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SEF Working paper: 11/2014

Floods and spillovers: Households after the 2011 great flood in Thailand

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Working Paper 11/2014

ISSN 2230-259X (Print)

ISSN 2230-2603 (Online)

Floods and Spillovers:

Households After the 2011 Great Flood in Thailand

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September, 2014

Abstract

In 2011, Thailand experienced its worst flooding in decades; it caused widespread damages, and a considerable loss of life. Using data from the Thai Household Socio-Economic Survey (THSES), this paper analyses its economic impacts. In the 2012 THSES, households answered a set of questions on the extent of flooding they experienced in the 12 months prior. As the same households are followed over time, the timing of the survey and its panel structure allows us to analyse household welfare before and after the flood, for both affected households and for those who were not directly flooded. We can thus measure the true impact of the disaster on income, expenditure, assets, debt and savings levels as well as labour market outcomes. We analyse flood impacts across different socio-economic groups and livelihoods, and identify spillover effects on those households that were not directly affected by the flooding.

JEL:

Keywords: disaster, flood, Thailand, economic impact

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1. Introduction

In 2011, Thailand experienced its worst flooding in decades. Not only did the flood cause widespread damages; atypically for slow-moving floods, it resulted in a considerable loss of life as well. The World Bank's Impact Assessment Report (2012) estimated there were 800 fatalities and a total loss of THB 1.43 trillion (USD 46.5 billion). According to current GDP figures, the estimated direct loss of property and infrastructure due to flooding amounts to nearly 13% of the Thai economy. Flooding affected many provinces (including most importantly the commercial hub of Bangkok) and had an estimated duration of 6 months.

Figure 1 maps cumulative annual rainfall in 2011, providing insight on both the severity and incidence of flooding across the country. According to the Thai Meteorological Department, mean annual rainfall reached its peak in 2011 representing a 24% deviation from normal. Alongside record-breaking rainfall, Poapongsakorn (2012) attributes the extensive damage to Thailand's inefficient water management, unplanned urbanisation and lack of reliable warning systems. He argues that economic and human losses could have been contained through the implementation of effective ex ante prevention and mitigation policies.

In terms of macroeconomic impacts, the sustained flooding resulted in a loss of production with the manufacturing sector accounting for an estimated 70% of the total damage (World Bank, 2012). GDP growth fell sharply in 2011 as seen in figure 2. Following manufacturing, the housing and agricultural sectors suffered the greatest losses. By some estimates, THB 110 billion were lost in wages, 1.9 million houses were affected and around 12.5% of the cultivated land in Thailand was damaged (Aon Benfield, 2012 & World Bank, 2012). With the country's rural population reliant on agriculture for their living, these impacts could have had potentially large welfare implications. Of note is that only 25% of total losses were covered by insurance.[1]

Understanding the impact such a momentous event had on Thai households is clearly important. It is necessary to evaluate this impact carefully not only so that ex-post assistance is well desgined and adequate, but so that the cost-benefit calculus of ex-ante prevention and mitigation policies are comprehensive and reflect a correct evaluation of possible scenarios. Interestingly, there is not much assessment of the impact of large sudden-onset events on household incomes and expenditures in middle-income countries. The little assessment that exists is either focused on households in high-

[1] This lack of insruance is typical for middle-income countries; and may suggest the prospect of a prolonged recovery period (Munich Re, 2012). Low- and middle-income countries do not have well functioning markets for insuring natural hazard risks, and many high-income countries are also signficantly under-provided with natural hazard insurance products.

income countries (especially in Japan and the USA) or the impact of slow-onset droughts on rural households in low-income countries (most common case study is Ethiopia).[2]

An investigation of the impact of a large adverse shocks on household income and expenditure patterns is crucial as their actions and experiences in the aftermath of the disaster can undermine their ability to fully recover. The risk of this possible 'disaster-poverty trap' is especially acute if households have limited external support and lack access to formal risk coping strategies such as insurance. Coping strategies such as selling off assets, reducing caloric consumption, reducing investment in education, or borrowing at punative interest rates, can all result in long-term welfare losses (Linnerooth-Bayer and Mechler, 2009; Janzen and Carter, 2013; Van den berg, 2010; Skoufias, 2003; Sharma et al, 2011; and Carter and Barrett, 2006). This ex post behaviour can impact their long term welfare and lead to persistent poverty.

Using data from the Thai Household Socio-Economic Survey (THSES), this paper analyses the economic impacts of the 2011 floods. In the THSES, households answered a set of questions in the 2012 version on the extent of flooding they experienced in the 12 months prior to the survey. As households are followed over time—surveyed in 2005, 2006,2007, 2010 and 2012—the timing of the survey, the detailed geographical information it includes, and its panel structure allows us to analyse household welfare before and after the flood. We investigate how the floods affected households that experienced direct flooding damage, and how it impacted those who were not flooded. This difference-in-difference approach can help us measure the true indirect impact of the disaster on variables such as income, expenditure, assets, debt and savings levels as well as labour market outcomes. We also analyse flood impacts across different socio-economic groups and livelihoods, characterize the spill-over effects, and validate our results with several robustness tests.

The rest of this paper is structured as follows. Section 2 reviews the relevant literature; it predominantly focuses on disasters that have occurred in developing countries and their effect on household welfare and poverty. Section 3 provides information on our data; Section 4 outlines the research methodology; and Section 5 presents the key results. Lastly, section 6 concludes and presents ideas for future research in this area.

2. Literature Review

The literature on natural disaster impacts has predominantly focussed on assessing impacts at the aggregate macroeconomic level (Noy, 2009; Kellenburg and Mobarak, 2011; Toya & Skidmore, 2007).

[2] See Karim and Noy (2013) for a survey of this literature.

This involves examining the effect of shocks on macroeconomic variables such as GDP growth using cross country data. Although studies show mixed results in terms of the impact of disasters on GDP, there seems to be a consensus that a country's level of development and their quality of institutions play an important role in the determination of overall economic costs.[3]

However, what about economic costs at the micro-economic level? Taking the macroeconomic view does not provide insight into the possible heterogeneous impacts that may exist within countries and the distiributional as well as the aggregate impacts. It is important to understand how natural disasters may impact household welfare; focussing on such variables as income, consumption and asset accumulation. Understanding the heterogenous impacts, and their distributional consequences, through studies such as our own, can help guide government policy in mitigating (and preventing) the potentially adverse impacts of natural disasters on households. This is especially important for middle-income countries, where many ordinary households lack the capacity to adequately respond to shocks, but the government has the resources to adapt policy to that reality.

There is very little literature that examines the impacts of disasters on firms' operations. Exceptions include several papers that trace the impact of the Japanese earthquake/tsunami of March 11th, 2011, on the Japanese firms' supply chains (e.g., XXX). Hallward-Driemeier and Rijkers (2011) focussed their gaze on Indonesian firms during the aftermatho of the 2004 Indian Ocean tsunami, and conclude that firm exits increased; their work failed to find any positive Schumpeterian 'creative destruction' effect. Chongvilaivan (2012) who provides a short descriptive investigation of the impact of the Bangkok floods on long supply chains.

While the literature on households and disasters is larger in scale and scope in comparison to micro firm-level studies, it still is fairly limited in its ability to identify and characterize impacts. Anttila-Hughes and Hsiang (2013) analyse the ex-post economic and health effects of typhoons in the Philippines. The authors use household panel data alongside variation in physical storm data to identify impacts on household income, consumption, and assets. Their results show that exposure to typhoons reduce household income by 6.6%, where this effect is consistent across different income groups. Further, this loss in income "translates nearly one-for one" in a reduction in household expenditure which decreases by 7.1% (p. 5). This implies an absence of consumption smoothing by households, who seemed to predominantly make adjustments to the level of their human capital expenditure. This research, however, focusses on regularly occuring events (typhoons in the Philippines) rather than on exceptional and unexpected ones.

[3] Cavallo and Noy (2011) provide a survey of this literature.

Similar to the 2011 floods in Thailand, Bangladesh experienced "the flood of the century" in 1998 (Del Ninno et al, 2001, p.15). Analysing the impact on household welfare, Del Ninno et al. find that more than half of those affected by the flood experienced a loss in assets, employment and days worked decreased in the agricultural sector, food insecurity was highly prevalent and many households faced severe health problems. An analysis of coping strategies showed that around 60% of households borrowed to maintain their expenditure levels. Mueller and Quisumbing (2010) build on this work by analysing the long run impact of the flood on household wages. The authors use a household panel dataset expanding five years after the disaster in order to gage both the short term and longer term impacts. Results show that long term impacts are more damaging as households saw wages decline by 4-5% when flood depth deviated from normal conditions.

Other studies which analyse long term welfare by focussing on rainfall and drought events in Ethiopia are Dercon (2004) and Carter et al (2007). Examining the effect of rainfall on consumption growth in rural Ethiopia, Dercon (2004) finds that shocks' impact persist over time. In particular, a 10% decrease in rainfall reduces food consumption by 3% several years after the event. Thus, apart from the immediate decrease in income caused by the drought, he identifies long-term welfare effects. Carter et al (2007) examine the long term impact on asset holdings of two natural disaster events: Hurricane Mitch and the Ethiopian drought. In the wake of these disasters, the authors examine the behaviour of households. They hypothesise that poorer households will engage in asset smoothing (since they face a higher risk of persistent poverty) whilst those well off will more likely smooth their consumption by running down assets. Results show that poorer households affected by Hurricane Mitch were most likely to reduce their assets ex post and they also faced lower asset growth thereafter. Similarly, data several years after the drought in Ethiopia show less wealthy households unable to recover their asset levels.

A recent paper by Janzen and Carter (2013) combines the literature on post-disaster poverty traps, assets and micro insurance. The authors evaluate the asset dynamics of households who received an insurance pay-out following a drought in Northern Kenya in comparison to those households who did not. Using instrumental variables to account for selection bias, their results show that households that received an insurance payment were 22-36 percentage points less likely to run down their assets. Further, they find a "critical behavioural threshold" (p.2). Households with asset holdings above a certain level are more likely to smooth consumption whereas those below the threshold display asset smoothing behaviour. Consequently, insurance pay-outs have a heterogeneous impact; they help stabilise consumption for less wealthy households and help protect assets for those who are relatively well-off. These results provide insight on the important role insurance can play in preventing households from engaging in costly/welfare-destroying coping strategies. Unfortunately, our data on Thai households does not include any information on insurance take up so this type of analysis is beyond the scope of this paper. In general, micro insurance evaluation in general, and index insurance related to natural hazards in particular, is an area which lacks robust empirical evidence. This is mainly due to data availability, very low insurance take up rates and selection bias in those who choose to insure.

In addition to this, there are a number of papers who look into analysing the impacts of excessive rainfall and drought spells rather than one-off natural disasters (see Assimwe, 2007 and Thomas et al 2010). The latter study shows how droughts can be more welfare damaging for households then floods, especially for those who work in agriculture. In general, the effects of droughts are hard to measure as they often have a slow but longer term impact on households.

Lastly, a recent paper by Poaponsakorn (2012) is the only systemic study to look at the impact of the 2011 Thailand floods on household welfare. As well as giving an overview of the immediate impact and causes of widespread damage, Poaponsakorn uses cross sectional household survey data alongside satellite images to determine the impact of the flood on household expenditure and income. Satellite data is used to determine which provinces were flooded and this information is matched with household addresses reported in the survey. Results show a negative impact, with expenditure decreasing by 6.7% for flooded households in comparison to those who were not flooded. Interestingly, non-flooded households were also negatively affected by the floods but by a smaller magnitude. The author attributes this result to the existence of indirect effects or negative spill overs due to a reduction in overall economic activity. Additionally, the stratification of households by income shows that the middle class showed a larger welfare impact in comparison to groups at the tail end.

The author does acknowledge the limitations of the use of satellite images to determine impacts and proposes future research with the use of digital elevation maps. Our study compliments as well as advances the work done by Poaponsakorn through our use of a unique panel data set where individuals self-report being affected by the flood. The self-reporting of shocks provides for a more reliable 'treatment' group as households have a better understanding of whether they have been affected by the flood or not. In contrast, the use of satellite images may only identify 'treated' households impercisely.[4]

Overall, it seems that economic impact of a natural disaster crucially depends on a household's ability to cope with the shock ex-post and their degree of exposure to the shock ex-ante. Most of the

[4] We use the satellite data in our robustness checks.

literature studied above links external meteorological measures with household survey data in order to determine the effect of natural disasters on households using cross sectional data. In this respect, our paper provides a valuable contribution. Instead of relying on external rainfall data, which is both infrequent and impercise, our analysis makes use of both self-reported shocks and publically-collected data to determine the impact of Thailand's worst natural disaster in recent years. Self-reported shocks are likely to be most relevant considering the floods were a result of heavy rainfall in the mountainous areas. The most heavily impacted regions did not necessarily experience the highest amounts of rainfall. This divergence enables our identification, coupled with the use of panel data, to provide the opportunity to obtain richer and more precise results.

3. Data

The data used in this paper comes primarily from the *Household Socio-Economic Survey* conducted by the National Statistical Office of Thailand. The survey was carried out over five different years (2005, 2006, 2007, 2010 and 2012 – data was collected Q2 and Q3 of each year), covers around 6000 households and provides data at both the individual and household level. The uniqueness of this dataset is that it tracks the same households across the five waves, providing a dynamic view of household characteristics on economic measurables such as income, expenditure, asset holdings, employment, savings and debt, and other socio-economic indicators such as health conditions.

3.1. The Shock Module: Identifying Flood Impact

Additionally, the 2010 and 2012 waves included a module on shocks faced by households and the coping strategies used to overcome them. Respondents were asked whether they were affected by particular shocks (including flooding) and were then required to provide details on the extent of damage caused, the loss of income experienced and the types of strategies used during their recovery. In 2012, 1067 households reported they were affected by flooding in comparison to only 122 households in 2010. We use these households that reported flooding in the 2012 survey as our 'treatment group' in analysing economic impacts. Our benchmark control group will be all the households that did not report being affected by flooding in the 2012 survey. Given the panel structure of the data, these groups can then be compared over time to analyse the economic impacts of the flood. Since we would like to use both the cross-section and time series available to us, we restrict the sample on which we conduct statistical analysis to those households which we observe for both the 2010 and 2012 waves. The survey maintains around 6000 observations per wave by adding new households if some houses drop from the sample. Fortunately for us, we have about 5100 households that are observed for both 2010 and 2012. An attrition rate of around 15%, while present, is not that severe and is unlikely to bias our results by much.

