1586
Total consumption per capita	1740	2005	1278
Consumption per capita for foods	871	919	644
Consumption per capita for non-food	442	523	301
Consumption per capita for rice	284	339	195
Consumption per capita for education	111	130	74
Consumption per capita for health care	42	28	59
N (households)	*15962*	*7978*	*7984*

Note: Consumption and income variables have been converted to 2005 USD.

Source: Sample of panel household data 2007, 2008, 2010, 2013; author's calculation.

Table 3 show mean of annual household consumption per capita. On average of annual total consumption per capita is 1740 USD, this is roughly 90% of their income per capita. The mean per capita in Thailand is consistently higher than in Vietnam, as a result of higher income. However, families in Thailand spend about 95% of their income, compared to only 81% in Vietnam. It can be seen that the distribution of consumption is mainly for food and rice - about 65% of the total - while the expenditure on education and health are only 6% and 3%

[6] The dependency ratio is a measure showing the ratio of the number of dependents aged 0 to 14 and over the age of 65 to the total population aged 15 to 64.

respectively. Health expenditure in Thailand is lower than in Vietnam, since access to free health cards in Thailand is very high at 95%, while only 56% of households in the sample of Vietnam have free health cards.

Figure 2 : The mean of each village floodwater area per year, by province

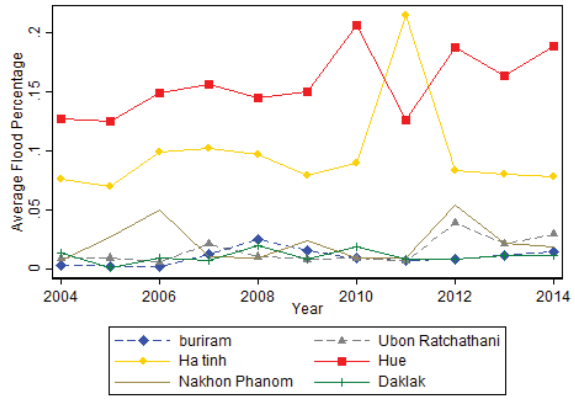
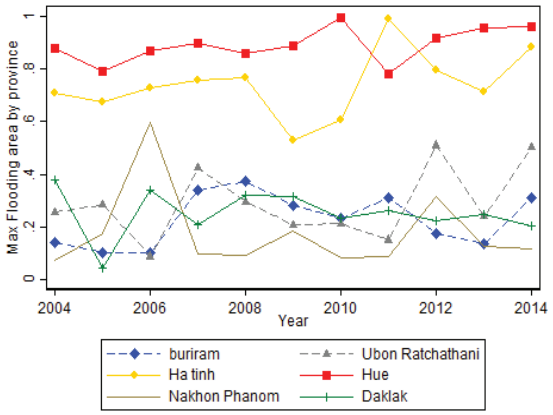


Figure 3: The maximum of village floodwater area per year, by province



Flood data of 440 villages in 10 years

Source: author's calculations

Figure 2 shows the average proportion of each village floods per year by province. The two most affected provinces are Hatinh and Hue in Vietnam, which continuously exhibited larger average flood levels, the two least effected provinces are Buriram in Thailand and Daklak in Vietnam. While Figure 3 shows the maximum of village floodwater areas per year by province. The most affected villages in Hue province, Vietnam experience between 80 – 99% of floodwater area. The variation of the maximum floodwater areas fluctuates throughout the year, but the most affected provinces have large floodwater in every year.

2.4 Empirical strategy

The effects of floods on household welfare are analysed using a three-part regression setup. First, we examine the direct effects of floods on household incomes and consumptions including health expenditure per capita. Second, we investigate how households are living with floods through analysis their coping strategies. Third, we study the relationship between floods and household subjective wellbeing. The baseline specifications for each part may be found below:

$$W_{hvt} = \beta_0 + \alpha_1 F_{vt} + \beta_1 H_{hvt} + \delta_p + \rho_t + \varepsilon_{hvt} \qquad (1)$$

Where W_{hvt} denotes the outcomes of household welfare for each household h, living in village v in year t. The outcome W_{hvt} is measured in three different ways, namely: household income compositions, household consumption categories, health expenditure per capita in households. Variables of incomes and consumptions are logged before analysis.

F_{vt} represents a continuous flood indicator, measuring the average of the proportion of a village's area that has been covered by floodwater in the previous and the year of survey, and ranging from 0 to 1. The average flood of two consecutive years is analyzed instead of floods in the current year due to planting and harvesting seasons.

The matrix H_{hvt} captures the socio-demographic characteristics of households including households' wealth, agriculture assets and land usage for agriculture production, also infrastructure index of village when households are living.

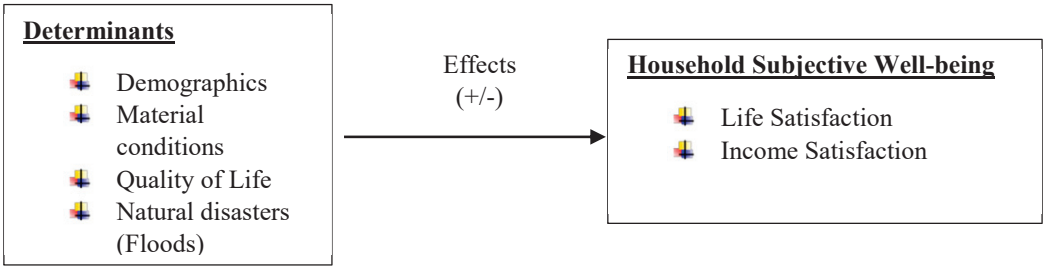
δ_p and ρ_t are full set of province and wave fixed-effects to account for unobserved differences between provinces (p) and surveys years (t). The use of a long-term panel data with province and wave fixed effects provides a feasible way to protect incomes and consumption estimates from time-invariant unobserved heterogeneity across localities. We estimate this effect by assuming that the remaining variation in flood levels across villages between

years is independent of the unobserved heterogeneities in welfare outcomes of the households. ε_{hvt} is the error term with standard errors clustered at the village level.[7] The coefficient of interest is α_1, which yields the direct effect of floods on household welfare outcomes caused by switching from having no flood to being covered totally by floodwater (F_{vt} =1).

Further, we use the same models (1) and add the interaction term $\alpha_2 F_{vt} * C_{hvt}$, in which C_{hvt} indicates the set of coping mechanisms including: public free health card and private health insurances, intra-house insurance schemes (such as assets, saving, remittance, off-farm income, social network). We also examine the actual ability of households to cope with flood shocks. The coefficients of interest are α_1, α_2, and $(\alpha_1 + \alpha_2)$. The estimate of α_1 gives the effect of floods on outcome if households do not use the coping strategy. The estimate of α_2 gives the reduction (or exacerbation) effect of floods due to applying the coping strategies. The sum of coefficient $(\alpha_1 + \alpha_2)$ shows the total effect of floods on the outcomes if a household has the coping strategy.

To study the effects of foods on household subjective wellbeing, we follow the OECD guideline in measuring subjective wellbeing.

