ESSAYS ON
DISASTER RISK AND ECONOMIC DEVELOPMENT

BY

AZREEN KARIM

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DECLARATION

This is to declare that this thesis contains no material that has been accepted for the award of any other degree or diploma in any university or equivalent institution, and that to the best of my knowledge and belief, this thesis contains no material previously published or written by other person, except where due reference is made in the text of this thesis.

This thesis contains four publishable papers of which the candidate was the sole researcher and first author. The first paper has been accepted for publication, the second and third paper are currently in the submission process.

AZREEN KARIM

Dedicated to my beloved parents

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ABSTRACT

This thesis consists of four self-contained papers in the areas of disaster risk and economic development. Chapter One provides a qualitative survey of the empirical literature on the nexus among poverty, inequality and natural disasters. The last few years have seen an explosion of economic research on the consequences of natural disasters. This new interest is attributable first and foremost to a growing awareness of the potentially catastrophic nature of these events, but also a result of the increasing awareness that natural disasters are social and economic events. Here, we survey the literature that examines the direct and indirect impact of natural disaster events specifically on the poor and their impact on the distribution of income within affected communities and societies.

With a meta-regression analysis of the existing literature on the impacts of disasters on households in Chapter Two, we observe several general patterns. Incomes are clearly impacted adversely, with the impact observed specifically in per-capita measures. Consumption is also reduced, but to a lesser extent than incomes. Poor households appear to smooth their food consumption by reducing the consumption of non-food items; in particular health and education, and this suggests potentially long-term adverse consequences. Given the limits of our methodology and the paucity of research, we find no consistent patterns in long-term outcomes. We place disaster risk to the poor within the context of sustainable development and future climatic change.

Our objective In Chapter Three is to identify all of the directly observable determinants' of publicly allocated and realized spending for disaster risk reduction (DRR) at the local government (sub-district) level in Bangladesh. We employ the Heckman two-stage selection model with detailed public finance and other data from 483 sub-districts (Upazilas) across the country. While some of our results conform with our priors, our estimations surprisingly find that government does not respond to the sub-district's risk exposure as a factor affecting the DRR financing mechanism. This variable is consistently counter-intuitively statistically insignificant. The DRR regional allocations do not seem to be determined by risk and exposure, only weakly by vulnerability, nor even by more transparent political economy motivations.

In Chapter Four, we examine the short-run economic impacts of recurrent flooding on Bangladeshi households surveyed in 2000, 2005 and 2010. In 2010 Household Income and Expenditure Survey (HIES), households answered a set of questions' on whether they were affected by flood and its likely impacts. We identify two treatment (affected) groups by using the self-reported data and historical rainfall data based flood risk index. We estimate a difference-in-difference (DID) model to quantify the impacts on income, expenditure, asset and labour market outcomes and further extend our analysis to different income and expenditure brackets. Overall, we find robust evidence of negative impacts on agricultural income and expenditure. Intriguingly, the extreme poor (i.e. the bottom 15th quintile) experience significant positive impacts on agricultural income in the self-reported treatment case.

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INTRODUCTION OF THE THESIS:

Natural disasters - earthquakes, typhoons, hurricanes, floods, cold and heat waves, droughts and volcanic eruptions - are a constant presence in all our lives and there had been an explosion of economic research on their consequences in the last few years. In addition to a growing awareness of the potentially catastrophic nature of these events, this is also a result of the increasing awareness that natural disasters are social and economic events. Hence, their impact is shaped as much by the structure and characteristics of the countries they hit as by their physical attributes. This research had also been flourished on the potential changes that will occur in the pattern and intensity of future natural events that is associated with anthropogenic climate change. Despite the fact that disasters occur everywhere with increasing direct financial costs for the past several decades, they are especially prevalent in the most populous region of the world (e.g. Asia) and most catastrophic in the destruction they wreak in the poorest countries (e.g., Haiti in 2010). The need to understand the role of disasters and their impacts on the poor, in creating and sustaining poverty, and in generating poverty traps, is even more acute as the changes due to human-induced climate change are predicted to be more extreme in poorer countries and will thus place additional barriers to poverty alleviation.

These intersecting themes of disasters, climate change, and poverty are gaining even more prominence now with the ongoing negotiations of three new comprehensive international treaties under the aegis of the United Nations: on disaster risk reduction (a successor to the Hyogo Framework for Action), on climate change mitigation and adaptation (a successor to the Kyoto Protocol), and on sustainable development (a successor to the Millennium Development Goals). All of these are scheduled to conclude in 2015.