Since floods are a re-occurring event in Thailand, the self-reported shock in the survey could be picking up flooding that occurred in other parts of the country and were unrelated to the Greater Bangkok mega-flood associated with the monsoon season of 2011. Poapongsakorn (2012) identifies 26 provinces (out of 77) which were most affected by the mega-flood event. We use this information to define our treatment variable so that $Flood_i$=1 if the household reported being flooded *and* the household resides in one of the 26 affected provinces. This restriction is also applied to our alternative flood measures used to test the robustness of the self-reported shock indicator. After accoounting also for some missing data, we end up with full surveys on 591 flood-impacted households and 4500 households that were not impacted by the 2011 floods.

Table 1 provides a few summary statistics for those who reported being affected by the flood in 2012. On average, households impacted by the flood were impacted for 4.2 months. All impacted households reported losses of property, while over sixty percent of affected households reported a loss of income; the average value of property damage and of loss of income was both close to 40,000 THB. Households, however, have been differentially impacted by the shocks, with very large variance in reported losses of both property and income. The reported rise in expenditures, by household, was about half as large – almost 20,000 THB.

While we do not use this information in our statistical analysis, households also reported their use of coping strategies (this information is available in Appendix Table 1). Accumulated savings and regular cash income were the dominant strategies used by households to recover from the disaster. This was followed by informal financial support from relatives and children. Very few households made use of other possible coping mechanisms, such as selling off assets. Reported expenditure reductions were spread equally over certain categories including entertainment, leisure and clothing.[5]

3.2. Other Data from Household Survey

Several adjustments were made to the data available from the survey prior to conducting the statistical analysis. Variables of interest such as income, expenditure, debt and savings were all reported at the individual level while agricultural income and asset holdings were provided for the household unit. This required aggregating data across individual household members. It is possible that this may result in some double counting; which is most concerning with the expenditure data as

[5] Below, we examine actual reported changes in expenditure patterns by comparing 2012 to 2010 expenditure patterns, rather than rely on these changes as they are self-reported in the shock module.

multiple members may report spending on big items that benefit the whole household. To account for this, we create two expenditure variables: i) expenditure by household head only and ii) expenditure by all adult household members. Both income and expenditure variables are also aggregated by different sub-categories to provide additional insights. All monetary values are adjusted for inflation using CPI data from the Bank of Thailand to allow for comparisons across different years. Further, all variables are transformed into per capita terms and an additional precaution is taken by also creating per capita adult equivalent variables (dividing the data by household members above the age of 15).

The survery does not provide a measure of the stock of wealth owned by households, and it is therefore impossible to directly determine the household's socio-economic status. However, the survey provides information on asset holdings (livestock, housing, land, consumer durables and vehicles). It is impossible to aggregate these in order to get a measure for household wealth as asset values or quantities are not reported.[6] Therefore, we use principal components analysis to create an asset index which we then use in our statistical analysis.[7] For our purposes, the variables used to construct the index include the ownership of consumer durables (TV, fridge, phone, oven etc), the type of fuel used for cooking and the source of drinking water. The latter variables were re-coded into binary indicators. Land and house ownership, housing structure and indicators of access to basic utilities were excluded from the index since they displayed very little variation across households. Additional detail on the creation of the index as well as the weights used is provided in Appendix A. Table 3 shows summary statistics on household characteristics, including the asset index, broken down by treatment status and survey wave.

3.3. Other Data

Lastly, while the reliance on self-reported observations on flooding has some advantages, we see other advantages in using alternative measures of flood impact; self-reported shocks are, after all, potentially endogeneous and subjective (Thomas et al, 2010). Households may perceive interviewers as represtantive of assistance organizations, and misreport being affected by the flood or overestimate the damages caused in order to gain compensation. Further, households may have

[6] The total values for the vehicles and livestock owned by households before the 2011 floods (in the 2010 wave) are reported; this data is described in table 2.

[7] Principal component analysis is a method of data reduction commonly used for binary indicators in socio-economic surveys. The method uses the variation in asset ownership across households to assign weights or factor scores to each variable (Filmer and Pritchett, 2001; McKenzie, 2005). An asset which is owned by nearly all households will receive a lower weight than one which is owned by a select few. The weights are also dependent on the correlations between different assets and can take on negative values. For example, if owning a bicycle is correlated with assets of low socio-economic status (such as a mud house) it will receive a lower weight. These weights can then be used to construct a household index (Vyas and Kumaranayake, 2006).

implemented certain ex-ante strategies to ensure they are protected from any shock or have the means to cope with it ex-post. This may impact how and whether or not they report being affected. While these are all possible sources of biases, the shock module used in this survey asks a binary question of whether the household was affected by the flood or not. This significantly reduces ambiguity and the bias associated with misreporting. This study uses panel data to analyse impacts; comparing the same households across time controls for time-invariant factors such as the use of ex ante strategies for dealing with weather related risks.

In order to verify that our results are robust to any mismeasurement arising from our use of the shock module in the survey, we also use government data on flooded sub-districts as an 'alternative' measure of flood in order to test the robustness of the self-reported shocks. Thus, we identify flood-impacted households as those households that reside in sub-districts that the government reported as being flooded. Above, we have noted that 591 households in our survey self-reported being affected by the flood, of these, only 21 did not reside in these sub-districts that were affected according to the Thai government data. There were additional 1303 households that resided in the affected sub-districts but did not report being flooded. This alternative treatment group allows us to differentiate between directly-impacted households (those that reported being impacted), and indirectly-impacted households (those that reported not being impacted but resided in sub-districts that were impacted).

The Thai Government data on affected sub-districts also includes information about the duration of the flood in each area; distinguishing between floods that lasted less or more than two weeks. We use that information to identify whether long-lasting floods imposed higher costs on households (both directly and indirectly).

Finally, besides the survey data, and the Thai government lists of affected sub-districts, we also use measured rainfall data to control for any economic impact of rainfall that is unrelated to the flooding. Without accounting for rainfall, it is possible that some of our identified flood impact is just a function of the increased rainfall in affected areas (while we are more interested in the catastrophic incidence of floods).

3.4. Descriptive Statistics

Table 2 describes the households as they are observed prior to the 2011 floods, and compares our treatment and control sub-samples. We observe that income and outstanding debt is only marginally higher (about 5%) for the treatment group. The difference betwee treatment and control for business income and household expenditures, however, is larger; business income in the treatment group is, on average, more than twice as large, while total expenditures is about 50% higher. Correspondingly, average saving is also higher for the treatment group. The monetary values of assets are also higher for the treatment group, consistent with our observations that that the flood-impacted households were generally wealthier than their counterparts that were not impacted. This is largely because most of the impacted households reside in Greater Bangkok or the Central regions, and these are the wealthiest regions in the country. This is also evident when we examine the geographical distribution of households according to their socio-economic asset-index classification; see Figure 3 (the asset index is described in section 3.2).

It is important to note that the households in all regions are very diverse (with very large standard errors associated with all these measureable differences) so that none of the differences between the treatment and control observations detailed above are statistically signficant. In their demographic and labour force participation characteristics, the treatment and control households appear almost identical (see Appendix Table 1).

4. Estimation Methodology

The existence of treatment and control groups observed both before and after the flood provides an ideal setting to conduct a difference-in-difference analysis. In contrast to Poapongsakorn (2012), who used provincial level data, we will be using household panel data which provides both a cross-sectional and time series view of key outcome variables. The panel structure has several advantages. First, it helps overcome the problem of some unobserved heterogeneity; since we have several data points on the same household, we can take account of omitted time-invariant factors that differ across households. As we detailed in the previous section, this is especially important for the 2011 floods, as they occurred in the wealthiest region in Thailand. Second, the use of panel data allows us to control for long term trends or "dynamic changes" in outcome variables.

We start with a standard difference-in-difference model of the form:

$$y_{it} = \beta_0 + \beta_1 post_t + \beta_2 flood_i + \beta_3 post_t flood_i + \beta_4 X_{it} + \beta_5 post_t C_i + u_{it} \quad (1)$$

where $post_t = 1$ if the observation is from 2012 (post flood), $flood_i = 1$ if household reports being impacted by the mega-flood of 2011 (note this is not subscripted by *t*). If we were to estimate this model, we would be identifying the impact of flood on flooded households (β_3) and controlling for time specific effect (β_1), flooded household group specific effect (β_2), other time invariant factors (C_i), and other time-varying effects (X_{it}).

Because of the panel nature of this dataset, this model can be modified to control for household specific effect (instead of only for treatment/control group effect) by replacing $\beta_2 flood_i$ with household fixed effects model (δ_i).

$$y_{it} = \beta_0 + \beta_1 post_t + \delta_i + \beta_3 post_t flood_i + \beta_4 X_{it} + \beta_5 post_t C_i + u_{it} \qquad (2)$$

The potential sets of X_{it} to be included are deviation of yearly rainfall from normal (available at provincial level), government reported of other disasters, e.g., dummy of other flood in each year, dummy of drought in each year, we may try dummies for other disasters. This can be extracted from the self-reporting shock module at individual level.

A fixed effects regression is appropriate in this case due to our use of self-reported shocks. It is likely that there are unobservable time invariant factors (such as the degree of risk aversion) which drive the reporting of shocks by households and their impact. This could generate biased results. Thus, our model assumes that this unobservable effect (δ_i), may be correlated with our variable of interest; $E(\delta_i|Flood_{it}) \neq 0$. However, the exogeneity assumption regarding the error term still holds; $E(u_{it}|Flood_{it}\delta_i) = 0$. We use additional controls in our estimation in order to account for observable time-varying effects that may impact outcomes in the absence of floods. We estimate our model for two time periods only where 2010 is the year before the flood and 2012 is the year after. We can also estimate this model with location dummies at the provincial or district level, but estimations using these location dummies do not change any of our key findings (except for very small changes in our point estimates). We therefore do not report these regressions.

This 'treatment' effect assumes that both groups are facing the same time trends prior to the floods. As Meyer (1995) states, although we cannot assume that both the control and treatment groups are similar in every respect, we can make the more plausible assumption that any unobserved differences between these groups are constant over time—i.e., they display parallel trends in the dependent variables before the shock. Since these unobserved time-invariant differences are controlled for, we are able to estimate the true impact of the disaster on affected households. This assumption, however, may not always hold. If groups are being differentially impacted by other exogenous shocks, they will display non-parallel trends prior to the flood. The additional variables in the specification we estimate (X_{it}) are inserted in order to control for these additional exogenous differential changes. These include the education level of the household head, number of dependents, age of household head, the asset (socio-economic) index, the proportion of adults working in the household in the last 12 months, the gender status of the household head, a dummy variable indicating whether the household owns their own house, the deviation from the norm in annual rainfall and the presence of any other observable natural shocks (such as droughts).

We estimate equation (2) using a set of outcome/LHS variables (y_{it}): income, income by category, expenditure, expenditure by category, labour market outcomes, savings and debt. For the last three, we observe no statistically measurable impact of the floods, and we therefore do not report these regressions (these results are available upon request). We further differentiate between the effect of flooding on these outcomes variables across different groups; focusing in particular on socio-economic status and livelihoods (farm vs. non-farm) as determining the differential impacts. We use robust standard errors clustered at the sub-district level since we hyopthetsize that households residing within the same sub-district are more likely to experience similar outcomes.

5. Estimation Results

We start by presenting our results for a becnhmark restricted treatment (flood-impacted) variable: households that self-reported being affected by flooding in the latter half of 2011 and that reside in the 26 provinces that were affected by the mega-flood event associated with the monsoon season of 2011. We then discuss how these impacts are different across socio-economic status and livelihood (agriculturalists and non-ag) and spill-over impacts from affected households to unaffected households in regions that were impacted. The rest of the section is devoted to several attempts to further establish the robustness of our results using different measures of treatment and estimation techniques. In all tables, dependent variables are listed in the column headings. All variables are in real terms unless stated otherwise.

5.1. Self-Reported Shock

In our benchmark result, presented in table 3 column 1, we find that households who reported being flooded saw a negative impact on income (estimated to be around THB 4000; column 1, row 2). Many of the coefficients in our benchmark specification are not statistically different from zero, but those that are have the expected signs and magnitudes. Age seems to be associated with lower income. The number of adults working in the household is positively associated with household income, while the number of dependents is negatively associated with that measure. The amount of land owned by the household is positively associated with aggregate income. Overall, however, the ability of our model to explain the level of household income is fairly weak. This makes our results for the flood impact (the coefficient for *Post*Flood*) all the more remarkable, given their consistently statistically significant magnitude across many specifications.

The rest of table 3 includes a breakdown of income to its various components, as they are provided in the survey. The flood appeared to have negative impact, on average, on both agricultural and non-agricultural incomes, but it is only the impact on non-agricultural income (column 2) that is also statistically significant. When we break non-agricultural income into wage and business incomes, we find that this negative result is driven by the adverse and statistically significant impact of the floods on business income. So, maybe counter-intutively, the main impact is of the floods on business income rather than on agriculatural income.

Lastly, in our benchmark results in table 3, we also examine income from government support. We expect government support to increase after a natural disaster of this magnitude. We indeed find that on average government support did indeed increase for flooded households (relative to non-flooded households), but that this increase was very small relative to the amount of lost income these households experienced as a result of the flood. We also estimated the impact for household income without accounting for household size (i.e., not in per-capita terms). Results are very similar and are available in a web appendix.

Household per capita expenditures are described in table 4. Overall, flooded households did not change their spending levels in any statistically observalbe manner (the coefficient on *Post*Flood* is small and statisitically insigificant). This can be expected as households experienced, on average, decreases in income, and while they probably need to spend more following the floods, they are also likely to be more credit constrained. We do observe that flooded households experienced an increase in spending in the 'housing' category (which includes spending on housing repair and furniture – column 2). On the other hand, spending on luxuries decreased in equal measure (column 7). The coefficient estimates of the flood impact on spending on food, health, and education, are all negative, but statistically insignificant. Beyond our key independent variable of interest, we generally find the spending is higher for households with a higher socio-economic asset index, higher for household that have more adults working and fewer dependents. Households that owned a house spend less, on average, on housing expenses and more on luxuries (services or goods).

In separate regressions, which we do not report here, we examined the impact of the 2011 floods on labour market variables such as unemployment periods and the average number of jobs held, and changes in debt and savings levels. In all of these, the flood impact coefficient is always small and stasticially insignificant, while the models also have very poor explanatory power.