Figure 4 : A simple model of Household Subjective Well- Being (SWB)



The purpose of the simple model of household subjective wellbeing in Figure 4 is not to provide a comprehensive framework covering all possible elements of household subjective wellbeing. Rather, we intend to control for all core aspects in measuring SWB, which we are able to create within our dataset.

The Determinants include: *Demographics* (age groups shares, gender of household head, marital status of household head, family type, household size, ethnic/ religion identification), the surveys are conducted in rural areas therefore the classification of urban/rural is not necessary in this study; *Material conditions* (household wealth, fluctuation of income, housing quality); and *Quality of life* (employment in household, health status in household, education of household members and household head, social connections, security in living community). In total, we create 35 elements for controls. (For the detail, see Appendix A4)

The household subjective wellbeing (SWB) is an assessment of household subjective life satisfaction based on their evaluation of their household own wellbeing as a whole, and their subjective comparison with other households in their community. In addition, the income satisfaction is created by the ratio of the difference between the expected incomes with the actual income relative to its actual income. The quintile groups indicate the satisfaction levels.

We use the ordinal logit model:

$$SWB_{hvt} = \beta_0 + \alpha_1 F_{vt} + \beta_1 X_{hvt} + \varepsilon_{hvt} \quad (2)$$

Where SWB_{hvt} denotes the outcomes of household subjective wellbeing for each household h, living in village v in year t. The outcome is measured in ordinal scale from 1 to 5, where (1) denotes for very dissatisfied (2) dissatisfied (3) neither satisfied nor dissatisfied (4) satisfied (5) very satisfied.

The matrix X_{hvt} captures a variety of core aspects in measuring subjective wellbeing, including Demographics, Material conditions, Quality of life. The logit coefficient α_1 is in log-odds unit, this coefficient only returns whether the flood variable has a negative or positive influence on the outcomes. To interpret the effect of

[7] The survey used a three-stage clustered sampling approach. Provinces were targeted, sub-districts were selected with probability proportional to population size (PPS), followed by a simple random PPS sample of two villages from each sampled sub-district. Lastly, households were randomly sampled with implicit stratification by household size. We account for the survey design using sample weights.

floods on outcomes, we need to estimate marginal effects on probabilities for each category if floodwater changes from 0 to 1.

3 Findings

This section of the paper presents the empirical results of our analysis. We use the proportion of floodwater area in villages as the main indicator of flood. First, we categorize household income and consumption into different sources to analyze the effects of floods on various aspects of households'life. Second, we examine various coping strategies in households. Further, we investigate the relationship between floods and household subjective wellbeing. Moreover, we run separate regressions for two alternative indicators of flood as robustness checks. All the results shown use heteroscedasticity robust standard errors clustered at the village level.

3.1 The effects of floods on household incomes

Table 4 paints a picture of impacts of floods on incomes dependent on natural sources. Hunting and aquaculture income is most affected with approximately 103% decrease if the village is flooded totally (max flood=0.99). Livestock income is reduced by roughly 41.5%. Total crops income declines by around 26.4% (total crops income includes incomes from rice, field crops, garden crops or permanent crops, and forest).

Table 4: The effects of flood on incomes directly dependent on natural sources

	(1) Hunting Income	(2) Livestock Income	(3) Crop Income
Flood	-1.030*	-0.415	-0.264
	(-2.36)	(-0.75)	(-1.25)
Observations	9024	7533	7445
Adjusted R2	0.162	0.142	0.190
Wave –FE	Yes	Yes	Yes
Province –FE	Yes	Yes	Yes
Other controls	Yes	Yes	Yes

OLS regressions: Standard errors, clustered at village level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$;

Dependent variables: (1) Log of household hunting and aquaculture income, (2) Log of household livestock income, (3) Log of household crop income;

Other controls: Household variables, Land use variables, village variables.

Source: Author's calculations. (The detail result table is provided in Appendix A2).

Table 5 presents the effects of floods on household incomes, which are not directly dependent on natural resources. Since the household's occupational activities can be assumed to be an important factor in estimating its vulnerability to floods, the results suggest that households who are highly dependent on agriculture may be more vulnerable to floods than households that have capacity to diversify into non-farm occupations. In the sample of study, there are roughly 88% of households involved in agricultural activities; however, members of households often have a second job outside agriculture, the share of non-agricultural employment in households being on average 40% (cross-refer to Table 1). This fact might imply that households take up additional jobs or family members go away seeking jobs as a coping strategy. The results in the column (1-2) reflect those possibilities.

Table 5: The effects of floods on incomes not directly dependent on natural sources

	(1) Self-Employment	(2) Remittance	(3) Off-farm	(4) Total
Flood	1.284*	1.744***	0.0795	0.110
	(1.99)	(4.88)	(0.23)	(1.20)
Observations	10282	12424	10351	10617
Adjusted R2	0.102	0.101	0.0776	0.280
Wave –FE	Yes	Yes	Yes	Yes

Province –FE	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes

OLS regressions: Standard errors, clustered at village level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$;

Dependent variables: (1) Log of household self-employment income, (2) Log of household remittance income, (3) Log of household off-farm income, (4) Log of household total income;

Other controls: Household variables, village variables;

Source: Author's calculations. (The detail result table is provided in Appendix A2).

There are three types of incomes are examined: (1) non-farm self-employment income that households have an own-account worker or run own business with family workers, (2) remittance income that households receive from family members or relatives who living away from home, (3) off-farm income that households receive from waged-employed activities. In a village experiencing 100% of floodwater, households receive more than 128% of their income from self-employment, and 174% from remittances from family members. Column (3) shows a positive relationship between flooding and off-farm income, but the coefficient only 7% and not significant. The findings show that households are seeking jobs to compensate their lost agricultural incomes by non-agricultural incomes.

Findings reported in this section show a shift of employment from agricultural sector to other sectors of the economy. This shift might be leaded by the opportunities for labor absorption in other sectors in different countries. To clarify this inquiry, we have run separate regressions for Vietnam and Thailand.

Table 6: The effects of flood on incomes: Vietnam vs Thailand

	(1) Hunting	(2) Livestock	(3) Crop	(4) Self employed	(5) Remittance	(6) Off-farm	(7) Total
Vietnam							
Flood	-0.743	-0.340	-0.348	1.021	1.970***	0.101	0.144
	(-1.61)	(-0.58)	(-1.64)	(1.51)	(5.38)	(0.30)	(1.59)
Thai Land							
Flood	-0.667	-2.589	-1.199	1.554	-0.488	-1.613	-0.650
	(-0.53)	(-1.27)	(-1.81)	(1.01)	(-0.36)	(-0.74)	(-1.62)
Wave –FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province –FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes

OLS regressions: Standard errors, clustered at village level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$;

Dependent variables: (1) Log of household hunting and aquaculture income, (2) Log of household livestock income, (3) Log of household crop income (4) Log of household self-employment income, (5) Log of household remittance income, (6) Log of household off-farm income.

Other controls: Household variables, village variables.