Therefore, in Chapter One, we aim to contribute to these international discussions by first surveying the existing literature on the impact of natural disasters on poverty and the poor, their impact on income distribution within affected communities and societies, discuss some of the limitations associated with this literature, and outline a future agenda of investigation that can contribute to better-informed policymaking. We argue that perhaps it is even more important to determine the long-term effects of catastrophic disasters on various income groups, rather than only their direct and indirect short-term impacts as despite the limited empirical evidence available, data suggest that large natural shocks can have important regional consequences that may persist for decades.

The poor, both in low- and higher-income countries are especially vulnerable to the impact of disasters, so that disasters are not only of interest to social scientists because of society-wide economic impact, their impact on the public sector which bears the costs of reconstruction, or because of their environmental impact, but also because of their importance in the processes of development, income growth, and income distribution. The research on the impact of disaster shocks specifically on the poor is one branch of this wider 'disaster' literature that has not yet been adequately summarized, nor has there appeared to be any attempt to reach any general conclusions from the numerous case studies (country-specific, disaster-type-specific, or disaster-event-specific) that constitute the bulk of this research stream. This lacuna is at least in part attributable to the complex nature of the inter-relationship between disaster impacts and poverty and welfare outcomes, and the consequent diversity of impacts across the investigated case studies. An additional difficulty, given this diversity of outcomes, is in identifying the precise channels - both direct and indirect - that describe the causal mechanisms. We aim to fill this lacuna using meta-regression analysis in Chapter Two. Our contribution here is the synthesis of the microeconomic literature examining the heterogeneity of impact of disasters on the poor complementing the macroeconomic insights derived from previous work.

A burgeoning literature has emerged investigating the efficacy of public spending in lower income countries. This literature assumes that public spending is indeed geared towards achieving the relevant favourable outcomes—productivity growth for infrastructure spending, better health service utilization for health spending, or improved literacy for education spending. More importantly, this literature implicitly assumes that funding is allocated optimally given these desired outcomes and the perceived community needs. It is this last assumption that we examine in Chapter Three. Our focus here amounts to answering a basic question: 'what determines public spending in disaster risk reduction and mitigation in Bangladesh?' We focus on Bangladesh as it is widely perceived as a poster-child for successful spending on DRR by a developing country. In particular, Bangladesh is often mentioned for its successful early warning programmes for cyclones, which is frequently favourably contrasted with neighbouring Burma after its catastrophic experience with cyclone *Nargis* in 2008. We believe that this particular question has important implications not only for DRR spending in Bangladesh but also to DRR spending elsewhere, and more generally for government spending in low income countries and its challenges.

The 'disaster-development' literature has made considerably less progress on the use of self-reported data to empirically estimate the impacts of natural disasters on development outcomes in least developed countries with high climatic risks. In Chapter Four, we examine the short-run economic impacts of recurrent flooding on Bangladeshi households surveyed in 2000, 2005 and 2010. In 2010 Household Income and Expenditure Survey (HIES), households answered a set of questions' on whether they were affected by flood and its likely impacts. In this paper, we ask: 'what are the impacts on household income, expenditure, asset and labour market outcomes of recurrent flooding in Bangladesh?' This paper makes two key contributions: First, we develop a difference-in-difference (DID) model and estimate the impacts of recurrent flooding through identification of two different treatment (affected) groups using self-reported information and historical rainfall data based flood risk index for Bangladesh. We further extend our analysis using a quantile regression and quantify the impacts on the 'ultra' (extreme) poor. The development responses of the climatic disasters may therefore depend on the novel approach i.e. accuracy in identifying the treatment groups using self- and non-self-reported data. Second, we show that there is inconsistency between self- and non-self-reported information based estimates with literature outcomes questioning the designation of survey questions (related to natural shocks) and their usefulness to capture development impacts.

CHAPTER ONE

POVERTY AND NATURAL DISASTERS – A QUALITATIVE SURVEY OF THE EMPIRICAL LITERATURE

1.1 ECONOMIC RESEARCH ON DISASTER IMPACT

The last few years have seen an explosion of economic research on the consequences of natural disasters. This is probably attributable first and foremost to a growing awareness of the potentially catastrophic nature of these events as evident, for example, in the earthquake and tsunami in South-East Asia in 2004, the 2010 Port-au-Prince earthquake, and the 2011 triple earthquake/tsunami/nuclear disaster in Japan. It is also a result of the increasing awareness that natural disasters are social and economic events: their impact is shaped as much by the structure and characteristics of the countries they hit as by their physical attributes such as wind speed and rainfall for tropical storms, or the energy unleashed in an earthquake.