5.2. *Socio-Economic Status and Livelihood*

We use the durable asset index we created as a proxy for household wealth[8], to assist us in determining wheter we observe heterogeneous impacts of flooding across households with differing socio-economic status. The define households using their corresponding asset index into quartiles representing poor (Q1), middle income (Q2 & Q3) and rich (Q4) households. Table 5 provides a summary of results for our co-efficient of interest (*Post*Flood*), separately for each income group. We report only the coffient on the flood impact, but all other results are available upon request.

Results show a large and striking decrease in agricultural income for poor households which drives their decrease in total income (on average almost 70% of their decline in total income appears to be associated with agricultural income). For richer households (Q3 & Q4), the decline in income is mostly associated with declines in business income; the impact of the floods on agricultural income seems to be very varied (as relatively few rich households even have agricultural income. Intriguingly, and maybe disappointingly, the increase in government support is most pronounced for higher SES households (Q4) with, on average, increases in support of about THB 500 compared to THB 200 for the poorest quartile (Q1). As before, we observe that the magnitude of government support is not even close to being adequate in insuring (implicitly) households from the income shock associated with the flood.

The estimation of flood's impact on expenditure across households with different socio-economic index is also described in table 5. We fail to observe a consistent pattern. The richest households (in assets) tend to increase their spending the most on housing, significantly more than the poorer ones. Possible explanations for this is both that poorer households may lack the means to protect themselves against risk in the face of a shock and thus to pay immediately for reconstruction, and that the housing for richer households is more expensive to fix.

It is important to note that our results for household with different socio-economic status are somewhat less robust as the distribution of households across the SES index is not identical for the treatment and control groups. Unlike instances of other disasters (most frequently floods or droughts) richer households were more likely to be impacted by the 2011 floods than poorer ones – the richest quartile includes 40% of the treatment observations (flood impacted households) while only 15% of these are from the poorest quartile.

[8] See Filmer and Pritchett (2001) and McKenzie (2005) for similar uses of this type of information.

Next, we estimate our model separately for farm and non-farm households. Farm households are categorised as any household that answered 'yes' to the question 'Does anyone in your household work in agriculture?'. Approximately half of survey respondents work in agriculture. However, most agricultural households still reported non-agricultural earnings suggesting that households in this category diversified their income across different sources. Results show that non-farm households had a larger negative impact relative to those who were not affected and relative to flooded agricultural households. Business income decreased by 5,859 THB while expenditure on housing and repair increased significantly by 1,425 THB. Farm households also experienced a decrease in business income but the magnitude was much lower. Further, agricultural income increased for this group but this result was not statistically significant. Some of the ambiguity around flood impacts on agricultural income could be due to changes in agricultural product prices following the flood. It is likely that the prices of agricultural products, most notably rice, increased following the floods, thus increasing farmers' income. This will be explored later.

Overall, our results by SES and livelihood are consistent. Middle-income and richer households who work in the non-agricultural sector have been most affected by flooding. These outcomes are notably different from other cases of natural disasters whereby the burden of impact is on those who are most vulnerable (see literature review). We can get a clearer picture of why this has occurred by looking at household distributions. As we already noted, most of our treatment group is clustered around the Bangkok and Central regions and most of these flooded households have a higher socio-economic status. Additionally, figure 5 illustrates the type of household that live in the most affected areas; more non-farm households live in Bangkok and the Central regions, and these areas are highly populated by rich and middle income households. Given these distributions, it is clear why we are seeing greater impacts on richer and non-farm households.

5.3. Spillovers

Until now, we have estimated the impact of the floods on households that were directly impacted. However, it is likely that the floods also imposed indirect costs on households that did not suffer direct damages from the floods. These households are unlikely to be reporting having experienced the flood, but their incomes may have been affected as the regional economy suffers a slowdown, as supply chain are being distrupted, and as impacted businesses lay off workers. Furthermore, the floods are also likely to have changed relative prices in the impacted regions, thereby imposing further impacts on households that have not been directly affected.

In order to account for these spillover effects, we estimate the following model that allows us to identify both direct effect of the flood on flooded households and separately spillover effects on unaffected households located in the flooded areas. Uniquely for this paper, our data allows us to do that as we observe two different flood measures: household-survey self-reported flood measure $flood_i$ and the district-level flood areas $flood_d$ that is obtained from satelite data. Equation in 2 becomes

$$y_{it} = \beta_0 + \beta_1 post_t + \delta_i + \beta_3 post_t flood_i + \beta_6 spillover_i + \beta_4 X_{it} + \beta_5 post_t C_i + u_{it} \quad (3)$$

where $spillover_i = flood_d - flood_i \geq 0$. Intriguingly, we find that while our results for the direct impacts carry through, with an estimated average decrease in income of about THB 7600 for directly impacted households, households that were indirectly impacted suffer an almost equivalent decrease in income: about THB 6700. This result seems to be caused, as before, by a reduction in business income. Directly impacted households experience an average decrease in business income of THB 7200, while the spillovers cause other neighboring households to experience a decline in business income of THB 4500.

This is an important result. We show that accounting for the direct impacts of disasters on affected households is not a sufficient measure of the total cost of a disaster. Other neighboring but directly-unaffected households also experience a decrease in incomes, which can be, as in this case, almost as large as the adverse impact on the households that were directly damaged. This suggests that our traditional measures of disaster costs may be underestimating the true economic costs of disasters; and that this underestimate may be quite significantly too low.

Our claim that the costs may be underestimated is also reflected in our finding that government support does not increase for indirectly-impacted households; in fact the coefficient on the flood impact on government support for indirectly-impacted households is negative (though stastistically insignificant). It is not only our cost measures that may be ignoring these indirect costs, but also government policy.

As we already described, due to the widespread damage caused by the flood, households who did not report being flooded were still *indirectly* affected through a slowdown in overall economic activity, employee lay-offs, production stoppages etc. To further establish the robustness of this claim, we can test for the existence of spill over effects by modifying our model for a different control group. This modified control group excludes all households who did not report being affected but live in the 26 flood-affected provinces. For this new control group we would expect minimal spillover effects, as these households are located far away from any flooded areas. As we project, the negative impact on income with this new control group (one that is not contaminated by indirectly-affected households) is larger relative to our original control group which included non-flooded households located in flooded provinces (these results are available upon request).

5.4. Unobserved and Spurious Time-Varying Effects: Placebo Tests

Although our fixed effects model has controlled for any unobservable time invariant factors, there could still exist observed/unobserved time varying factors which we have been unable to account for in our regression and are systematically different between treatment and control. Both treatment and control households could be affected differently by other systematic shocks between 2010 and 2012 which could be driving the negative impact on income and expenditure. After all, the directly impacted households were not randomly chosen out of the total population of Thailand, and are more concentrated in some regions and in some income levels (see figure 4). We can test for any difference between the treatment and control households by examing placebo floods in previous years.

The results we presented up to now are based on using 2010 as pre-flood year; thus only using the 2010 and 2012 survey waves in our estimations. We now estimate a different model using all the years of survey waves available. In other word, will estimate

$$y_{it} = \beta_0 + \sum \beta_{1y} year_y + \delta_i + \sum \beta_{3y} year_y flood_i + \beta_4 X_{it} + \sum \beta_{5y} year_y C_i + u_{it} \qquad (4)$$

where $year_t$ are now a set of year dummies ($year_{2012} = 1$ if year=2012, $year_{2010} = 1$ if year=2010…using the oldest year as reference). The second term controls for year-specific fixed effect and the sixth term control for time invariant facts. The coefficients of interest are in the forth term; we estimate the flood impact variable specifically for each year β_{3y}. If our controls are appropriate, we expect β_{3y} to be insignificantly different from zero in all the years prior to 2012 (as in those years the treated households were in reality not exposed to exceptional flooding) and only significant in the year of flood 2012. We plot the coefficient for β_{3y} and 95% confident interval by year by outcome variables (see figure 5). We find these placebo results generally confirm both our model choice and the finding that the adverse impact is concentrated in business income, and that both government support and spending on housing increase, and that spending on luxury goods decreased. In this case, we also present some wekaer results identifying a decrease in spending on education.[9] The negative coefficient on education was present also earlier, but is not always

[9] These results are not exactly equivalent to the results we presented earlier, as in this case we estimated the model on household-level variables rather than on their per capita equivalent (income per household, rather than income per-capita per household, etc.)

statistically signficant; we thus hesitate to draw any firm conclusions from this potentially adverse finding.

5.5. Agricultural Income

The absence of any adverse impact on agricultural income (in some cases the coefficeint on flood impact for agricultural income is even positive) can be attributed to positive changes in prices and some agricultural outputs following the floods. Previous literature showed that, as opposed to other natural disasters such as droughts, floods can have a positive impact on the agricultural sector (Fomby et al., 2013; Loayza et al., 2012). Of course this depends on the intensity and timing of flooding as well as the production cycle of different crops. A report by the Bank of Thailand re-affirm this finding (Bank of Thailand, 2011); it states the agricultural sector "remained resilient" following the natural disaster, with production increasing by 3.8% for the year (p.2). Additionally, with extensive damage to rice crops in the central region, agricultural prices rose with sugar cane and palm oil production also benefitting from heavier rainfall. The rise in output and prices improved farm income. We indeed observe, using simple before-after regressions, that relative to other income categories we see a large significant increase in agricultural income for unaffected households. The magnitude of this positive effect gets larger as we reduce our sample to only 26 provinces whereas the effect on other income categories becomes insignificant (these results are available upon request).

5.6. The Intensity of the Flood

As we noted earlier, we also obtained some measure of the intensity of the flood experienced by households. In particular, the subdistrict satellite data that we use distinguishes between: (1) no flood areas, (2) flood less than 2 weeks and (3) flood more than 2 weeks.[10] This data thus enables us to distinguish, albeit somewhat crudely, between heavily flooded areas and less intense flooding. A better measure would also account for the depth of flooding (as a proxy for how much of the property was submerged), but this data is not available. We note that only 58 out of 467 of impacted households appeared to have experienced a flood of less than two weeks, and unfortunately, we do not have a more detailed measure of longer duration. In any case, we re-estimate our benchmark model, but instead of using a *flood* binary measure, we use separate binary measures for *big-flood* and *small-flood.*

We present the estimation results for flood intensity on income in table 8 and on expenditures in table 9. Maybe not surprisingly, but reassuringly, bigger floods appear to impose higher costs on

[10] The satellite readings are only available for Central and Northeastern provinces, and during the mega flood (Aug-Nov) only. Any estimates using this variable thus use a smaller sample.

households. In particular, those households that experienced the bigger floods (more than two weeks of flooding) experienced decreases in non-agricultural income that was about 40% larger than those households experiencing floods of shorter-duration. This is evident especially for wage income. Interestingly, government support seems to be unable to distinguish these more heavily affected households, and we see no increase in government support for them (if anything we observe a statistically insignificant decrease).

For expenditures, the results are somewhat less precise. We observe no difference between the increase in spending on housing between the long- and short-duration flooded households, nor between the decrease in spending on luxuries; and in both cases, the splitting of our treatment sample also meant that some of the statistical significance of our earlier results is no longer present.

5.7. Quintile Regressions: Using the Wealth Asset Index

In order to further examine the differential impact of the floods across different types of households, we use the asset index described earlier to examine the impact of the floods across asset-index quintiles. We present these results in table 10. We generally find that indeed wealthier households experienced larger losses in these floods, and also observe a corresponding larger increase in expenditures for these households. These results, however, are not uniform nor linear. In a few cases, the distribution of impacts across households wealth index measures, are rather more nuanced. For agricultural income, for example, the poorest households clearly suffer a significant decline, but so do the households belonging to the fourth quintile. The richest quintile, on the other hand, actually experiences an increase in agricutural income following the floods. This result may be a reflection of the wealthiest household's ability to have an impact on the flood mitigation policies, and in equal measure to take advantage of the increase in agricultural product prices in the post-flood period.

6. Concluding Remarks

This paper uses self-reported shocks from the Thai Household Socio-Economic Survey to analyse the economic impact of the 2011 floods on households. A difference-in-difference analysis shows that business income is driving the negative impacts on flooded households relative to the control group. This average negative impact on business income is coupled with a (much smaller) increase in government support. The significant decline in business income is consistent with both the geographic incidence of flooding and the aggregate decrease in manufacturing production reported in the World Bank's impact assessment report. Since the floods were centred around the central region, which includes the commercial hub of Greater Bangkok, we would expect business profits to drop on impact.

Further, we are able to identify the spillover effects on households that were not directly affected by the flood. The existence of these spillover effects mean that businesses were also indirectly and significantly affected by the natural disaster through a decline in overall economic activity.

When spending is examined, we find the flood induced an increase in housing expenditure alongside reductions in luxury and education spending. The latter result was somewhat concerning considering its negative long term implications. Aggregate impacts are being driven by richer households who work in the non-agricultural sector. Again, this result can be attributed to the location of flooding and the type of households representing the treatment group. In terms of labour market outcomes, however, the poor were the most affected; most likely due to lack of job security for low-skill jobs.

The above results were found to be consistent against a series of robustness checks including an alternative flood measure. There are, however, some limitations to our analysis. Our results do not provide any insight into savings and debt levels following the floods. Assuming households engaged in consumption smoothing we would expect a decline in savings or alternatively an increase in the amount of debt households take on. This is especially true given the excessive smoothness of the asset index and the (statistically) insignificant movement in ownership measures of other assets, such as livestock and land. Given that flooded households explicitly reported using savings as a 'coping strategy,' future research may want to more closely analyse saving dynamics; our own analysis has not been able to empirically quantify this channel.

We also note that households were followed at their physical location (their address). The followup in 2012 therefore did not include households that were forced to emigrate to another region as a result of the damage they experienced. If this is indeed an important oversight of our research, we should interpret our findings as an under-estimate of the true impact. It is likely that the most heavily impacted households were the ones that were forced to move, and thus our failure to identify and observe them may bias our findings downward.

Future research could also look at the impacts of flooding by duration and intensity. It is possible that the strength of flooding was different for households depending on their location and this information is not captured by our self-reported shock. We would have also liked to have more data on the different components of education spending and business income. In terms of the former, this would have helped us better predict any potential long term welfare implications through human capital accumulation. If children were being pulled out of school as a result of the disaster, this would have negative implications for a household's future income sustainability.