Source: Author's calculations.

Results in Table 6 provide clear evidence that floods reduce incomes dependent on natural sources in both countries. However, the shift of seeking other jobs in Vietnam is mainly toward outside of villages, which is reflected in remittance income (5); while the shift in Thailand has remained inside the villages, which reflects in non-farm self-employed income (4). In total come, households in Thailand are more affected than households in Vietnam. However, this is not necessary a good news for Vietnam, this finding tells a fact that in Vietnam households cope through labor migration to urban areas. This finding matches with the conclusion in one paper published by (Gröger and Zylberberg, 2016), the authors use the same household data for Vietnam to analysis how internal labor migration facilitates shock coping to a Typoon Ketsana in Vietnam during the 2009 monsoon season. The authors find that "*households with settled migrants ex ante receive more remittances, non-migrant households react by sending new members away who then remit similar amounts than established migrants. This mechanism is most effective with long-distance migration, while local networks fail to provide insurance*". In last decade, there has been waves of people leaving their homeland to seek jobs in cities, this is the major cause for the phenomenon 'transferring the rural poverty to urban poverty' when large amount of illiterate and unskilled migrations moves into urban areas.

3.2 The effects of floods on household consumption

The results in Table 7 show that overall floods increase all kinds of consumption in households. Health expenditure is the most affected, with a 47% increase in most affected villages (flood=0.99) and a 44.8% increase on education expenditure. These results can be explained by the share of household members still in school being quite high in the sample at around 28% on average. Floods also increase both non-food and food consumption, respectively 21.2% and 11%, but only have a slight effect on rice consumption; this phenomenon is explained by the fact that rice yields in flooded villages are better than in non-affected villages.[8] In total, floods increase household consumption by roughly 18%. These results are equivalent to the average amounts increase in per-capita expenditures for health by roughly 18 USD, education by 50 USD, non-food by 94 USD, food by 96 USD, and the total expenditure increase by 312 USD (cross-refer to Table 3).

Table 7: The effects of flood on household consumption

	(1) Health	(2) Education	(3) Non-food	(4) Food	(5) Rice	(6) Total
Flood	0.471*	0.448*	0.212*	0.110	0.029	0.179*
	(2.34)	(2.04)	(2.18)	(1.38)	(0.38)	(2.28)
Observations	7475	7493	7105	7076	7076	7481
Adjusted R2	0.170	0.394	0.373	0.272	0.165	0.390
Wave –FE	Yes	Yes	Yes	Yes	Yes	Yes
Province –FE	Yes	Yes	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes	Yes	Yes

OLS regressions: Standard errors, clustered at village level. $^{*}\ p < 0.05$, $^{**}\ p < 0.01$, $^{***}\ p < 0.001$;

Dependent variables: (1) Log of household health expenditure per cap, (2) Log of household education expenditure per cap (3) Log of household non-food expenditure per cap, (4) Log of household food expenditure per cap, (5) Log of household rice; expenditure per cap, (6) Log of household total expenditure per cap;

Other controls: Household variables, village variables.

Source: Author's calculations. (The detail result table is provided in Appendix 3)

The results in section 3.1 and 3.2 show an overview picture of floods on households' income and expenditure in rural Southeast Asia, with negative impacts on both sides. On the one hand, floods reduce agriculture-based incomes and drive away household members to earn money from non-agriculture sources. On the other hand, flood-related impacts increase spending in all aspects of life. This picture suggests to us a hypothesis that "rural households cope with flood shocks by leaving agriculture for seeking extra-income from non-agriculture". In the next section, we will examine this hypothesis.

3.3 Living with floods: coping strategies

From a policy perspective, it will be useful to identify which coping mechanisms are best suited to reduce flood related vulnerability. In this section, we examine how households in rural areas respond to floods through an analysis of their coping strategies. We study both ex-ante and ex-post coping strategies, also both formal and informal coping mechanisms. First, we look at health insurances in coping with cost of flood-related health impacts. Second, we explore several potential intra-channels that households can use as coping strategies to smooth household consumption consequent upon flood shock; in our analysis we use off-farm income, remittances, savings, and help from social networks. Table 8 and Table 9 present results for coping strategies, modelled by interacting the floodwater indicator with variables reflecting various coping strategies variables in the household survey. Negative coefficients on the interaction terms would indicate that coping strategies reduces vulnerability to floods.

[8] Using the same data sets, in our paper: Le Thi Ngoc Tu, Sebastian Vollmer, Felix Stips (2018). "The effects of floods on agricultural production: a mixed blessing", we find that the effects of floods on agricultural production is mixed. While floods increase expenditures and reduce incomes, they can also increase rice productivity.

Coping through public and private health insurance mechanisms

Health insurances used in this analysis are public health card for poor households[9] and private health insurance for individual. Table 8 present regression results for using health insurance as coping strategies to health-related impacts. Results in column (2) show that private health insurance can reduce the financial burden for households dealing with the effect of floods by around 48.5%, while a free public health card increases the cost for poor households by around 25.9% (column 1). Since the free health for poor mainly targets household vulnerable to poverty and economic shocks, it is reasonable that households generally display higher risk. Being a part of the program can reduce the cost of health care for poor household around 25.5% in normal situation, however, does not lead to a reduced vulnerability to flood-related health expenditure.

Table 8: Public and private health insurance as coping strategies

	(1) Health Expenditure	(2) Health Expenditure
Flood	0.285	0.584*
	(1.05)	(2.36)
Flood* Free Health Card	0.259	
	(0.87)	
Flood* Private Health Insurance		-0.485
		(-0.59)
Free Health Card	-0.255***	
	(-4.17)	
Private Health Insurance		0.257*
		(2.42)
Observations	7473	11060
Adjusted R2	0.172	0.169
Wave –FE	Yes	Yes
Province –FE	Yes	Yes
Other controls	Yes	Yes

OLS regressions: Standard errors, clustered at village level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$;

Dependent variables: Log of household health expenditure per capita;

Other controls: Household variables, village variables.

Source: Author's calculations.

The results in this section should be understood as indicative, rather than casual effects. In these results, self-selection might play a major role since people are using private insurance more likely because they are suffering from a worse health condition. In developing countries like Vietnam and Thailand, the coverage of the free medical system is much less than ideal. When patients go to hospitals with free public health card, they have to wait so long to get the service, they have to go through many cumbersome procedures and sometimes they also receive cold attention from doctors, therefore in many cases they choose other services for better treatments (Jeffrey Hays, 2012). Therefore, the insignificant coefficients might not justify making direct inferences about free health card program, but possibly reflect the ways it is implemented in the healthcare systems.

[9] In Thailand, the Universal Coverage Scheme(USC) has flowed a long string of efforts to improve equity in health. By 2001, the UCS was covering 48 million members and their families, leaving less than 2 percent of the Thai population without health insurance coverage (Wagstaff & Manachotphong, 2012).

In Vietnam, the Vietnamese Government offers the program Health Card for the Poor (HCFP) in 2003. This card was designed to support poor households and ethnic minorities. The program covers inpatient and outpatient health care costs at public providers (Somanathan, Tandon, Dao, Hurt, & Fuenzalida-Puelma, 2014).