In addition to this growing interest in the social and economic aspects of the risk that natural hazards pose, the increasing awareness of climatic change is also playing an important role. Much discussion in the past few years had focused on the potential changes that will occur in the pattern and intensity of future events that is associated with human-induced climate change. A summary of these intersecting literatures was recently undertaken by the Intergovernmental Panel on Climate Change (IPCC, 2012).

Recent research projects have evaluated the growth impact of natural disasters in the short- and medium-long terms, the fiscal impact of disasters (again for various time horizons), the impact on international trade and financial flows, the impact on populations through migration and fertility choices, the impact on human capital, the importance of political economy questions in shaping the disasters' aftermath, and on other related topics. Intriguingly, there is less research on the impact of natural disaster events specifically on the poor and on income distribution (on inequality).

These intersecting themes of disasters, climate change, and poverty are gaining even more prominence now with the ongoing negotiations of three new comprehensive international treaties under the aegis of the United Nations: on disaster risk reduction (a successor to the Hyogo Framework for Action), on climate change mitigation and adaptation (a successor to the Kyoto Protocol), and on sustainable development (a successor to the Millennium Development Goals). All of these are scheduled to conclude in 2015.

Here, we aim to contribute to these international discussions by first surveying the existing literature on the impact of natural disasters on poverty and the poor, discussing some of the limitations associated with this literature, and outlining a future agenda of investigation that can contribute to better-informed policymaking. A companion paper, Karim and Noy (2014), generalizes some insights from a subset of the empirical research papers described here using a meta-regression technique.

1.2 A TYPOLOGY OF IMPACTS

Before we discuss this literature, we need to clarify what we mean by disaster impacts, and what are some of the methodological decisions that are inherent in this choice. ECLAC (2003) distinguish between the direct impact of sudden-onset disasters (the immediate mortality, morbidity, and physical damage) and the indirect impact that affects the economy in the aftermath of the actual damage caused (including secondary mortality and morbidity, and an impact on economic activity). The World Bank in their survey *Natural Hazards Unnatural Disasters* (2010) employs a different terminology that makes essentially the same distinction: first-order and higher-order effects.

The terminology of n-order effects might be preferable in theory since it enables one to potentially distinguish between second-order effects (e.g., the immediate decline in production as a result of the destruction of productive capital), and third-order (or even higher) effects (e.g., the decline in production that results from the decline in imported inputs that resulted from exchange rate and terms-of-trade changes following a disaster).

These distinctions between second-order and higher-order effects is however difficult to operationalize into a precise typology. We, therefore, refrain from using this terminology and persist in using the more coarse distinction between direct and indirect effects (Cavallo and Noy, 2011). Here, our interest is understanding both the immediate (direct or first-order) effect of disasters on poverty and income distribution and also the consequent indirect (higher-order) effects that have an impact on the lives of the poor and on distribution of incomes and resources within societies.

Another potentially important distinction lies between natural disasters that are frequent and occur regularly and those disasters whose nature or magnitude is unusual (and therefore probably unexpected). The distribution of disaster damages is highly skewed, with presence of very extreme - “fat tail” - disasters, whose costs (in terms of mortality, morbidity, and/or physical destruction) are significantly higher than the average disaster costs. The Haiti earthquake of January 2010, for example, led to a mortality that was at least 10 standard deviations higher than in earthquakes of similar or higher strength (Noy, 2013). The 2004 earthquake/tsunami in the Indian Ocean and cyclone *Nargis* in Myanmar in 2008 are also examples of these fat-tail events.

Fat-tail events would be typically associated with extremely small probabilities in common risk assessments, but are nevertheless quite common occurrences worldwide. Importantly, since the probability that these catastrophic events will occur is thought to be so small, policymakers will tend to ignore them and societies will generally be underprepared for them.

Our interest in this survey paper is to discuss the impact of natural disasters - both direct and indirect - on poverty and income distribution. In this description, we will distinguish between the impact of sudden-onset catastrophic events and more regular natural hazards that occur in many countries (e.g., typhoons in the Philippines or the annual monsoon floods in Bangladesh).

1.3 THE DIRECT IMPACTS OF DISASTERS ON THE POOR: SUDDEN-ONSET EVENTS

The direct damages from a disaster are not evenly distributed. Comparison between countries clearly shows that richer countries can prevent or mitigate disasters' impact more effectively and therefore the cost they bear (as a fraction of their economic size) is significantly smaller (Kahn, 2005). The reasoning that appears to explain why these cross-country differences depend on average incomes has, firstly, to do with the most obvious channel: preventive measures are normal (or luxury) investment goods, so countries with higher permanent incomes or wealth will be able to devote more resources to prevention or mitigation.