Additionally, data on household insurance take up would have helped in determining differential impacts of the flood for households who were formally protected against risk in comparison to those who were not. These results can inform government policy by providing insight on the role of insurance in cushioning the effects of the disaster. With the growth of microinsurance and other financial risk-transfer tools in Thailand and in other middle-income countries, this type of impact analysis will be both important and relevant. We leave this to future research.

The question of external validity - how relevant are our findings for other disaster events? – is clearly one that should also be asked. Of course any event is unique, but there are several characteristics of this event that we think make it relevant elsewhere. Most predictions of the future intensity and frequency of disaser events are fairly confident that flooding will increase as a result of climate change (no such consensus exists for other types of natural disasters). Many countries have a similar geographical distribution in which a central area (the most developed, industrialized and richer region) is also part of a major river delta and highly vulnerable to flooding. Examples include many of Thailand's neighbours (e.g., Vietnam and Burma). Furthermore, the predictibilty of the monsoon rains (even if their intensity was exceptional in 2011), suggest that mitigation is still far from sufficient in rapidly developing and urbanizing countries like Thailand. If anything, we believe that our results raise a warning flag regarding the disaster preparedness of many countries and their ability to reduce, mitigate, or adapt to future disaster risk.

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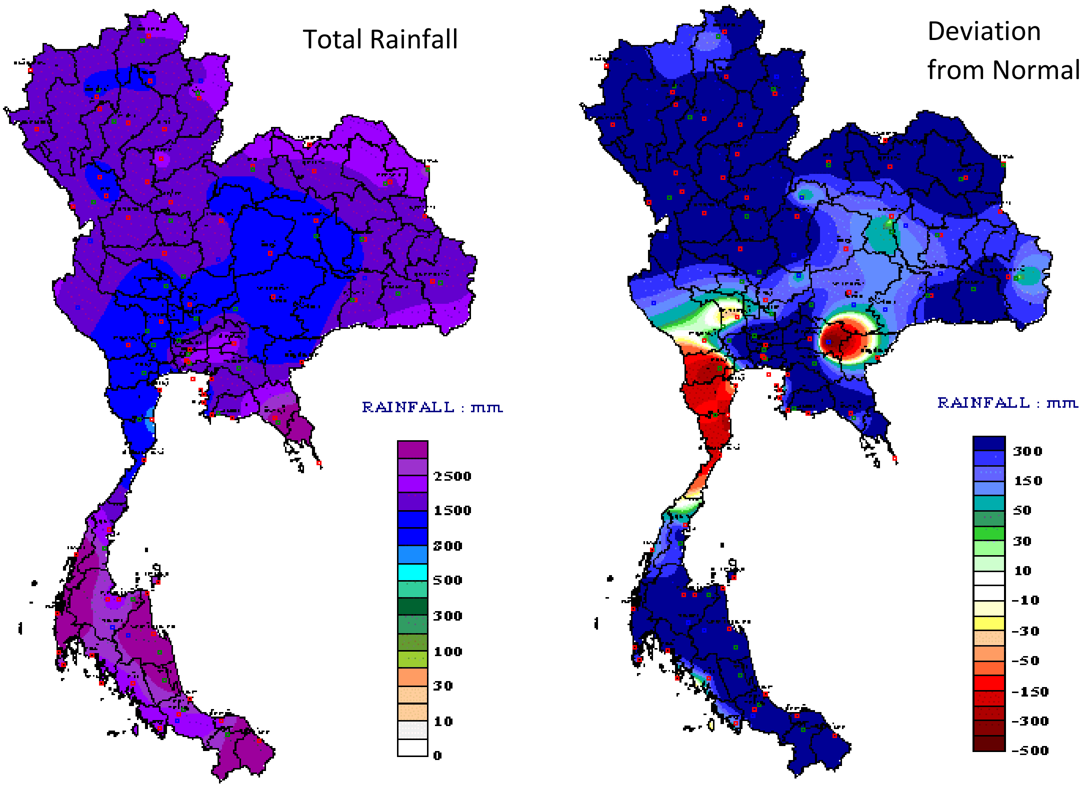
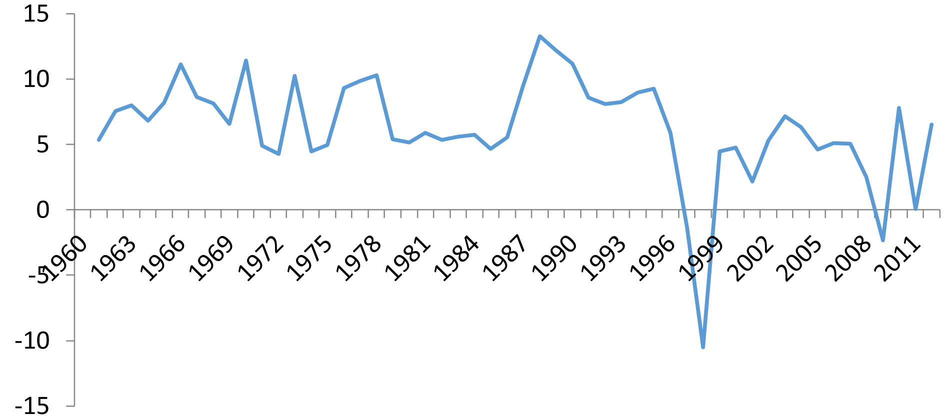
Figure 1: Annual Rainfall in Thailand 2011



Source: Thai Meteorological Department

Figure 2: GDP Growth in Thailand (%)



Source: World Bank

Figure 3

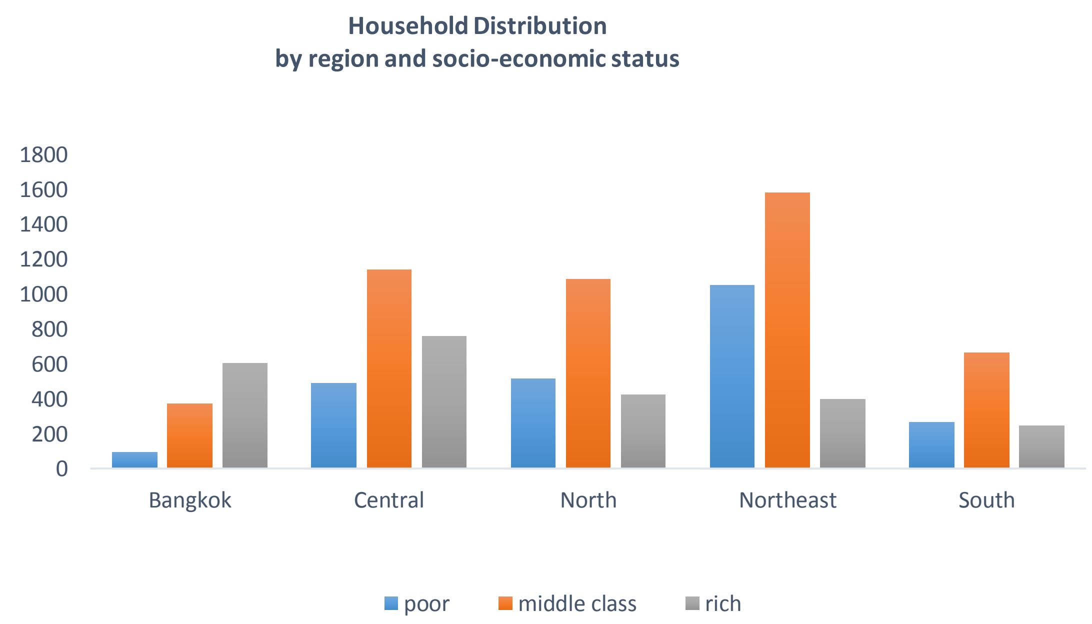


Figure 4

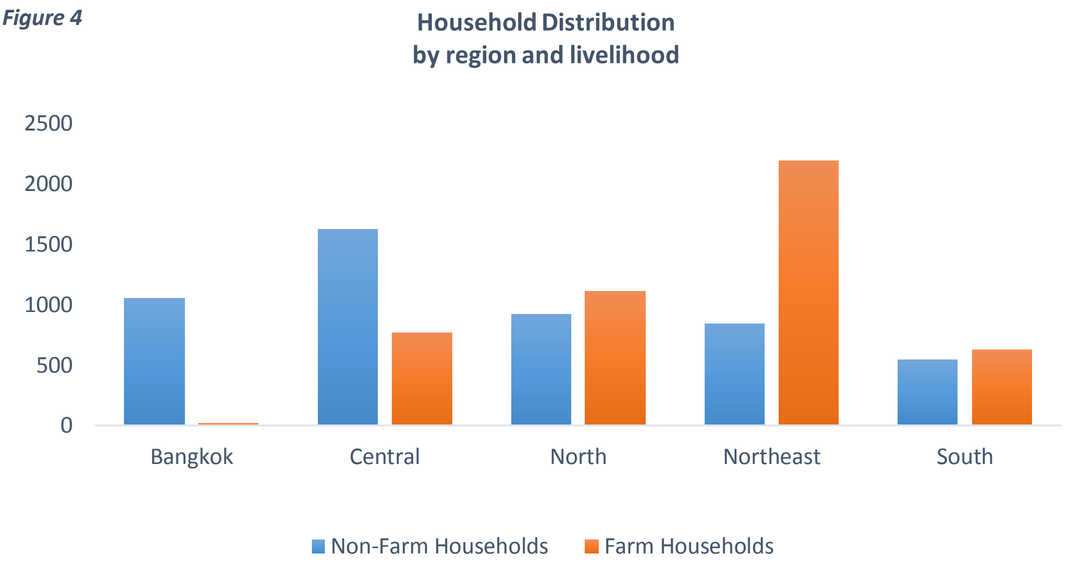
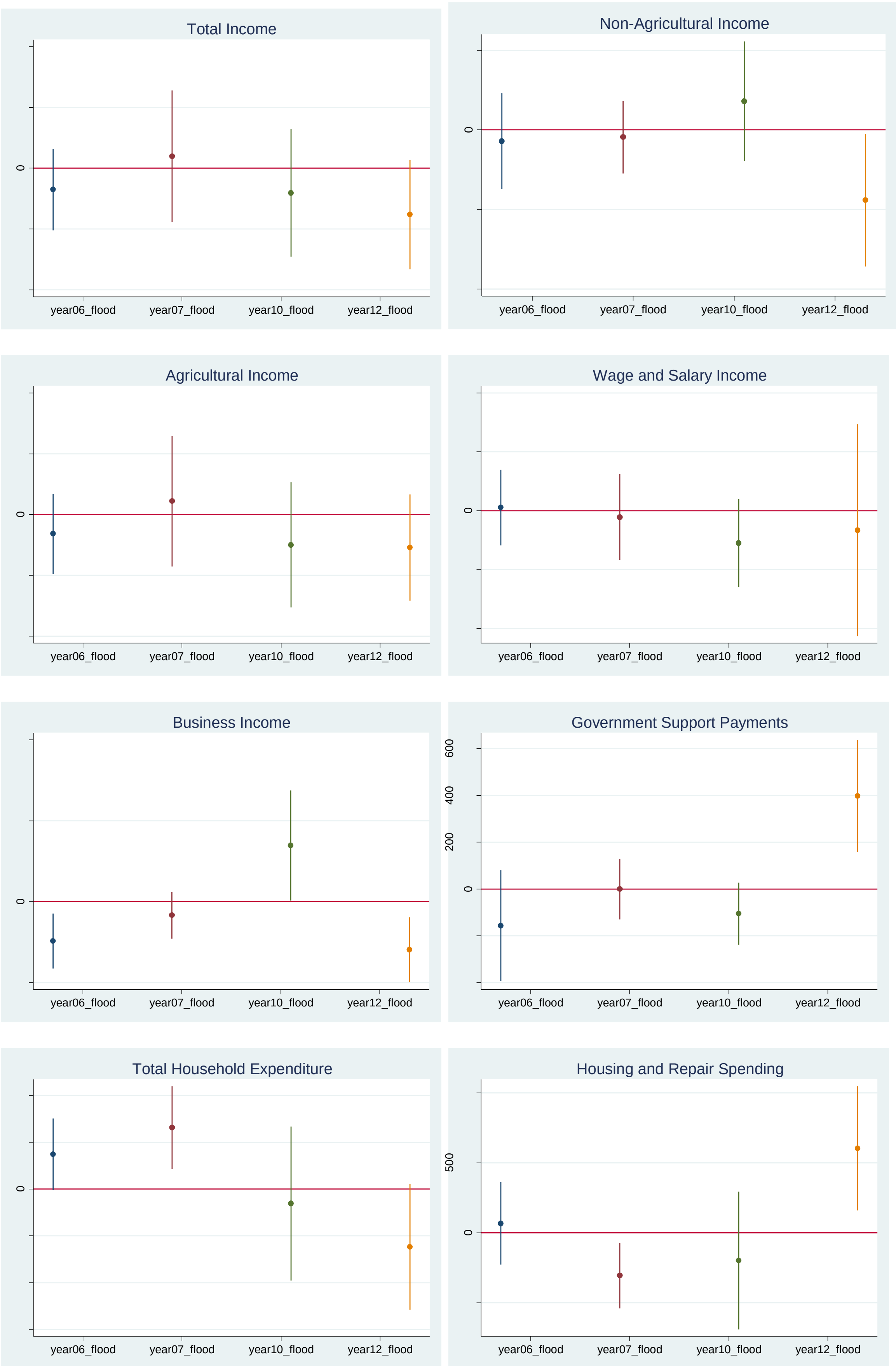

Household Distribution
by region and livelihood
2500
2000
1500
1000
500
0
Bangkok
Central
North
Northeast
South
Non-Farm Households
Farm Households

Figure 5: Placebo Treatments in Previous Survey Waves – Coefficient on Flood Impact