Coping through intra-household insurance schemes

In Table 9, the interaction terms present the roles of intra-household insurance in coping with the effects of floods on total consumption. Assets, Savings and Remittances indicate significant roles in smoothing household consumptions when dealing with flood shock, while social network tells a story that for households in need of help because they are more vulnerable to flood shock, off-farm income only contributes a small influence.

Table 9: Informal insurance schemes in households as coping strategies

	(1) Total Expenditure	(2) Total Expenditure	(3) Total Expenditure	(4) Total Expenditure	(5) Total Expenditure
Flood	0.422***	0.238**	0.297***	0.258*	0.0880
	(3.43)	(2.81)	(3.46)	(2.58)	(1.02)
Flood* Assets	-0.0843*				
	(-2.46)				
Flood*Saving		-0.205*			
		(-2.03)			
Flood* Remittance			-0.0461***		
			(-3.62)		
Flood*Off-farm				-0.0249	
				(-1.58)	
Flood*Social network					0.151*
					(2.29)
Assets	0.185***				
	(31.37)				
Saving		0.160***			
		(8.27)			
Remittance			0.0267***		
			(12.29)		
Off-farm income				-0.00982***	
				(-3.57)	
Social network					-0.140***
					(-9.01)
Observations	11568	7479	7481	7481	7481
Adjusted R2	0.421	0.396	0.404	0.392	0.398
Wave –FE	Yes	Yes	Yes	Yes	Yes
Province –FE	Yes	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes	Yes

OLS regressions: Standard errors, clustered at village level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$;

Dependent variables: Log of household total expenditure per cap;

Coping strategies: (1) Quintile of household assets, (2) Saving: value 1 if household has a saving, (3) Remittance: Log of household remittance, (4) Off-farm income: Log of household off-farm income, (5) Social network: value 1 if household has any informal social option to ask for when household needs money;

Other controls: Household variables, village variables.

Source: Author's calculations.

Column (1) presents evidence that assets-richer household can cope better with floods, while a reduction of around 8.43% in the effects of flood on household expenditure per capita is seen if the household's assets are one quintile higher. Column (2) shows a 20.5% decrease of the effect of flooding on household expenditure per capita if a household has any savings account. Column (3) shows that a household receiving 10% higher remittances can reduce by around 4.6% the impact on household expenditure per capita. Column (4) shows an insignificantly small (2.4%) reduction in household expenditure per capita if the household has 10% higher off-farm income. Column (5) indicates that a household which has a social network option to source help in hardship is more affected by floods, the impact of floods on their total consumption being around 15% higher than a household without a social network option.

In this rural sample, by far, when coping with shocks, a household faces a form of portfolio-choice problem. The portfolio could include everything from economic actions and sales, through borrowing and saving, changing demographics or helps from relatives. However, these rural households have very limited portfolio-choice, the most frequently reported coping strategies to deal with shocks are 'take up additional occupation' (16%), 'use saving' (13.5%), and 'borrowing or helps from relatives and friends' (14.5%). One of the reasons for this limited choice set is the unavailability of formal supports from public services. There is only 7% reported supports from all Government, Banks, and NGOs. Another reason for the limited choice set is the nature of natural disaster. The floods affect the majority of households in their community simultaneously, and therefore, informal channel such as social networks, do not provide effective method.

The results in this section report a relevant evidence on which coping strategies as used most frequently and effectively in rural areas.

3.4 The effects of flood on household's subjective wellbeing

Table 10 presents the ordinal logit regressions for assessment of a household's subjective wellbeing (SWB). Household subjective wellbeing variables (SWB1 and SWB3) are measured based on the average score of 'household life satisfaction' and 'subjective comparison wealth to other residents of village and of country'. Level of income satisfaction has been added to created SWB2 and SWB4. Reference time for SWB1 and SWB2 is from the previous year of the survey year to the next year. Reference time for SWB3 and SWB4 is from five year ago to next five years.

Where the coefficients in column (1) and (2) are significantly negative, then we can say that floodwater has a significant negative influence on a household's wellbeing, measured in the short term. Columns (3) and (4) show that floodwater also has a negative on a household's wellbeing measured in the long term, but the effect is weaker and not significant.

Table 100: The effects of flood on household subjective wellbeing

	(1) SWB1	(2) SWB2	(3) SWB3	(4) SWB4
Flood	-0.403*	-0.427*	-0.288	-0.319
	(-2.24)	(-2.19)	(-1.68)	(-1.73)
Observations	8118	8118	8118	8118
Categories	5	5	5	5
Pseudo R2	0.0975	0.0873	0.0795	0.0806
chi2	1533.9	1704.0	1371.7	1558.5
Other controls	Yes	Yes	Yes	Yes

Ordinal Logit: Standard errors, clustered at village level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Dependent variables: Household subjective wellbeing variables

Other controls: Household demographics, household material situations, household's quality of life, social connection and security.

Analysis is following the OECD guideline in measuring subjective wellbeing.

Source: Author's calculations. (The detail result table is provided in Appendix A4)

Table 11 presents the change in prediction for a household's wellbeing if floodwater area changes from 0 to a maximum of 0.99. The results in column (1) indicate that the probability of 'very dissatisfied' increases around 4.31% when floodwater changes from 0 to 0.99, and all other control variables are held at their constant mean values. Similarly, we can say the probability of 'dissatisfied' increases about 5.56%, the probability of 'neither dissatisfied nor satisfied', 'satisfied' and 'very satisfied' decrease roughly 4.49%, 5.14% and 0.23% respectively. Making a comparison between SWB1 and SWB2, when income satisfaction has been taken into account, the probability of 'very dissatisfied' keep increasing while the probability of 'satisfied' keeps decreasing. Similar interpretations apply to columns (3) and (4).

Table 11: The change in predictions for subjective wellbeing level from flood=0 to flood=0.99

SWB Levels	(1) SWB1	(2) SWB2	(3) SWB3	(4) SWB4
Very dissatisfied	0.0431	0.0636	0.0239	0.0608
Dissatisfied	0.0556	0.0414	0.0395	0.0150
Neither dissatisfied nor satisfied	-0.0449	-0.0339	-0.0085	-0.0448
Satisfied	-0.0514	-0.0623	-0.0447	-0.0129
Very satisfied	-0.0023	-0.0087	-0.0102	-0.0181

Source: Author's calculations.

4 Robustness check

In this section, we use two alternative flood indicators as a robustness check for the validity of the main flood indicator used in our Findings section.