Escaleras et al. (2007), however, argue that corruption explains a lot of the cross-country differences in initial impacts of similar events, and it is well documented that corruption is inversely related to average per capita income. Kellenberg and Mobarak (2008) find evidence for a non-linear cross-country relationship between average incomes and direct impacts, where (for some types of disasters) the costs initially increase with incomes, and above a certain threshold (which they typically identify as per capita income level of a lower middle-income country) it starts to decrease.

Most of these papers that identify the cross-country pattern of correlation between income levels and direct disaster impact conclude that this evidence also represent the time-series relationship; i.e., a country whose incomes will grow over time, will, according to Kellenberg and Mobarak (2008) initially experience higher disaster costs (measured by mortality) and then eventually, as average incomes increase further, lower disaster costs. The evidence regarding this question however is rather less clear. Hallegatte (2012), for example, points out that when these figures are aggregated worldwide, the World's GDP has been growing at about 4 percent a year in the past several decades, while disaster losses (as measured by EM-DAT[1]) have been growing, on average, at about 6 percent. This implies that as the world continues to grow, the cost of disasters is going to increase (relative to the World's economy).

Ultimately, however, identifying the direct impact of disasters on the poor (in magnitude, and relative to the rich) cannot be answered by examining the cross-country distribution of costs and economic activity, since this evidence may be more related to country-wide differences in institutional capacity and policy that are correlated with incomes rather than dependent on incomes directly. In any case, most of our conceptions and measurements of poverty are based on national identification.

The evidence on the distribution of the direct impact of a disaster within a country on households in various income levels is less well understood; the evidence that does exist generally suggests that poorer households are more vulnerable and will bear the direct damages disproportionately at higher levels and as higher shares of their households' income.

A salient feature of disaster risk exposure is the choice of millions of people to live in disaster-prone areas, and these are in many cases predominantly the poor (e.g., Boustan et al., 2012). Examining geographical distribution to test for the poor's exposure to natural disasters, Kim (2012) argues that, on average, the poor are at least two times more exposed relative to the non-poor globally.

A more detailed effort by Baez and Mason (2008) to identify the regional hot spots of increased weather variability reveals that central and southern Peru and western Bolivia proves to be most vulnerable to heavy rains and flood among Latin America and Caribbean (LAC) regions; these are regions that are associated with high poverty and population density. Supporting evidence on other Latin American countries as well as relevant social protection solutions have

[1] EM-DAT is an international disaster database compiled and managed by CRED (Centre for Research on the Epidemiology of Disasters), Université catholique de Louvain (UCL), Belgium.

been documented by De la Fuente (2010). Tesliuc and Lindert (2002) present evidence from Guatemala, where the poor seems to be more exposed to natural shocks than the non-poor (though the reverse is true in the case of man-made shocks).[2] Tesliuc and Lindert (2002) report that in Guatemala 35.4 percent of the poorest quintile is affected by natural shocks compared to 21.2 percent of the richest quintile.

A study by UNISDR (2012) in Syria, Jordan and Yemen shows that poverty is most severe in rural non-diversified economies where agriculture is severely limited by low rainfall, degraded lands, erosion and desertification. The study concludes that low productivity and water shortage leads to stagnating rural incomes increasing poverty in Syria and Yemen. In Jordan, these dynamics are more severe in urban areas. Rains, flash floods and snowstorms affect the densely populated areas possessing the largest share of the country's poor, particularly women. In short, while poverty is clearly associated with increased exposure to hazards, the exact causality is often country-specific, and probably quite complex.

Neumayer and Plumper (2007) investigate gender differences in disaster-related mortality, and conclude that generally women are more likely to die than men, or at a much younger age, especially when they come from a disadvantaged socioeconomic background.[3] By one estimate, women represented 70 percent of casualties after the 2004 Indian Ocean in Aceh, Indonesia (World Bank, 2011).

Only a few attempts to analyze the direct impacts of specific natural disasters by examining various indices of poverty, income inequality and human development have been concluded (e.g., Datt and Hoogeveen, 2003; Reardon and Taylor, 1996; Lal, Singh and Holland, 2009 and Rodriguez-Oreggia et al., 2013). A full picture of these impacts is not yet within reach, and whether these are due to direct or indirect channels is not easy to determine.