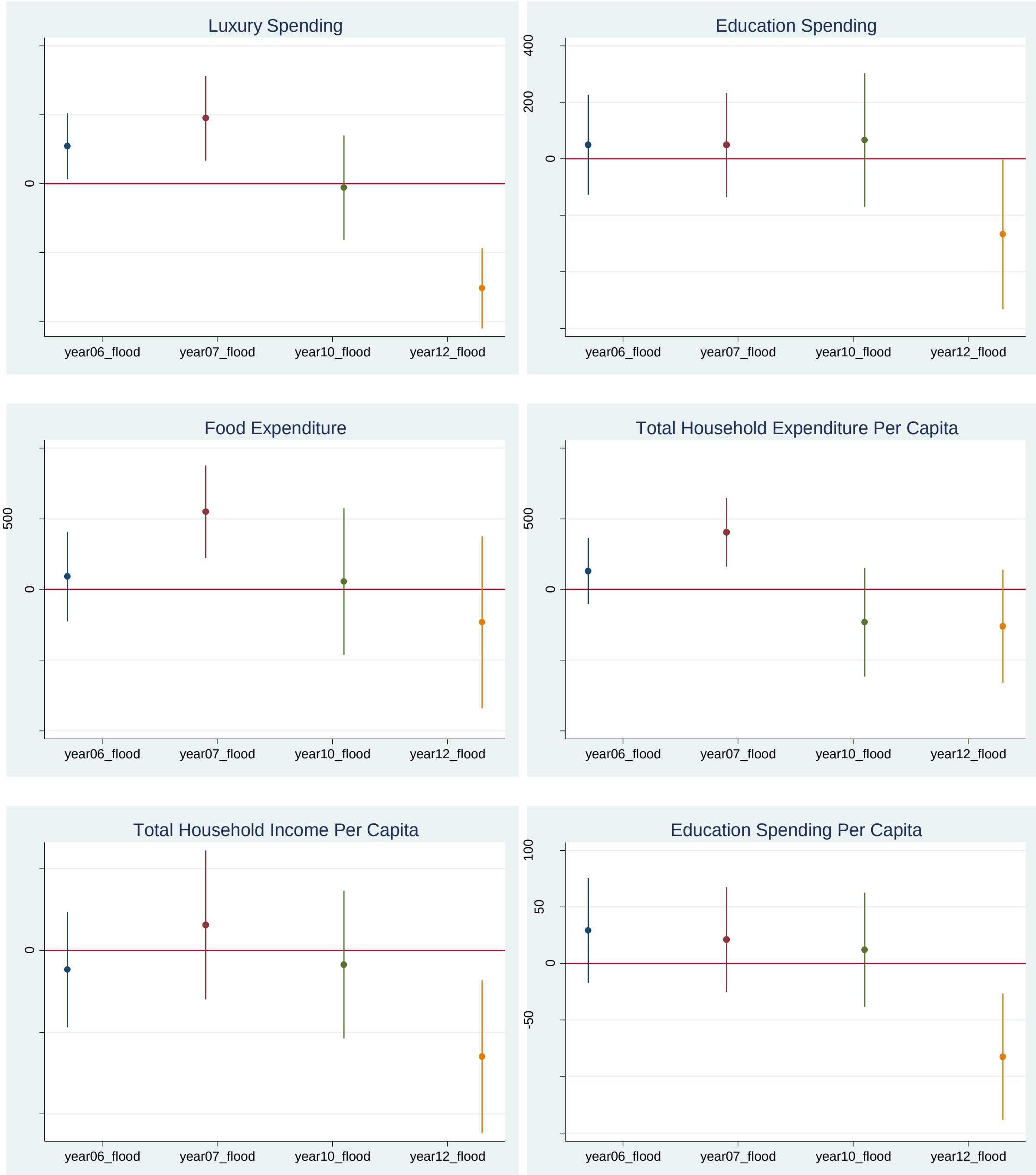

Luxury Spending
0
year06_flood
year07_flood
year10_flood
year12_flood
Education Spending
400
200
0
year06_flood
year07_flood
year10_flood
year12_flood
Food Expenditure
500
0
year06_flood
year07_flood
year10_flood
year12_flood
Total Household Expenditure Per Capita
500
0
year06_flood
year07_flood
year10_flood
year12_flood
Total Household Income Per Capita
0
year06_flood
year07_flood
year10_flood
year12_flood
Education Spending Per Capita
100
50
0
-50
year06_flood
year07_flood
year10_flood
year12_flood

Table 1: Summary Statistics: Loss and Damage Occurred

Loss/Damage	Mean	Std. Dev	Obs.
Months affected	4.2	2.88	1067
Value of property damage	37,988	229,168	1065
Value of loss in income	39,093	92,867	647
Value of expenditure rise	19,225	57,586	450

Table 2 Summary Statistics: Key Variables Prior to Shock (2010 wave)*					
	Treatment	**Control**		**Treatment**	**Control**
Total Income			**Value of Livestock**		
Mean	63,956	60,442	Mean	117,141	51,488
Standard deviation	140,192	134, 272	Standard deviation	377,691	134,699
Observations	591	4500	*Observations*	53	922
Business Income			**Value of Vehicles**		
Mean	10,255	4,774	Mean	242,032	211,123
Standard deviation	53,269	22,105	Standard deviation	350,192	392,069
Observations	591	4500	*Observations*	529	4090
Total Expenditure			**Total Government Support**		
Mean	18,220	13,393	Mean	516	570
Standard deviation	23,675	13,348	Standard deviation	832	1,256
Observations	591	4500	*Observations*	591	4500
Average Savings per Month			**Total Expenditure by Head**		
Mean	5,242	3,618	Mean	8,765	6,962
Standard deviation	10,139	10,240	Standard deviation	10,050	9,729
Observations	591	4500	*Observations*	590	4495
Outstanding Debt			**Total Income per Capita**		
Mean	218,384	192,878	Mean	18,136	17,711
Standard deviation	662,263	589,984	Standard deviation	33,431	37,056
Observations	591	4500	*Observations*	591	4500

*All variables are adjusted for inflation and measured in units of Thai Baht (THB)

	(1)	(2)	(3)	(4)	(5)	(6)
Table 3: Income Per Capita	Total Income	Non-Ag Income	Ag Income	Wage Income	Business Income	Gov't Support
Post	8,218**	1,907	15,348	1,173	513.1	205.8
	(3,634)	(1,212)	(13,678)	(782.0)	(620.1)	(225.1)
Post*Flood	-4,078**	-1,844**	-2,408	138.6	-1,701***	106.2***
	(1,984)	(863.7)	(5,736)	(575.4)	(642.4)	(38.45)
Educ*Post	377.7	633.1	2,544	307.5	285.5	-16.97
	(578.2)	(414.8)	(1,686)	(347.7)	(230.3)	(11.77)
Gender*Post	-3,050	-738.3	-8,182	-297.1	-243.1	-79.92
	(2,020)	(783.6)	(5,190)	(650.5)	(425.7)	(57.45)
Age*Post	-86.79**	-21.69	-73.79	-4.004	-18.43*	1.230
	(42.75)	(14.42)	(92.48)	(8.928)	(9.722)	(1.441)
Durable Asset Index	-128.3	580.7***	-2,669	246.3***	218.0	-19.19
	(760.9)	(181.4)	(2,409)	(93.76)	(152.3)	(16.57)
Proportion Working	9,838***	3,294***	10,178**	3,092***	1,178**	-22.74
	(1,985)	(714.7)	(5,186)	(341.8)	(563.9)	(93.52)
House Ownership* Post	1,362	-657.3	-3,755	-1,251	681.1	-67.51
	(2,223)	(1,727)	(10,500)	(1,653)	(516.5)	(86.82)
Dependents	-3,364***	-1,148***	-4,292***	-443.4***	-430.3***	-13.12
	(755.5)	(258.9)	(1,484)	(113.5)	(166.3)	(15.03)
Land Owned	570.4**	-4.256	491.0	13.75	-8.557	-1.301
	(273.5)	(22.55)	(303.1)	(19.88)	(8.196)	(1.170)
Livestock Value	0.0247	-0.0183	0.0256	0.000115	-0.0178	-8.20e-05
	(0.0522)	(0.0143)	(0.0528)	(0.000974)	(0.0144)	(0.000127)
Rainfall Deviation	4.939	0.551	6.960	0.279	-0.00347	-0.0428
	(3.253)	(0.929)	(5.963)	(0.664)	(0.514)	(0.0738)
Other Floods	3,165*	1,698	1,806	1,327	82.93	92.21
	(1,819)	(1,547)	(2,070)	(1,503)	(316.3)	(109.9)
Drought Spells	-254.1	-1,316	2,911	-879.3	-593.7	30.94
	(2,217)	(1,049)	(3,815)	(968.0)	(387.8)	(34.80)
Pest Infestations	453.4	-73.66	3,531	-203.5	-14.10	50.80
	(1,792)	(1,114)	(2,801)	(1,062)	(345.8)	(42.78)
Constant	5,965	1,682	16,569	-294.8	447.0	207.8
	(3,850)	(1,727)	(11,155)	(1,494)	(759.0)	(206.9)
Observations	9,290	9,290	4,413	9,290	9,290	9,290
R-squared	0.026	0.014	0.028	0.005	0.018	0.008
Number of id	4,810	4,810	2,552	4,810	4,810	4,810

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Table 4: Expenditure Per Capita	Total	Housing	Food	Health	Education	Other	Luxury
Post	439.3	78.67	282.3**	18.64	45.53	-77.03	44.51
	(466.6)	(173.0)	(138.6)	(44.12)	(83.78)	(103.6)	(297.8)
Post*Flood	-17.37	252.4***	-46.42	-0.225	-58.09	51.92	-224.6*
	(264.2)	(92.81)	(85.90)	(19.39)	(35.51)	(63.42)	(127.2)
Educ*Post	-69.78	26.51	-39.77*	0.893	11.85	10.33	-139.4**
	(75.73)	(22.43)	(20.94)	(7.519)	(16.70)	(17.22)	(57.20)
Gender*Post	-75.52	-45.56	-21.46	-7.953	12.19	12.65	-19.11
	(185.2)	(56.79)	(45.31)	(19.35)	(21.96)	(45.14)	(135.1)
Age*Post	-5.062	1.321	-2.213	-0.474	-0.422	-1.367	-2.208
	(5.651)	(2.176)	(1.770)	(0.615)	(0.715)	(1.010)	(3.112)
Durable Asset Index	454.4***	67.98**	98.89***	14.91**	13.75	20.26	252.6***
	(80.09)	(26.62)	(21.60)	(7.588)	(10.19)	(16.52)	(58.33)
Proportion Working	1,646***	261.6***	529.9***	-16.65	-94.31***	162.7***	826.4***
	(203.1)	(57.67)	(76.90)	(25.64)	(26.40)	(51.47)	(132.5)
House Ownership*Post	168.5	-195.6**	0.859	-9.921	-45.82	126.7	339.8**
	(241.5)	(81.41)	(82.69)	(17.63)	(33.45)	(82.27)	(161.5)
Dependents	-727.9***	-72.12**	-216.4***	-0.964	8.690	-63.98***	-408.5***
	(79.17)	(31.46)	(28.82)	(6.948)	(11.71)	(19.11)	(49.27)
Land Owned	2.944	0.211	-1.743	1.734*	0.326	-3.846	6.464
	(10.13)	(1.288)	(1.902)	(0.983)	(0.478)	(2.960)	(7.875)
Livestock Value	0.000408	-0.00115	4.94e-05	-0.000256	-5.42e-05	0.000123	0.00169
	(0.000880)	(0.00114)	(0.000203)	(0.000194)	(0.000162)	(0.000159)	(0.00126)
Rainfall Deviation	0.197	-0.0624	0.0434	-0.00561	0.0139	-0.0396	0.262
	(0.294)	(0.0690)	(0.0588)	(0.0276)	(0.0231)	(0.0509)	(0.238)
Flood Other	-369.4**	-242.3***	-116.8**	-10.99	42.64*	-35.48	3.053
	(178.7)	(86.67)	(48.77)	(36.61)	(23.18)	(44.58)	(98.54)
Drought Spells	296.9*	50.51	8.499	21.68	42.23*	-9.021	154.5*
	(170.1)	(54.32)	(52.58)	(22.18)	(24.58)	(50.16)	(92.17)
Pest Infestations	189.3	-38.83	5.424	-23.65	20.47	-25.99	211.2**
	(148.0)	(52.40)	(42.37)	(17.59)	(19.89)	(43.97)	(104.3)
Constant	1,960***	309.1**	1,117***	48.48	91.69*	212.4**	278.0
	(410.7)	(136.9)	(116.9)	(50.95)	(49.05)	(85.38)	(294.4)
Observations	9,290	9,290	9,290	9,290	9,290	9,290	9,290
R-squared	0.026	0.017	0.026	0.005	0.004	0.006	0.021
Number of id	4,810	4,810	4,810	4,810	4,810	4,810	4,810

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 5: Breakdown by Socio-Economic Status*						
Income						
	Total Income	Non-Agri Income	Agricultural Income	Wage & Sala Income	Business Income	Govt Support
Q1	-13,267***	-4,164*	-9,103**	-2,146	-1,127**	196.6
	(4,613)	(2,324)	(4,042)	(2,162)	(450.8)	(198.8)
Q2	-485.7	-4,572	4,086	1,114	-3,307	399.6
	(10,958)	(3,820)	(10,277)	(2,181)	(2,900)	(265.3)
Q3	-13,909	-4,807	-9,102	85.19	-5,714**	337.1
	(15,958)	(3,332)	(15,795)	(2,342)	(2,351)	(231.2)
Q4	5,475 (25,415)	-6,193 (6,582)	11,668 (24,594)	3,025 (4,140)	-9,199* (5,386)	516.1** (241.5)
Expenditu						
	Total	**Housing**	**Luxuries**	**Health**	**Education**	**Food**
Q1	503.3	240.6	-164.4	78.38*	17.17	289.6
	(550.0)	(249.5)	(292.5)	(46.76)	(31.55)	(378.0)
Q2	-105.7	472.5*	-295.9	51.31	-246.8	301.7
	(1,024)	(260.0)	(518.5)	(65.41)	(151.3)	(490.7)
Q3	-2,969**	81.96	-1,543*	1.007	-333.0	-1,037*
	(1,475)	(467.6)	(816.4)	(104.6)	(679.7)	(552.9)
Q4	234.0	1,995***	-1,496	227.4	-60.33	-452.2
	(1,862)	(575.8)	(1,210)	(193.1)	(424.9)	(631.5)

*Breakdown is using durable asset index where Q1 represents a household with the lowest socio-economic status and Q4 the highest. Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