4.1 Alternative flood indicators

Table 12 shows the relationship between the number of flooding days in a year and household incomes; these regressions are repeated regressions from Table 4 & Table 5, with replacement of variable *flooding days* for the variable *Flood*. These results tell the same story as those in Table 4 & Table 5: flooding days bring negative effects to incomes from crops, livestock, and hunting, and push households away from their farms for seeking incomes from non-agricultural activities. The results in Table 12 can be interpreted as follows: two households have similar conditions living in two different villages. Village A has no flood and village B has 175 flooding days in one year (maximum of the variable *flooding days).* The household in village B has a lower income from hunting, livestock, and crops; 121%, 101% and 56% respectively. Similarly, in comparison with Table 2b, which demonstrate the relationship between floodwater area with incomes from non-agricultural activities, Table 12 presents the same direction of impacts of flooding days on those incomes. If a village has more than 10 flooding days, the incomes from non-agricultural activities changes as follows: off-farm income decreases by 3.1%, self-employment income increases by 8.5%, remittances received from household members or relative increases by 11.7%.

Adjusted-R2 in Table 4 & Table 5 are very similar with that in Table 12. This shows using floodwater area or flooding days as a flood indicator provides the same coefficient of determination. However, floodwater area is preferred to flooding days because floodwater area can show the intensity of flood, while flooding days only count the days but do not consider the area of floodwater.

Observing flood maps of villages in the study areas over years, we can see that the more affected villages have floodwater more often than the less affected villages. This fact raises an interesting question "whether households suffers much more if there is too much flooding". We try to answer this inquiry by adding the variation of floodwater into analysis. The variation of floodwater is measure by the deviation of floodwater area in current year with the average floodwater area during last five years. Table 13 shows both the results of the direct effect of floodwater on outcomes and the effect of flood variations. Overall, floodwater variation has a small effect on hunting

income, livestock income, and self-employed incomes. However, variation of floodwater has negative impacts on crops income, off-farm income, and remittance. In extremes case, if floodwater area in the current year is three standard deviations larger than normal floodwater area in the same village, the incomes from crops, off-farm income, and remittance income will reduce by about 15%, 39%, 22% respectively.

Table 12: Floods and household incomes

	(1) Hunting	(2) Livestock	(3) Crop	(4) Off-farm	(5) Self-Employed	(6) Remittance
Flooding days	-0.0069	-0.0058	-0.0032	-0.0031	0.0085*	0.0117***
	(-1.94)	(-1.37)	(-1.68)	(-0.94)	(2.07)	(4.59)
*Table **Error! No text of specified style in document.**.13 :*						
Flood	-0.968*	-0.320	-0.225	0.220	1.265	1.837***
	(-2.21)	(-0.59)	(-1.05)	(0.64)	(1.94)	(5.10)
Flood	0.0028	0.0272	-0.0513	-0.132	0.0053	-0.0738
variations	(0.03)	(0.26)	(-1.18)	(-1.45)	(0.05)	(-0.81)
Observations	9024	7533	7445	10343	10274	12413
Adjusted R2	0.160	0.143	0.191	0.0808	0.102	0.111
Wave –FE	Yes	Yes	Yes	Yes	Yes	Yes
Province –FE	Yes	Yes	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes	Yes	Yes

OLS regressions: Standard errors, clustered at village level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$;

Dependent variables: (1) Log of household hunting and aquaculture income, (2) Log of household livestock income, (3) Log of household crop income. (4) Log of household off-farm income, (5) Log of household self-employment income, (6) Log of household remittance income;

Other controls: Household variables, Land use variables, village variables.

Source: Author's calculations.

However, this result should only be used for reference rather than for main finding. One of the limitations of this study is that we only have flood data for ten years from 2003 to 2013 because satellite images of floodwater provided by NASA only from 2002, while our household data is from 2007. In order to create a good indicator of flood's variation, we should have a long-time flood data about twenty years or more.

Overall, we can confidently conclude that two variables, floodwater area and flooding days, provide similar results; however, floodwater area provides a better interpretation. The variation of the floodwater indicator indicates the places in the village where are flooded in the current year, which might not be normally affected during the last five years. As expected, the larger floodwater area in a village compared with the normal level causes negative effects on household incomes; however, as a general conclusion, the effects of variation of floodwater in villages would cause a small underestimate of the effect of floodwater on household welfare.

4.2 Province-year Fixed effects

Much of the empirical literature has so far assumed flood measures to be exogenous. Despite measurement, objective measures may yield biased estimates. First, the repeated occurrence of floods in an area is likely correlated with the possibility of it occurring in the first place, which may in turn affect the level of incomes and expenditures. Second, households in affected areas have likely adapted to these circumstances by coping strategies or building successful livelihood systems called "living with floods". To relieve that worry, we shall compare households from the same province and the same time, who should face a similar flood trend. We perform a robustness check with province-wave fixed effects to account for changes in living conditions over time in each province.

The results in Table 14 & Table15 give us a very similar result compared with the main findings in sections 3.1 and 3.2. This shows that we can be confident to use the province fixed effects and year fixed effects to control for time-invariant unobserved heterogeneity across locations.

Table 14: Flood and household incomes

	(1) Hunting	(2) Livestock	(3) Crop	(1) Off-farm	(2) Self employed	(3) Remittance
Flood	-0.909*	-0.292	-0.373	0.00458	1.264	1.851***
	(-2.10)	(-0.53)	(-1.72)	(0.01)	(1.94)	(5.25)
Observations	9024	7533	7445	10343	10274	12413
Adjusted R2	0.174	0.146	0.207	0.0829	0.102	0.125
Wave –FE	Yes	Yes	Yes	Yes	Yes	Yes
Province –FE	Yes	Yes	Yes	Yes	Yes	Yes
Province*Wave -FE	Yes	Yes	Yes	Yes	Yes	Yes

OLS regressions: Standard errors, clustered at village level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Dependent variables: (1) Log of household hunting and aquaculture income, (2) Log of household livestock income, (3) Log of household crop income. (4) Log of household off-farm income, (5) Log of household self-employment income, (6) Log of household remittance income;

Other controls: Household variables, Land use variables, village variables.

Source: Author's calculations.

Table 15: Flood and household consumptions

	(1) Health	(2) Education	(3) Non-food	(4) Food	(5) Rice	(6) Total
Flood	0.485*	0.422	0.223*	0.104	0.0346	0.129
	(2.29)	(1.87)	(2.42)	(1.44)	(0.49)	(1.85)
Observations	7475	7493	7105	7076	7076	7481
Adjusted R2	0.174	0.396	0.394	0.332	0.205	0.420
Wave –FE	Yes	Yes	Yes	Yes	Yes	Yes
Province –FE	Yes	Yes	Yes	Yes	Yes	Yes
Province*Wave - FE	Yes	Yes	Yes	Yes	Yes	Yes

OLS regressions: Standard errors, clustered at village level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$;

Dependent variables: (1) Log of household health expenditure per cap, (2) Log of household education expenditure per cap (3) Log of household non-food expenditure per cap, (4) Log of household food expenditure per cap, (5) Log of household rice expenditure per cap, (6) Log of household total expenditure per cap;

Other controls: Household variables, village variables.

Source: Author's calculations.

5 CONCLUSIONS

This study contributes to the existing literature in two significant ways. First, we construct an external data sets on local flood maps obtained from satellite observations to measure floodwater. This has an advantage of highly precise and objective geographical satellite data. Second, we have completed a previously puzzling picture of the effects of flood on household welfare, in which we look at a multi-dimensional representation of the effects. In general, floodwater reduces household incomes dependent on natural sources, while flooding pushes farmers out of the fields to search for extra income from non-agricultural activities. Moreover, floodwater increases all consumption categories, and creates additional financial cost on health care expenditure. As a result, people living in flooding zone have lower scores of wellbeing. In addition, this research illuminates the efforts that households go to when trying to cope with the impact of flooding. They use both formal and informal coping mechanisms; however, in reality, intra-household coping strategies are commonly used in rural areas and are also effective methods as far as they go. Nevertheless, the results show that the scale of the impact is large to be coped at household level. We therefore conclude that the experience of living in villages that are subject to flooding is not a happy one.

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Appendix A

Table A 1: Variable definitions

Variable	Definition
Access to fixed line telephone	Percentage of households in village with access to fixed line telephone
Access to electricity	Percentage of households in village with access to electricity
Access to internet	Percentage of households in village with access to internet
Access to public waste disposal	Percentage of households in village with access to public waste disposal
Access to public water	Percentage of households in village with access to public water
Access to sanitation	Percentage of households in village with access to sanitation
Agriculture assets	Household total present value of agriculture asset items
Agriculture land (1/0)	Dummy variable, takes the value 1 if land is mainly used for agricultural purposes
Agriculture land area	Household total agriculture land area (ha)
Agriculture Village (1/0)	Dummy variable, takes the value 1 if the main employment in the village is agriculture
Area Planted	Household total crop area planted (ha), or households total rice area planted (ha)
Cooking fuel (1/0)	Dummy variable, takes the value 1 if household uses gas or electric for cooking
Cope (1/0)	Dummy variable, takes the value 1 if household took any ex-post coping activities to deal with flood event
Crop Land (1/0)	Dummy variable, takes the value 1 if land is mainly used to grow crops
Dependency ratio	Number of dependents / number of aged 15 to 64
Epidemic in village (1/0)	Dummy variable, takes the value 1 if village has epidemic problem
Female head (1/0)	Dummy variable, takes the value 1 for households that are headed by a woman
Firm density in village	Number of firms in village per 100 inhabitant
Flooding days	The number of days in one year that a village has floodwater

Floodwater area	Average of the proportion of a village area that has been covered by floodwater in the previous year and current year
Floodwater variation	standard deviation of this year floodwater area from the average of last 5 year floodwater area
Free health card (1/0)	Household has free health card
Head education	Categorical variable, which takes values 0-6 0: No education 1: Primary not completed 2: Primary completed 3: Lower secondary completed 4: High school / vocational completed 5: Some college / advanced vocational completed 6: University or higher
Health insurance	Member has private health insurance
Household Assets	Household total present value of asset items
Household crop expenditures	Household total expenditure for all crop production, includes expenditures for machinery, hired labor, seeds and seeding, fertilizer materials, pesticides materials, and irrigation
Household crop income	Household annual income from crop production
Household hunting income	Household total income from fishing, hunting, collecting, or logging activities
Household income	Household total annual income
Household income per capita	Household total annual income per capita
Household livestock income	Household annual income from livestock
Household produce crops	Households that grow rice, field crops, permanent crops, or forest in the year of study
Household size	Household nucleus size, includes only members of the family who stay in the household for more than 6 months
Income fluctuation (1/0)	Dummy variable, takes the value 1 if household has income fluctuation in last 12 months
Land in Village (1/0)	Dummy variable, takes the value 1 if planted parcel land in the same village
Land Tenure (1/0)	Dummy variable, takes the value 1 of household owned land
Majority (1/0)	Household is majority group (Kinh in Vietnam, Thai in Thailand)
Married (1/0)	Household head is living with married partner

Mechanic Irrigation (1/0)	Dummy variable, takes the value 1 if the farmer uses mechanic irrigation to grow crops (pipe, tap, pumped from public irrigation canal)
Non-farm employee (1/0)	Household has non-farm employee
Own house (1/0)	Household owns the house
Persons per room	Household size / number of rooms
Poor household (1/0)	Dummy variable, takes the value 1 for poor families that have an income per capita below the poverty line (1.9 USD per day)
Private toilet (1/0)	Household has a private toilet
Rain Irrigation (1/0)	Dummy variable, takes the value 1 if farmer depends on rain for irrigation to grow crops
Religion (1/0)	Household has a religion
Rice Village (1/0)	Dummy variable, takes the value 1 if main agriculture activity in village is rice production
Saving (1/0)	Dummy variable, takes the value 1 if household has any saving account
Share children	Proportion of children in household = (number of aged from 0 to 15 / household size)
Share elder	Proportion of elder in household = (number of aged from 60 / household size)
Share good health	Proportion of members of household with a good health status
Share health insurance	Proportion of members in household using private health insurance
Share in school	Proportion of members in household still in school
Share infant	Proportion of infant in household = (number of aged from 0 to 5 / household size)
Share male	Proportion of adult male in household
Social problem in village (1/0)	Dummy variable, takes the value 1 if village has any social problem
Solid house (1/0)	Household is living in solid house (house is constructed by wooden or cement)
Time to town	Travel time from village to the district town in minutes
Use Fertilizer (1/0)	Dummy variable, takes the value 1 if the farmer spends money on fertilizer to grow crops (or rice)
Use Pesticides (1/0)	Dummy variable, takes the value 1 if the farmer spends money on pesticides to grow crops (or rice)
Village infrastructure	Village infrastructure index in quintiles
Village join agriculture program (1/0)	Dummy variable, takes the value 1 if the village participates in one of the agricultural programs (OTOP in Thailand, program 135 or 147 in Vietnam)
Wage employee (1/0)	Household has wage employee

Notes: Expenditure and income variables have been converted to 2005 USD *Source*: Author's calculation

Table A 2: The effects of floods on household incomes

	(1) Hunting	(2) Livestock	(3) Crop	(4) Off-farm	(5) Self-Employment	(6) Remittance	(7) Total
Flood	-1.030*	-0.415	-0.264	0.0795	1.284*	1.744***	0.110
	(-2.36)	(-0.75)	(-1.25)	(0.23)	(1.99)	(4.88)	(1.20)
Assets	-0.134***	0.134***	0.162***	-0.0259	0.615***	0.166***	0.252***
	(-8.85)	(5.94)	(13.14)	(-0.69)	(18.59)	(6.40)	(27.43)
Household size	0.142***	0.157***	0.0760***	0.491***	0.128***	-0.281***	0.120***
	(7.62)	(6.07)	(6.34)	(16.59)	(4.83)	(-13.44)	(18.56)
Head Education	-0.161***	0.0362	0.0356	0.414***	0.253***	-0.211***	0.107***
	(-5.34)	(0.81)	(1.68)	(7.89)	(5.46)	(-5.74)	(10.08)
Share working age	0.0739	0.178**	0.0819*				
	(1.44)	(2.76)	(2.40)				
Crop Land (1/0)	0.253***	0.307**	0.322***				0.0341
	(3.48)	(3.11)	(5.99)				(1.44)
Agriculture Village	0.431	0.685	0.409	-1.376***	-0.645	-0.482*	
	(1.11)	(1.50)	(1.70)	(-4.12)	(-1.92)	(-2.33)	
Village join Agriculture Program	0.0343	0.163	0.0384	-0.118	-0.0673		
	(0.39)	(1.58)	(0.78)	(-1.06)	(-0.66)		
Village's infrastructure index	-0.131**	-0.0553	-0.0296	0.0353	0.0344		
	(-3.27)	(-1.22)	(-1.40)	(0.75)	(0.80)		
Area Planted			0.00225**				
			(2.67)				
Land Tenure			0.229***				
			(3.43)				
Mechanic Irrigation			0.149*				
			(2.51)				