	(1)	(2)	(3)	(4)	(5)	(6)
Table 6: Income Spillovers	Total Income	Non-Agri Income	Agri Income	Wage Income	Business Income	Govt Support
Post	33,354**	9,808***	23,546*	4,466**	3,711*	834.7
	(14,044)	(3,369)	(13,570)	(2,054)	(2,207)	(882.3)
Post*Flood	-7,337	-7,619***	282.2	70.93	-7,229***	324.2*
	(9,124)	(2,571)	(8,735)	(1,598)	(2,021)	(174.1)
Spillover	-4,366	-6,717***	2,351	-1,643	-4,476***	-166.1
	(6,556)	(1,695)	(6,275)	(1,048)	(1,379)	(148.8)
Educ*Post	-453.5	749.0	-1,203	149.6	583.3	-51.08
	(1,580)	(715.1)	(1,398)	(445.8)	(557.8)	(40.07)
Gender*Post	-6,770	-730.6	-6,039	-99.19	-22.48	-207.2
	(6,524)	(1,466)	(6,351)	(936.8)	(1,106)	(163.8)
Age*Post	-373.9**	-85.45**	-288.5*	-22.91	-46.53	1.407
	(155.4)	(42.29)	(147.3)	(23.13)	(32.95)	(4.465)
Durable Asset Index	5,625	3,497***	2,128	1,295***	1,574***	-11.22
	(3,455)	(661.2)	(3,385)	(317.0)	(608.4)	(50.99)
Proportion Working	20,007***	6,995***	13,012*	6,885***	2,457*	-31.75
	(6,998)	(1,795)	(6,673)	(846.6)	(1,485)	(256.6)
House Ownership*Post	5,750	-553.6	6,304	-1,459	675.7	-259.4
	(5,874)	(2,484)	(5,305)	(2,046)	(1,423)	(345.1)
Dependents	-158.8	667.4	-826.2	733.7*	-196.3	98.17
	(3,149)	(863.8)	(3,050)	(424.7)	(679.8)	(64.81)
Land Owned	1,839*	33.82	1,805*	62.47	-18.84	-2.296
	(1,013)	(85.07)	(949.0)	(77.58)	(27.75)	(4.171)
Livestock Value	0.122	-0.0652	0.187	0.000543	-0.0660	-0.000414
	(0.240)	(0.0569)	(0.223)	(0.00237)	(0.0572)	(0.000591)
Rainfall Deviation	9.600	-1.534	11.13*	-0.442	-1.090	-0.302
	(6.737)	(2.115)	(6.465)	(1.427)	(1.364)	(0.287)
Flood Other	6,224*	2,171	4,053	943.2	360.8	197.9
	(3,759)	(2,314)	(3,104)	(1,941)	(1,145)	(245.1)
Drought Spells	632.8	-3,120*	3,753	-491.9	-2,565*	26.23
	(8,656)	(1,819)	(8,422)	(1,118)	(1,421)	(91.41)
Pest Infestations	-203.8	-1,393	1,190	158.7	-1,659	40.42
	(6,050)	(1,822)	(5,643)	(1,334)	(1,237)	(114.2)
Constant	3,189	1,814	1,375	281.6	-842.8	468.0
	(13,861)	(3,820)	(13,282)	(2,196)	(3,081)	(469.4)
Observations	9,290	9,290	9,290	9,290	9,290	9,290
R-squared	0.022	0.033	0.020	0.014	0.026	0.009
Number of id	4,810	4,810	4,810	4,810	4,810	4,810

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Table 7: Expenditure Spillovers	Total	Housing	Food	Health	Education	Other	Luxury
Post	2,820*	242.5	1,270**	114.3	281.1	-38.32	908.8
	(1,552)	(560.2)	(501.8)	(124.9)	(277.0)	(277.9)	(827.1)
Post*Flood	-1,063	584.1*	-267.3	-31.83	-239.2	-78.48	-1,158**
	(1,087)	(340.2)	(383.0)	(62.15)	(173.8)	(162.3)	(464.7)
Spillover	-1,167**	-70.58	-173.4	-104.7	-93.96	-290.7***	-533.8
	(505.1)	(153.9)	(214.2)	(71.99)	(115.7)	(104.5)	(332.7)
Educ*Post	-287.3	50.36	-124.5**	-12.53	24.97	39.95	-412.8***
	(203.0)	(67.13)	(61.91)	(22.59)	(55.86)	(40.71)	(139.6)
Gender*Post	278.0	-9.790	85.92	-21.47	94.69	75.49	4.811
	(478.0)	(174.6)	(167.3)	(45.27)	(82.49)	(91.41)	(274.0)
Age*Post	-40.27*	-1.613	-14.74**	-1.651	-2.455	-2.977	-18.81*
	(21.38)	(7.362)	(6.862)	(1.582)	(3.122)	(3.317)	(10.22)
Durable Asset Index	2,254***	304.6***	633.5***	47.20**	58.13	100.1*	1,157***
	(256.6)	(84.30)	(82.89)	(23.49)	(47.10)	(52.00)	(167.4)
Proportion Working	2,565***	394.0***	909.1***	-109.4	-390.0***	258.0**	1,514***
	(532.0)	(149.6)	(221.7)	(69.62)	(93.20)	(122.1)	(348.6)
House Ownership*Post	380.8	-267.2	-57.21	3.589	-192.2	177.1	749.7*
	(627.3)	(206.0)	(277.3)	(54.87)	(118.0)	(138.7)	(389.0)
Dependents	312.7	45.47	419.7***	59.42**	99.62*	30.42	-348.3**
	(289.6)	(109.0)	(141.1)	(25.55)	(54.75)	(60.71)	(168.6)
Land Owned	17.39	1.870	1.475	4.668*	1.249	-11.99	21.24
	(31.12)	(4.719)	(6.609)	(2.566)	(1.991)	(8.620)	(22.32)
Livestock Value	0.000869	-0.00339	-9.10e-06	-0.00133	-0.000214	0.000744	0.00511
	(0.00352)	(0.00344)	(0.000640)	(0.000984)	(0.000642)	(0.000554)	(0.00398)
Rainfall Deviation	-0.131	-0.269	0.0415	-0.0422	0.0286	-0.376***	0.540
	(0.686)	(0.254)	(0.208)	(0.0588)	(0.107)	(0.125)	(0.440)
Flood Other	-1,185**	-621.4**	-442.8***	17.11	67.34	-113.1	-58.58
	(521.5)	(250.0)	(170.2)	(56.19)	(110.6)	(117.9)	(266.5)
Drought Spells	866.3	149.4	-15.31	56.14	152.2	-9.183	429.9
	(622.1)	(199.3)	(218.9)	(64.57)	(96.53)	(111.5)	(280.6)
Pest Infestations	-99.82	-135.9	-96.77	-60.02	34.43	-312.0***	286.5
	(452.5)	(167.6)	(174.8)	(59.19)	(76.03)	(103.9)	(295.3)
Constant	3,817***	662.9	2,354***	126.8	455.9*	648.7***	-120.5
	(1,247)	(403.5)	(469.4)	(127.6)	(245.8)	(237.7)	(797.3)
Observations	9,290	9,290	9,290	9,290	9,290	9,290	9,290
R-squared	0.041	0.013	0.031	0.010	0.004	0.010	0.042
Number of id	4,810	4,810	4,810	4,810	4,810	4,810	4,810

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

	(1)	(2)	(3)	(4)	(5)	(6)
Table 8: Flood Intensity, Income	Total Income	Non-Agri Income	Agri Income	Wage Income	Business Income	Govt Support
Post	31,854**	8,682***	23,171*	4,489**	2,654	811.6
	(13,685)	(3,296)	(13,205)	(2,030)	(2,152)	(865.2)
Post*Big_flood	-5,846	-7,300***	1,454	-2,957**	-3,730**	-226.4*
	(5,527)	(2,145)	(4,993)	(1,478)	(1,818)	(117.9)
Post*Small_flood	-1,547	-5,264***	3,717	-1,287	-3,597***	135.2
	(6,472)	(1,683)	(6,207)	(970.7)	(1,390)	(137.1)
Educ*Post	-543.4	703.0	-1,246	159.6	528.7	-50.18
	(1,591)	(712.3)	(1,413)	(441.8)	(554.3)	(40.75)
Gender*Post	-6,619	-568.4	-6,050	-36.25	69.28	-209.0
	(6,531)	(1,470)	(6,356)	(944.3)	(1,105)	(162.4)
Age*Post	-379.8**	-89.07**	-290.7*	-21.18	-51.49	1.368
	(156.8)	(42.56)	(148.7)	(23.16)	(33.36)	(4.542)
Durable Asset Index	5,634	3,539***	2,096	1,316***	1,590***	-7.299
	(3,442)	(661.0)	(3,371)	(317.2)	(606.2)	(51.22)
Proportion Working	19,906***	6,925***	12,981*	6,863***	2,413	-32.01
	(6,992)	(1,795)	(6,667)	(847.8)	(1,486)	(256.1)
House Ownership*Post	5,975	-272.8	6,248	-1,505	970.5	-250.8
	(5,827)	(2,466)	(5,271)	(2,031)	(1,416)	(339.4)
Dependents	-192.8	656.9	-849.8	722.2*	-192.7	92.50
	(3,137)	(860.6)	(3,039)	(421.5)	(678.2)	(64.71)
Land Owned	1,833*	27.12	1,806*	61.34	-23.86	-2.445
	(1,013)	(83.18)	(950.8)	(77.00)	(27.85)	(4.209)
Livestock Value	0.122	-0.0651	0.187	0.000520	-0.0658	-0.000416
	(0.240)	(0.0569)	(0.223)	(0.00240)	(0.0573)	(0.000587)
Rainfall Deviation	11.25	-0.528	11.78*	-0.577	-0.0248	-0.289
	(7.092)	(2.132)	(6.776)	(1.462)	(1.360)	(0.274)
Flood Other	6,831*	2,412	4,419	829.6	699.8	197.0
	(3,779)	(2,341)	(3,107)	(1,971)	(1,159)	(245.8)
Drought Spells	723.6	-3,369*	4,092	-578.8	-2,715*	48.58
	(8,600)	(1,858)	(8,353)	(1,159)	(1,439)	(91.34)
Pest Infestations	191.0	-564.8	755.9	361.6	-1,126	94.77
	(5,538)	(1,694)	(5,182)	(1,232)	(1,152)	(112.8)
Constant	2,203	1,113	1,090	334.6	-1,530	437.8
	(13,764)	(3,799)	(13,184)	(2,217)	(3,032)	(475.3)
Observations	9,287	9,287	9,287	9,287	9,287	9,287
R-squared	0.021	0.031	0.020	0.014	0.023	0.008
Number of id	4,809	4,809	4,809	4,809	4,809	4,809

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Table 9: Flood Intensity, Expenditure	Total	Housing	Food	Health	Education	Other	Luxury
Post	2,582*	237.4	1,262**	96.36	249.1	-118.6	802.2
	(1,535)	(548.1)	(495.0)	(124.1)	(281.7)	(277.8)	(830.1)
Post*B_flood	-1,525	200.3	-1,099***	-25.60	-39.25	-154.8	-580.4
	(1,000)	(226.8)	(270.8)	(81.21)	(151.1)	(239.6)	(821.7)
Post*S_flood	-613.5	226.3	-205.4	-44.24	-84.98	14.48	-617.4**
	(588.6)	(183.6)	(230.0)	(61.84)	(116.5)	(106.2)	(301.1)
Educ*Post	-293.4	50.27	-117.4*	-13.50	22.52	37.20	-419.6***
	(202.9)	(67.90)	(61.84)	(22.53)	(55.78)	(40.70)	(137.8)
Gender*Post	301.6	-19.56	103.5	-21.50	97.13	72.76	24.38
	(483.3)	(176.2)	(169.6)	(45.41)	(83.08)	(91.62)	(273.9)
Age*Post	-40.97*	-1.611	-14.22**	-1.741	-2.639	-3.431	-19.33*
	(21.58)	(7.426)	(6.919)	(1.591)	(3.129)	(3.321)	(10.21)
Durable Asset Index	2,264***	308.3***	636.4***	48.21**	57.81	103.3**	1,157***
	(257.7)	(84.69)	(82.63)	(23.25)	(46.61)	(52.12)	(167.5)
Proportion Working	2,549***	401.0***	893.3***	-108.7	-391.0***	258.0**	1,505***
	(533.9)	(149.9)	(222.3)	(69.62)	(93.06)	(123.1)	(349.5)
House Ownership*Post	436.4	-248.3	-86.26	12.62	-184.0	208.2	768.0**
	(628.1)	(207.7)	(282.7)	(53.30)	(119.3)	(138.6)	(385.9)
Dependents	304.6	40.11	417.3***	58.74**	100.2*	26.25	-344.4**
	(289.1)	(109.0)	(140.3)	(25.49)	(54.65)	(60.72)	(168.9)
Land Owned	16.09	1.820	1.232	4.571*	1.126	-12.32	20.70
	(30.76)	(4.725)	(6.591)	(2.578)	(1.950)	(8.519)	(22.17)
Livestock Value	0.000899	-0.00340	-2.57e-06	-0.00133	-0.000208	0.000752	0.00513
	(0.00345)	(0.00344)	(0.000633)	(0.000976)	(0.000641)	(0.000546)	(0.00396)
Rainfall Deviation	0.0779	-0.279	0.0215	-0.0270	0.0657	-0.298**	0.657
	(0.658)	(0.247)	(0.201)	(0.0582)	(0.104)	(0.122)	(0.430)
Flood Other	-1,126**	-633.6**	-448.9***	19.55	80.89	-88.97	-20.13
	(517.4)	(251.8)	(169.1)	(56.40)	(112.0)	(118.0)	(265.0)
Drought Spells	858.5	175.7	-31.75	56.35	148.7	9.275	391.0
	(597.3)	(192.2)	(210.2)	(63.15)	(93.67)	(111.8)	(277.7)
Pest Infestations	50.12	-59.94	-154.5	-34.02	43.73	-239.4**	316.0
	(441.6)	(159.3)	(163.7)	(49.42)	(71.29)	(98.68)	(282.9)
Constant	3,662***	637.7	2,385***	110.9	434.8*	577.4**	-179.3
	(1,240)	(406.1)	(462.7)	(125.9)	(240.0)	(234.4)	(792.5)
Observations	9,287	9,287	9,287	9,287	9,287	9,287	9,287
R-squared	0.040	0.012	0.032	0.009	0.004	0.009	0.041
Number of id	4,809	4,809	4,809	4,809	4,809	4,809	4,809

Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 10	Wealth Quintiles				
Dependent Variable	I.	II.	III.	IV.	V.
Total Income					
	1,093	453.5	-323.2	-253.3	-3,807
	(878.3)	(964.7)	(1,454)	(1,734)	(5,439)
Business Income					
	-482.7	256.3	281.5	-1,192	-1,117
	(438.5)	(557.1)	(853.6)	(1,011)	(3,451)
Agricultural Income					
	-5,893*	-563.3	-1,837	-4,825	17,193
	(3,480)	(2,487)	(4,362)	(9,941)	(27,547)
Total Income: Households that own land					
	-6,487*	-3,656	-12,729***	-13,586	-11,781
	(3,901)	(4,029)	(4,413)	(9,653)	(32,474)
Total Income: Households not owning land					
	1,960***	1,217	1,813*	1,121	-1,216
	(520.1)	(946.3)	(931.3)	(1,505)	(3,235)
Total Expenditures					
	849.7***	1,508***	1,157**	1,694***	1,338
	(257.6)	(337.1)	(462.1)	(611.8)	(1,185)

This table only presents the coefficient estimates for the Post*Flood variable, our main estimated parameter. All other controls were included in these regressions, however, and are not presented because of space constraints. Full results are available. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Appendix 1: Coping Strategies and Expenditure Patterns Following the Shock*			
Coping Strategy	**Mean**	**Expenditure Decrease**	**Mean**
Used regular income	0.73	Clothing	0.20
Savings	0.54	Entertainment	0.17
Family support	0.18	Gambling & Vice	0.15
Sold Household Items	0.14	Reduced Food Intake	0.15
Informal borrowing	0.10	Removed Child from School	0.01
Borrowing from bank	0.13	Education	0.05
Sold assets	0.02		
Mortgaged house	0.01		

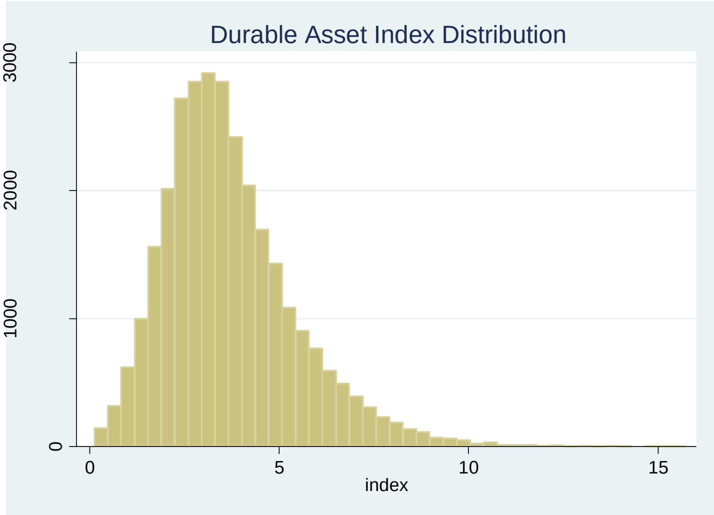
*All variables are binary. Mean values indicate the proportion of flooded households who decreased expenditure for that category or made use of the particular coping strategy

Appendix 2: Asset Index

Asset variables were assigned weights using the first principal component where each principal component gives us a linear weighted combination of all the different asset variables (Vyas & Kumaranayake, 2006). $PC_1 = a_{11}X_1 + a_{12}X_2 + \cdots + a_{1n}X_n$. In the following table are the weights assigned to our asset variables as well as a set of summary statistics. An index for each household is then created my multiplying each variable's factor score by the quantity of the asset held by the household. $y_i = a_1X_1 + a_2X_2 + \cdots = \sum_{k=1}^{n} a_kX_k$. The graph plots the distribution of the asset index upon calculating each individual household's score.

Principal Components Analysis Output

Variable	**Factor Score**	**Mean**	**Std. Dev.**	**Min**	**Max**
Sleeping rooms	0.2057	2.81	1.34	1	8
Electric cooking pot	0.1536	1.12	0.85	0	8
Microwave oven	0.2503	0.19	0.41	0	6
Refrigerator	0.2198	0.95	0.46	0	6
Electric iron	0.2185	0.86	0.47	0	8
Electric kettle	0.2119	0.68	0.51	0	6
Air conditioning	0.2640	0.27	0.72	0	8
Fan	0.2666	2.46	1.40	0	8
Radio/Stereo	0.2012	0.78	0.65	0	8
Television	0.2882	1.31	0.73	0	8
Video/DVD player	0.2521	0.80	0.64	0	8
Washing machine	0.2516	0.55	0.54	0	6
Hot water supply	0.2410	0.16	0.42	0	8
Cable TV	0.1472	0.06	0.25	0	6
Satellite dish	0.2381	0.29	0.50	0	6
Telephone	0.1148	0.14	0.36	0	4
Cellular Phone	0.2609	1.45	1.22	0	8
Facsimile	0.1055	0.02	0.18	0	6
Computer with internet	0.2140	0.14	0.42	0	8
Computer without internet	0.1250	0.10	0.33	0	8
Cooking Fuel*	0.1829	0.66	0.47	0	1
Drinking Water *	0.1250	0.62	0.49	0	1



Durable Asset Index Distribution
0
1000
2000
3000
0
5
10
15
index

Appendix Table 1

Table 2 Summary Statistics: by wave and treatment status				
	2010 Wave		**2012 Wave**	
	Treatment	Control	Treatment	Control
Age of Household Head				
Mean	54.49	54.08	56.46	56.40
Standard deviation	14.04	14.23	14.17	14.26
Observations	590	4495	584	4443
Education of Household Head**				
Mean	2.71	2.40	2.86	2.57
Standard deviation	1.72	1.46	1.63	1.38
Observations	567	4174	560	4129
Proportion of Land Owned				
Mean	81.41	88.66	68.46	81.08
Standard deviation	30.73	41.20	39.86	45.39
Observations	149	1849	176	2070
House Ownership*				
Mean	0.78	0.86	0.83	0.88
Standard deviation	0.41	0.34	0.37	0.33
Observations	590	4495	590	4477
Households Working in Agriculture*				
Mean	0.33	0.51	0.32	0.49
Standard deviation	0.47	0.50	0.47	0.50
Observations	591	4500	591	4500
Households Owning Livestock*				
Mean	0.27	0.40	0.21	0.28
Standard deviation	0.45	0.49	0.41	0.45
Observations	193	2306	188	2195
Proportion of Adults Working in Household				
Mean	0.72	0.74	0.69	0.71
Standard deviation	0.29	0.30	0.30	0.32
Observations	591	4497	591	4496
Household Members				
Mean	3.80	3.65	3.74	3.57
Standard deviation	1.91	1.76	1.82	1.78
Observations	591	4500	591	4500
Durable Asset Index				
Mean	4.61	3.95	4.83	4.11
Standard deviation	2.11	1.72	2.07	1.73
Observations	590	4495	590	4477

*Indicates binary variable. Mean value can be interpreted as a percentage.**Indicates categorical variable (ascending order)

I. Full sample

1. Income Per Capita	(1) Total Income	(2) Non-Agri Income	(3) Agricultural Income	(4) Total Wages	(5) Business Income	(6) Other Income	(7) Govt Support
Flood	-4,359**	-1,241*	-4,548	418.9	-1,455***	-205.6	111.1***
	(1,890)	(664.1)	(4,036)	(626.6)	(516.0)	(177.4)	(39.13)
Education	589.3	179.0	4,259	154.9	-120.5	144.6	6.685
	(490.9)	(269.8)	(2,909)	(213.4)	(135.1)	(87.02)	(7.687)
Age	-105.1**	-44.88**	-46.83	-24.23	-30.50**	9.850*	4.227
	(47.97)	(19.87)	(94.16)	(16.87)	(12.14)	(5.551)	(2.571)
Gender	-2,686	-734.9	-7,538**	-438.6	-419.3	123.0	-10.35
	(1,782)	(703.0)	(3,400)	(790.1)	(392.7)	(138.3)	(42.87)
Asset Index	-387.9	-526.7*	2,293	-378.1	1.171	-149.7***	-15.45
	(411.2)	(259.0)	(2,194)	(220.5)	(101.1)	(40.25)	(13.26)
Proportion Working	5,894**	840.4	14,818*	463.9	309.2	67.31	0.130
	(2,500)	(842.0)	(7,941)	(897.1)	(496.7)	(178.4)	(66.46)
House Ownership	4,063**	581.3	-1,830	221.2	417.5*	-57.45	-81.68
	(1,588)	(786.1)	(5,045)	(668.7)	(237.5)	(191.2)	(88.40)
Dependents	-414.9	-278.4	-1,342	-321.7	-37.53	80.82	-0.680
	(1,220)	(289.5)	(2,450)	(206.4)	(119.8)	(50.78)	(22.07)
Constant	5,753**	5,519***	-9,579	3,255***	2,444*	-179.1	-19.69
	(2,310)	(893.3)	(9,859)	(558.3)	(1,294)	(503.7)	(247.3)
Observations	4,543	4,543	1,944	4,543	4,543	4,543	4,543

2. Expenditure	(1) Total Expenditure	(3) Housing	(4) Luxury	(5) Food	(6) Health	(7) Education	(8) Other
Flood	96.13	801.4***	-632.3	-16.91	25.70	-192.7	110.9
	(1,207)	(283.2)	(446.5)	(472.1)	(43.11)	(192.7)	(105.7)
Education	104.8	96.92	-0.764	-99.60	-5.025	35.91	77.31
	(251.1)	(107.5)	(137.1)	(58.76)	(23.83)	(41.93)	(62.68)
Age	-51.88**	-5.110	-26.57***	-20.22**	0.0833	0.328	-0.395
	(19.64)	(6.042)	(9.195)	(8.614)	(1.424)	(2.056)	(2.263)
Gender	434.9	-39.42	182.2	43.00	-32.39	94.98	186.5***
	(495.9)	(142.2)	(246.9)	(187.4)	(39.18)	(87.07)	(60.75)
Asset Index	-799.1***	-1.156	-465.5***	-222.4**	-31.16*	-38.49	-40.47
	(266.1)	(41.99)	(135.9)	(93.77)	(16.24)	(30.81)	(28.74)
Proportion Working	-582.3	-49.27	-733.8*	-222.3	230.8**	138.5	53.68
	(563.3)	(143.6)	(398.1)	(178.7)	(105.5)	(150.2)	(110.6)
House Ownership	1,031	-40.90	1,059**	-100.1	41.40	-169.8*	241.0
	(1,160)	(186.3)	(383.9)	(511.3)	(68.64)	(90.11)	(195.2)
Dependents	-14.46	-3.720	-109.1	-25.61	14.30	131.1***	-21.46
	(231.3)	(59.50)	(130.6)	(68.77)	(30.49)	(35.97)	(57.67)
Constant	5,073***	212.6	2,782***	2,608***	-122.0	-13.41	-394.6*
	(1,030)	(444.6)	(650.2)	(535.3)	(174.2)	(155.6)	(211.8)
Observations	4,543	4,543	4,543	4,543	4,543	4,543	4,543

3. Savings & Debt	(1) Average Savings Per Month	(2) Debt Outstanding	(3) Savings Per Capita	(4) Debt Per Capita
Flood	1,285	27,397	670.4	17,962
	(1,317)	(35,764)	(581.1)	(17,222)
Education	-259.3	-2,316	-112.2	-2,229
	(221.2)	(9,439)	(90.33)	(3,063)
Age	4.609	880.8	3.138	167.6
	(15.61)	(607.0)	(6.267)	(209.3)
Gender	464.6	19,226	136.8	17,488*
	(543.8)	(25,870)	(211.0)	(9,890)
Asset Index	-587.6***	-8,231	-157.8**	-955.2
	(135.1)	(9,281)	(57.56)	(4,097)
Proportion Working	-1,296**	3,567	-857.0**	-9,943
	(551.1)	(35,567)	(346.1)	(17,062)
House Ownership	-178.6	-5,528	38.38	-14,067
	(716.9)	(27,316)	(281.8)	(14,486)
Dependents	151.5	-15,181	60.51	-1,512
	(118.1)	(9,439)	(55.81)	(3,666)
Constant	3,010	-20,963	1,083	5,664
	(1,922)	(71,815)	(805.4)	(32,073)
Observations	4,543	4,543	4,543	4,543

4. Assets	(1) Asset Index	(2) Livestock Value	(3) Vehicle Value	(4) Land Ownership	(5) House Value Per Capita
Flood	0.0607	-4,567	23,653	-0.268	805.3
	(0.0704)	(22,219)	(66,622)	(1.997)	(27,818)
Education	-0.0409***	-4,944	44,759	-0.371	10,921
	(0.0109)	(11,651)	(27,741)	(0.807)	(7,786)
Age	-0.00413**	-1,198*	1,751	-0.103	660.8*
	(0.00194)	(593.6)	(2,920)	(0.127)	(349.5)
Gender	0.0544	-148.5	65,191**	7.889**	-9,564
	(0.0551)	(7,477)	(29,040)	(3.241)	(16,584)
House Ownership	-0.0130	-34,893	-110,680	2.825	59,803**
	(0.0703)	(67,545)	(109,278)	(8.102)	(26,375)
Proportion Working	0.0476	-34,264	70,442	1.709	-65,018***
	(0.0608)	(34,487)	(84,701)	(5.507)	(21,363)
Dependents	0.0216	6,711	-22,925	1.486	-6,940
	(0.0196)	(6,060)	(18,436)	(1.054)	(4,473)
Asset Index		253.7	28,927***	-0.413	-6,626
		(8,073)	(9,206)	(0.949)	(4,703)
Constant	0.410**	146,637	-200,211	-6.261	4,232
	(0.194)	(85,827)	(188,321)	(13.66)	(52,037)
Observations	4,536	432	4,036	1,627	3,927

5. Labour Market (province dummies)	(1) Hours Worked Per Week	(2) Day Worked Per Month
Flood	2.219**	1.016**
	(0.946)	(0.463)
Education	-0.779***	-0.416***
	(0.0963)	(0.0622)
Age	-0.165***	-0.111***
	(0.0146)	(0.0116)
Gender	1.603**	0.814***
	(0.670)	(0.254)
Asset Index	0.614***	0.279***
	(0.168)	(0.0728)
Proportion Working	-20.21***	-10.86***
	(0.771)	(0.407)
House Ownership	-1.236	-0.724**
	(0.724)	(0.345)
Dependents	-1.045***	-0.451***
	(0.301)	(0.0964)
Province_1	0.423	0.0107
.	(1.595)	(0.477)
.		
.		
Constant	17.92***	12.38***
	(1.560)	(0.973)
Observations	4,543	4,543