Rain Irrigation			0.00474 (0.09)				
Land in Village			-0.117 (-1.41)				
Use Pesticides			0.370*** (7.09)				
Use Fertilizer			0.617*** (4.03)				
Share non Agriculture Employment							0.336*** (11.27)
Total Land							0.171*** (5.42)
Poor in previous wave							-0.310*** (-13.78)
_cons	3.861*** (9.28)	1.476** (2.86)	4.165*** (12.73)	2.546*** (5.45)	-3.246*** (-7.01)	4.496*** (15.19)	5.717*** (79.02)
Observations	9024	7533	7445	10351	10282	12424	10617
Adjusted R2	0.162	0.142	0.190	0.0776	0.102	0.101	0.280
Wave –FE	yes	yes	yes	yes	yes	yes	yes
Province –FE	yes	yes	yes	yes	yes	yes	yes

OLS regressions. Standard errors, clustered at village level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Dependent variables: (1) Log of household crop income, (2) Log of household livestock income, (3) Log of household hunting and aquaculture income, (4) Log of household off-farm income , (5) Log of household self-employment income, (6) Log of household remittance income, (7) Log of household total income;

Source: Author's calculations

Table A 3: The effects of flood on household consumption

	(1) Health	(2) Education	(3) Non-food	(4) Food	(5) Rice	(6) Total
Flood	0.471*	0.448*	0.212*	0.110	0.0292	0.179*
	(2.34)	(2.04)	(2.18)	(1.38)	(0.38)	(2.28)
Share infant in house	0.0541					
	(0.36)					
Share elder in house	0.761***					
	(9.22)					
Head Education	0.0129	0.115***	0.0899***	0.0410***	0.00357	0.0869***
	(0.60)	(3.95)	(8.87)	(5.54)	(0.40)	(10.78)
Assets value, lagged	0.106***	0.175***	0.196***	0.0754***	0.0432***	0.164***
	(6.50)	(10.72)	(26.89)	(11.81)	(5.89)	(26.88)
Private Toilet	0.172**			0.0555**	-0.0234	
	(2.81)			(2.60)	(-1.00)	
Cooking Fuel	0.261***			0.156***	-0.0684**	
	(5.11)			(7.97)	(-3.00)	
Access to Sanitation	0.00161**			-0.000129	-0.00144***	-0.000130
	(2.70)			(-0.35)	(-4.03)	(-0.42)
Access to waste disposal	-0.00112			-0.000956**	-0.00184***	-0.000390
	(-1.40)			(-2.61)	(-3.37)	(-1.23)
Time to town	0.000547	-0.000314	-0.00119	0.000498	0.000798	-0.000500
	(0.35)	(-0.19)	(-1.94)	(1.01)	(1.54)	(-0.91)
Village Infrastructure Index	0.0195	0.0608**	0.0202			
	(0.91)	(2.75)	(1.83)			
Epidemic in Village	-0.0585					
	(-0.74)					
Share in school		4.772***				

		(17.05)				
Access to electricity		0.00419** (3.13)	0.000963 (1.08)			0.00140 (1.87)
Access to Public water		-0.000677 (-0.83)	-0.0000404 (-0.11)			0.000230 (0.81)
Access to Line telephone		-0.00149* (-2.48)	-0.000661* (-2.32)			-0.00129*** (-5.42)
Access to Internet		0.00666 (1.14)	0.00733* (2.57)			0.00492** (2.69)
Dependency ratio			-0.188*** (-13.88)	-0.163*** (-15.52)	-0.144*** (-10.97)	-0.187*** (-17.56)
Agriculture village				-0.0735 (-1.15)	0.0750 (0.96)	-0.0597 (-0.93)
Village join Program				-0.0408 (-1.94)	-0.00342 (-0.13)	
_cons	0.164 (0.95)	-0.174 (-0.85)	4.198*** (37.11)	6.028*** (65.29)	5.316*** (48.25)	6.112*** (55.31)
Observations	7475	7493	7105	7076	7076	7481
Adjusted R2	0.170	0.394	0.373	0.272	0.165	0.390
Wave –FE	Yes	Yes	Yes	Yes	Yes	Yes
Province –FE	Yes	Yes	Yes	Yes	Yes	Yes

OLS regressions. Standard errors, clustered at village level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Dependent variables: (1) Log of household health expenditure per cap, (2) Log of household education expenditure per cap (3) Log of household non-food expenditure per cap, (4) Log of household food expenditure per cap, (5) Log of household rice expenditure per cap, (6) Log of household total expenditure per cap.

Other controls: Household variables, village variables. *Source:* Author's calculations

*Table A **Error! No text of specified style in document.**.4:* The effects of flood on household subjective wellbeing

	(1) SWB1	(2) SWB2	(3) SWB3	(4) SWB4
Flood	-0.403*	-0.427*	-0.288	-0.319
	(-2.24)	(-2.19)	(-1.68)	(-1.73)
Household size	0.0619**	0.0872***	0.0552**	0.0775***
	(3.22)	(4.91)	(2.92)	(4.38)
Share age 0_4	-0.484*	-0.561**	-0.368*	-0.503*
	(-2.57)	(-2.91)	(-2.04)	(-2.40)
Share age 15_18	-0.526***	-0.748***	-0.544***	-0.713***
	(-3.40)	(-5.09)	(-3.71)	(-4.70)
Share age 19_30	-0.0953	-0.169*	-0.0375	-0.0863
	(-1.27)	(-2.24)	(-0.52)	(-1.15)
Share age 31_40	0.0313	-0.0362	0.0410	-0.0241
	(0.28)	(-0.34)	(0.39)	(-0.22)
Share age 41_50	-0.241	-0.162	-0.284*	-0.299**
	(-1.96)	(-1.40)	(-2.36)	(-2.58)
Share age 51_60	-0.407**	-0.201	-0.632***	-0.439***
	(-3.23)	(-1.73)	(-5.18)	(-3.61)
Share age 5_14	-0.540***	-0.792***	-0.543***	-0.754***
	(-3.96)	(-5.70)	(-4.17)	(-5.45)
Share age 61_64	-0.431*	-0.125	-0.868***	-0.507**
	(-2.25)	(-0.66)	(-4.66)	(-2.72)
Share age 65_120	-0.665***	-0.228*	-0.989***	-0.665***
	(-5.62)	(-1.96)	(-8.64)	(-5.59)
Female head	-0.0319	-0.0631	0.00456	-0.0421
	(-0.41)	(-0.80)	(0.06)	(-0.52)
Household head married	0.204*	0.0555	0.137	0.0912
	(2.50)	(0.72)	(1.70)	(1.14)
Head education	0.118***	0.118***	0.144***	0.135***
	(4.70)	(4.78)	(5.38)	(5.36)
Share male	-0.141	0.0505	-0.0927	-0.00350
	(-1.18)	(0.45)	(-0.77)	(-0.03)
Majority	0.0542	0.129	-0.0712	0.0242
	(0.64)	(1.64)	(-0.84)	(0.30)
Has Religion	0.280***	0.00180	0.104	-0.0175
	(3.68)	(0.03)	(1.44)	(-0.24)
Assets value,	0.320***	0.337***	0.258***	0.289***

lagged	(16.64)	(17.73)	(13.88)	(15.56)
Income Fluctuation	-0.698*** (-18.43)	-0.660*** (-17.30)	-0.749*** (-18.94)	-0.710*** (-18.61)
Cooking Fuel	0.479*** (8.15)	0.364*** (6.25)	0.388*** (6.53)	0.374*** (6.41)
Private Toilet	0.282*** (4.43)	0.195** (2.93)	0.211*** (3.32)	0.174** (2.72)
Own house	0.370 (1.47)	0.557* (2.32)	0.366 (1.58)	0.489 (1.87)
Persons per Room	-0.0969*** (-4.73)	-0.109*** (-5.04)	-0.0742*** (-3.50)	-0.0839*** (-3.90)
Solid house	0.169** (3.16)	0.126* (2.38)	0.0986 (1.77)	0.102 (1.88)
Non-Farm Employment In house	0.200*** (3.77)	0.325*** (6.53)	0.163** (3.08)	0.285*** (5.52)
Waged employment In house	-0.0615 (-1.11)	0.0885 (1.55)	-0.0533 (-1.00)	0.0430 (0.78)
Share health Insurance	0.107 (1.05)	0.333*** (3.37)	0.226* (2.26)	0.370*** (3.59)
Share Good health In house	0.382*** (7.21)	0.304*** (5.66)	0.454*** (8.51)	0.392*** (7.20)
Social problem In village	0.161** (2.64)	0.0905 (1.58)	0.187** (3.02)	0.131* (2.21)
Epidemic in Village	-0.0711 (-0.78)	-0.0227 (-0.26)	-0.145 (-1.73)	-0.113 (-1.38)
Access to Electricity	-0.00214 (-1.15)	-0.00266 (-1.16)	-0.00372** (-2.58)	-0.00537** (-2.74)
Access to Public water	0.00217** (2.84)	0.00200** (2.65)	0.00137 (1.87)	0.00126 (1.67)
Access to Sanitation	0.000407 (0.54)	0.00163* (2.28)	0.000268 (0.35)	0.00119 (1.64)
Access to Waste disposal	-0.000308 (-0.36)	-0.000294 (-0.35)	-0.000235 (-0.24)	-0.000347 (-0.39)
Access to Line telephone	-0.00146* (-2.06)	-0.00284*** (-3.98)	-0.00197** (-2.72)	-0.00251*** (-3.61)
Access to	-0.00348	-0.00359	-0.00289	-0.00531

Internet	(-0.92)	(-1.15)	(-0.79)	(-1.81)
cut1				
_cons	0.319	0.982**	-1.006**	0.548
	(0.92)	(2.62)	(-3.13)	(1.47)
cut2				
_cons	2.104***	2.341***	0.592	2.000***
	(5.99)	(6.27)	(1.84)	(5.36)
cut3				
_cons	3.943***	3.777***	2.326***	3.686***
	(11.18)	(10.14)	(7.25)	(9.92)
cut4				
_cons	7.431***	6.317***	4.536***	4.329***
	(20.48)	(16.62)	(14.00)	(11.61)
Observations	8118	8118	8118	8118
Categories	5	5	5	5
Pseudo R2	0.0975	0.0873	0.0795	0.0806
chi2	1533.9	1704.0	1371.7	1558.5

Ordinal Logit. Standard errors, clustered at village level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Dependent variables: Household subjective wellbeing variables are measured based on the average score of (household life satisfaction) and (subjective comparison wealth to other residents of village and of country) and (income satisfaction). Reference time for SWB1 and SWB2 is from the previous year of the survey year to the next year. Reference time for SWB3 and SWB4 is from five year ago to next five years.

Other controls: Household demographics, household income situations, household employment status, housing conditions, health status in household, social connection and security.

Analysis is following the OECD guideline in measuring subjective wellbeing

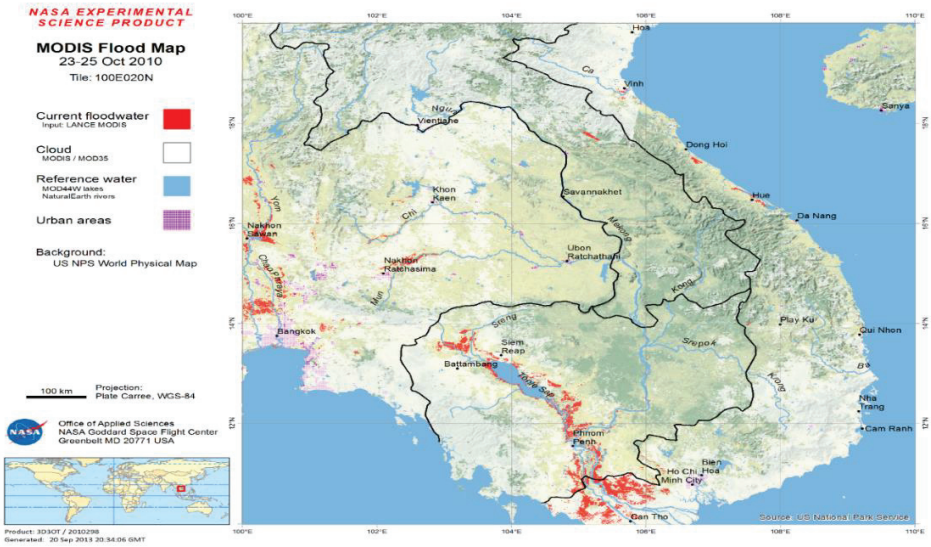
Source: Author's calculations

Appendix B

Figure B 1. Study areas of the "Vulnerability to poverty in Southeast Asia" survey

Source: ("Vulnerability in Southeast Asia - Overview," n.d.)

Figure B 2: MODIS Flood Map 23-23 October 2010, Tilte: 100E020N



Source: ("MFM_2010298_100E020N_3D3OT.Png (PNG Image, 3300 × 2550 Pixels) - Scaled (35%)")

Figure B 3: Coordinates on Google Earth of study village in Hue Province – Vietnam

Source: Author's work on Google Earth