II. 26 Provinces

1. Income	(1) Total Income	(2) Non-Agri Income	(3) Agricultural Income	(4) Wage & Salary Income	(5) Business Income	(6) Govt Support
Flood	1,141	-463.9	9,093	1,767	-2,585**	523.2***
	(10,096)	(1,740)	(27,626)	(1,550)	(1,121)	(107.1)
Education	385.6	-323.2	14,071	-803.2	546.8	6.007
	(3,628)	(778.2)	(12,054)	(514.9)	(829.6)	(20.78)
Age	-447.3	-101.8	-1,104	-49.46	-34.10	4.923
	(318.5)	(72.12)	(943.8)	(32.10)	(69.37)	(3.604)
Gender	-623.0	-1,793	-7,686	-539.0	-701.8	-71.60
	(7,496)	(1,978)	(18,071)	(2,051)	(1,063)	(74.90)
Asset Index	-3,507	-2,179***	5,731	-317.2	-1,506**	21.94
	(2,150)	(754.0)	(10,549)	(402.8)	(661.4)	(42.60)
Proportion Working	4,924	-965.4	22,453	207.5	-1,255	169.7
	(16,625)	(3,315)	(71,024)	(2,284)	(3,107)	(172.5)
House Ownership	11,323**	-401.4	23,556	-1,608	693.1	216.9**
	(5,130)	(3,367)	(19,880)	(1,903)	(2,017)	(84.34)
Dependents	1,391	-184.9	2,592	-404.5	281.8	9.102
	(4,288)	(1,492)	(7,646)	(341.3)	(1,177)	(38.48)
Constant	33,362	19,192***	-3,571	8,651***	7,759	-510.5
	(23,054)	(4,637)	(90,136)	(1,870)	(4,738)	(444.2)
Observations	2,003	2,003	693	2,003	2,003	2,003

2. Expenditure Per Capita	(1) Housing	(2) Food	(3) Health	(4) Education	(5) Luxuries	(6) Other
Flood	316.1**	133.2	22.39	-80.88*	-82.13	109.2
	(121.2)	(144.7)	(19.54)	(43.36)	(163.0)	(71.26)
Education	77.48**	-56.92**	-13.38	11.08	-53.82	0.800
	(32.30)	(26.37)	(9.766)	(25.24)	(56.40)	(24.81)
Age	-3.855	-8.673*	-0.334	-1.799**	-8.669**	-1.817
	(2.558)	(4.422)	(0.933)	(0.796)	(4.144)	(1.890)
Gender	-71.18	-7.417	-8.750	59.31	265.1***	84.83
	(56.21)	(116.4)	(18.67)	(37.67)	(90.78)	(77.22)
Asset Index	-10.61	-75.51***	-3.054	-11.08	-119.5	3.782
	(18.46)	(24.84)	(5.660)	(10.35)	(88.71)	(12.98)
Proportion Working	22.82	-299.2**	80.74	-14.41	-383.6***	-145.7
	(90.85)	(141.7)	(58.68)	(71.93)	(116.7)	(99.40)
House Ownership	-25.12	-95.43	-2.232	-41.86	577.1***	175.9
	(55.04)	(162.0)	(30.73)	(57.57)	(94.07)	(102.8)
dependents	-32.16	78.40	10.14	7.126	-40.80	11.36
	(28.73)	(52.91)	(9.245)	(14.33)	(60.48)	(20.44)
Constant	175.8	1,152***	-28.85	163.9**	711.1**	-72.66
	(204.1)	(316.7)	(96.25)	(67.28)	(305.5)	(99.09)
Observations	2,003	2,003	2,003	2,003	2,003	2,003

III. Central Region

1. Income	(1) Total Income	(2) Non-Agri Income	(3) Agricultural Income	(4) Wage Income	(5) Business Income	(6) Govt Support
Flood	9,844	-860.5	85,158	2,956	-4,378**	397.4**
	(10,920)	(2,635)	(89,778)	(2,443)	(1,546)	(165.6)
Education	-2,508	-546.1	6,862	-1,364*	848.1	29.75
	(3,039)	(1,134)	(26,808)	(703.5)	(1,171)	(25.07)
Age	-707.3	-84.23	-6,576	-70.10	-11.01	7.399
	(427.6)	(107.4)	(4,107)	(50.53)	(99.48)	(6.473)
Gender	-2,438	-2,472	6,530	-811.5	-643.7	-166.5
	(12,357)	(2,814)	(86,134)	(2,903)	(2,122)	(120.7)
Asset Index	-2,659*	-3,090***	19,655	-382.0	-2,051**	-1.975
	(1,313)	(931.0)	(23,559)	(567.7)	(874.3)	(51.33)
Proportion Working	-1,005	-3,128	82,350	-72.58	-2,329	319.4
	(25,664)	(6,134)	(295,631)	(4,196)	(5,351)	(314.1)
House Ownership	8,645	-476.3	88,939	-1,589	726.9	298.7**
	(10,183)	(4,272)	(94,284)	(2,303)	(2,259)	(111.2)
Dependents	-1,471	-153.2	-12,896	-1,151**	661.8	34.97
	(5,434)	(2,240)	(32,170)	(535.2)	(1,855)	(71.55)
Constant	56,456*	25,798***	143,820	12,208***	9,395	-626.8
	(28,438)	(7,820)	(326,452)	(2,599)	(7,689)	(694.6)
Observations	1,153	1,153	149	1,153	1,153	1,153

2. Expenditure Per Capita	(1) Housing	(2) Food	(3) Health	(4) Education	(5) Luxuries	(6) Other
Flood	531.1**	252.3	31.99	-103.0*	-101.8	172.1
	(197.5)	(252.1)	(30.15)	(53.39)	(205.1)	(112.1)
Education	102.0**	-75.38*	-16.57	11.98	-81.07	37.53**
	(40.42)	(37.79)	(15.84)	(32.72)	(94.44)	(17.79)
Age	-3.318	-12.22**	-0.445	-2.470**	-8.974	-1.255
	(2.743)	(4.946)	(1.403)	(0.958)	(7.589)	(3.332)
Gender	-126.3	-65.03	-22.59	109.5*	313.0**	-21.05
	(96.52)	(156.0)	(29.46)	(57.73)	(131.1)	(98.14)
Asset Index	-13.94	-104.0***	-3.265	-26.81	-154.2	5.556
	(28.13)	(17.55)	(5.764)	(15.47)	(125.9)	(21.48)
Proportion Working	-40.81	-442.2	102.4	-20.08	-174.8	-184.3*
	(163.8)	(263.7)	(93.75)	(102.8)	(156.4)	(98.75)
House Ownership	4.286	-97.31	-5.438	7.346	713.4***	31.43
	(73.03)	(160.8)	(43.94)	(82.71)	(134.1)	(111.9)
Dependents	-31.11	116.6	14.66	9.964	-51.52	42.05
	(41.22)	(71.59)	(18.22)	(23.71)	(83.25)	(39.31)
Constant	106.7	1,620***	-24.17	253.2***	822.3	-81.94
	(301.4)	(422.3)	(162.1)	(55.85)	(488.3)	(115.6)
Observations	1,153	1,153	1,153	1,153	1,153	1,153

I. Livelihood

1. **Income: Non-Farm**	(1) Total Income	(2) Non-Agri Income	(3) Wage & Salary	(4) Business Income	(5) Govt Support
Flood	-3,648	-4,837*	1,725	-5,859***	480.8***
	(3,170)	(2,636)	(2,066)	(1,434)	(141.9)
Education	845.4	635.7	-174.5	461.5	26.66**
	(1,026)	(675.1)	(453.2)	(603.9)	(11.34)
Age	-198.0*	-143.9**	-94.20**	-63.86	10.24**
	(96.94)	(66.39)	(33.41)	(53.66)	(4.582)
Gender	-4,010	-2,173	-196.1	-2,034	-64.47
	(3,837)	(2,847)	(2,302)	(1,679)	(73.20)
Asset Index	-2,166***	-2,319***	-841.3*	-1,061*	-16.33
	(596.4)	(525.9)	(414.4)	(614.3)	(38.57)
Proportion Working	-2,854	4,337	1,851	1,659	136.1
	(3,248)	(3,041)	(2,338)	(2,371)	(135.0)
House Ownership	-3,246	3,018	1,228	1,659	41.08
	(2,686)	(2,280)	(1,735)	(1,411)	(72.56)
Dependents	-1,123	294.3	-815.3*	916.4	5.713
	(1,555)	(1,494)	(459.6)	(1,008)	(46.98)
Constant	23,544**	16,230***	9,592***	6,808	-525.0
	(9,758)	(5,194)	(1,521)	(4,933)	(367.7)
Observations	2,377	2,377	2,377	2,377	2,377

2. **Expenditure Per Capita: Non-Farm**	(1) Housing	(2) Food	(3) Health	(4) Education	(5) Luxuries	(6) Other
Flood	442.7**	57.23	-4.253	-50.70	-38.91	115.7*
	(171.7)	(150.1)	(13.94)	(42.36)	(151.8)	(67.21)
Education	80.54*	-30.70*	-3.184	19.12	-26.82	33.55
	(39.74)	(14.98)	(11.42)	(13.61)	(61.76)	(19.51)
Age	0.575	-5.616**	-0.143	-0.736	-5.488*	-0.759
	(1.161)	(2.567)	(0.475)	(0.733)	(3.168)	(1.368)
Gender	-123.0*	-5.703	-2.603	31.77	207.3*	38.22
	(61.71)	(79.85)	(19.71)	(32.82)	(118.0)	(52.61)
Asset Index	-18.91	-81.73**	0.917	-18.79**	-136.2*	-4.203
	(17.03)	(29.36)	(3.995)	(7.999)	(78.06)	(7.311)
Proportion Working	18.63	-173.6	110.1	-4.675	-227.9*	-64.05
	(72.35)	(115.5)	(71.06)	(37.31)	(112.6)	(40.34)
House Ownership	-100.7	-26.47	11.58	-15.13	461.1***	59.82
	(73.56)	(137.5)	(26.54)	(41.50)	(156.5)	(78.09)
Dependents	-20.37	95.33**	-1.563	18.78	16.14	19.78
	(27.93)	(42.98)	(8.145)	(13.38)	(40.04)	(21.61)
Constant	14.31	861.2***	-82.30	93.71*	580.0***	-96.65
	(161.7)	(202.8)	(121.5)	(51.52)	(158.6)	(97.85)
Observations	2,377	2,377	2,377	2,377	2,377	2,377

3. **Income: Farm**	(1) Total Income	(2) Non-Agri Income	(3) Agricultural Income	(4) Wage Income	(5) Business Income	(6) Govt Support
Flood	4,141	-1,075	7,021	-315.8	-2,185**	399.7
	(20,255)	(1,415)	(24,479)	(807.1)	(947.5)	(270.3)
Education	6,467	-1,558**	8,464	-719.2*	-869.6	-13.66
	(10,729)	(565.2)	(12,100)	(412.9)	(540.4)	(65.31)
Age	-693.5	-158.8**	-501.4	-40.86*	-112.1**	3.565
	(449.1)	(58.53)	(428.3)	(20.20)	(48.13)	(14.19)
Gender	-24,775	-457.2	-25,291	2.059	423.1	-248.2
	(14,595)	(1,758)	(16,468)	(824.4)	(1,098)	(380.6)
Asset Index	4,330	653.8	3,936	471.2	783.7	-40.48
	(9,212)	(652.2)	(10,431)	(350.8)	(468.0)	(70.00)
Proportion Working	14,462	-4,807**	33,953	-2,907**	-1,876	-308.7
	(19,413)	(2,270)	(28,203)	(1,362)	(2,390)	(453.7)
House Ownership	-7,600	-11,707*	4,547	-10,580	-179.3	-2,548
	(16,860)	(6,741)	(15,819)	(6,309)	(2,297)	(2,971)
Dependents	5,100	92.62	5,654	-44.30	-72.91	75.05
	(6,074)	(642.7)	(6,352)	(315.8)	(434.9)	(147.3)
Constant	49,220	29,392***	737.2	15,705**	9,420*	3,166
	(31,486)	(8,115)	(31,189)	(6,519)	(5,030)	(4,266)
Observations	2,166	2,166	1,944	2,166	2,166	2,166

4. **Expenditure Per head: Farm**	(1) Total Expenditure	(2) Expenditure Per Capita	(3) Housing	(4) Luxuries	(5) Food	(6) Health	(7) Education	(8) Other
Flood	-671.4	-260.2**	-240.2	-430.1	233.0	7.053	-138.3**	-102.8
	(463.4)	(106.2)	(163.6)	(339.0)	(615.5)	(47.65)	(57.88)	(101.5)
Education	15.30	-123.6	-84.29	144.3	-18.90	4.842	12.09	-42.69
	(459.7)	(169.4)	(148.7)	(337.5)	(131.7)	(20.84)	(46.24)	(53.19)
Age	7.696	1.428	-3.159	-0.210	0.540	2.629**	5.159**	2.738
	(12.15)	(4.731)	(5.523)	(8.746)	(5.478)	(1.216)	(2.482)	(1.677)
Gender	-444.0	-168.8	144.8	-193.8	-394.7**	16.88	-106.7*	89.54
	(748.9)	(342.9)	(155.6)	(443.3)	(180.8)	(36.14)	(54.60)	(110.1)
Asset Index	-376.5	-47.81	-28.90	-275.5	-48.18	-35.95	4.182	7.911
	(315.4)	(147.2)	(45.33)	(236.2)	(61.12)	(32.31)	(16.53)	(39.93)
Proportion Working	-44.76	-228.9	-247.9	-448.0	129.1	101.7**	339.1**	81.35
	(935.3)	(459.6)	(264.5)	(729.3)	(313.9)	(40.19)	(149.2)	(271.1)
House Ownership	721.9	1,059	-206.0	552.2	-87.72	28.54	-5.102	439.9
	(1,174)	(913.1)	(222.8)	(616.0)	(407.0)	(116.8)	(131.5)	(445.5)
Dependents	178.7	23.33	-67.36	141.4	34.68	36.36*	76.09**	-42.45
	(149.6)	(82.84)	(55.23)	(115.8)	(70.15)	(20.57)	(29.21)	(32.57)
Constant	486.0	-305.7	902.0*	522.8	481.0	-189.8	-636.5**	-593.4
	(2,052)	(1,076)	(496.3)	(1,375)	(382.7)	(200.1)	(230.2)	(468.3)
Observations	2,132	2,132	2,132	2,132	2,132	2,132	2,132	2,132