[2] As coping with natural disasters is related to prior economic conditions, the average impacts of a fairly regular natural shock (e.g. periodic drought) is found to have a lesser impact compared to a sudden economic shock (e.g. financial crisis).

[3] A higher level of women's socio-economic rights appears to offset the negative effect of natural disasters on women (Neumayer and Plumper, 2007).

1.4 DROUGHTS AND RAINFALL FLUCTUATIONS

Droughts and extreme fluctuations in rainfall are also frequently disastrous, with very noticeable adverse consequences on human populations. In this case, unlike the sudden-onset case, the distinction between direct and indirect effects is less clear-cut. In this section, we therefore focus on the overall effects of these events rather than separating their immediate (direct) impacts and the longer-term indirect effects.

Despite evidence of the adverse changes in overall income in the aftermath of slow-onset natural catastrophes such as droughts, some projects conclude that these disasters do not have much impact on poverty and income distribution (and should be seen as across-the-board adverse shocks). Little et al. (2006), for example, find that droughts did not increase overall rates of poverty in the medium-term in Ethiopia. They suggest this is mainly due to increasing income diversification and less emphasis on rain-fed agriculture. However, if anything, the balance of the limited available evidence seems to suggest that droughts and extreme rainfall volatility do increase poverty even if poverty is also influenced by numerous other factors (see also Karim and Noy, 2014).

Several projects have analyzed the impacts of rainfall shocks and local rainfall variability on various household socio-economic indicators, including consumption growth, human capital accumulation, life expectancy, and adult and children's anthropometrics as a proxy for health/wellbeing outcomes (e.g., Jensen, 2000; Shah and Steinberg, 2012; Asiimwe and Mpuga, 2007; Hoddinott et al., 2011; Dercon, 2004; Hoddinott, 2006; Maccini and Yang, 2009; Tiwari et al., 2013, Neumayer and Plumper, 2007 and Bandyopadhyay and Skoufias, 2015).

An examination of children's educational investments in Côte d'Ivoire revealed, for example, that school enrolment rates declined by 20 percentage points (more than one-third of the original rate) in regions affected by adverse weather conditions (Jensen, 2000). Maccini and Yang (2009) report that a 20 percent increase in rainfall in Indonesia during early childhood led to 0.57cm greater height, 0.22 additional completed grades of schooling and to households' prosperity that is 0.12 standard deviation higher on an asset index scale. Another similar research project, in Nepal, found a 0.15 standard deviation increase in weight-for-age for children aged 0–36 months due to 10 percent higher rainfall (Tiwari et al., 2013). This has also been evident in Zimbabwe, where Hoddinott et al. (2006, 2011) showed lower annual growth in height of 1.5-2cm among children aged 12-24 months after drought with the most severe impacts on poor households. However, this finding did not seem uniform across regions within countries. In the Mexican case, Skoufias and Vinha (2012) pointed out that positive temperature shocks negatively impacted certain sub populations– namely boys, children between 12 and 23 months at the time of measurement, and children of less educated mothers in some regions.

Moreover, in the long run, children from relatively wealthier households recovered this lost physical growth while children from poorer homes did not (Hoddinott, 2006). The same study also found a decrease in women's body-mass index by about 3 percent in the aftermath of a 1994-95 drought. Similarly, in Ethiopia, Yamano et al. (2005) found that children of 6-24 months old experienced about 0.9cm less growth in communities with substantial crop damage after severe droughts while food aid acted as an effective insurance mechanism in reducing child malnutrition. Estimating the long-term impacts of 1984 Ethiopian famine, Porter (2008) reveals that children who were under the age of 36 months are years later shorter by almost 3 cm. An interesting article on the impacts of early childhood nutritional intervention in Guatemala by Hoddinott et al. (2008) demonstrates that improving nutritional status before age 3 could substantially increase wage rates for men compare to women justifying early childhood nutritional investments as long-term drivers of economic growth. However, positive rainfall shocks can also contribute to early childhood adverse nutritional changes with increasing risk of termination of breastfeeding in the Indian case (Mendiratta, 2012).

Evidence from India suggests that parents and children work less and have lower wages during drought years and the reverse case happens when households experience positive rainfall shocks (Shah and Steinberg, 2012). The same study further identified deleterious effects on health, schooling and more interestingly, on later-life wages due to early life exposure to droughts. An almost similar argument had also been posed by Banerjee (2007) in an earlier study on agricultural wages in Bangladesh. The author argues that floods have positive implications on wages in the long-run in flood months with declining wages in inundated areas. The study further identified productivity in line with labour demand along with land distribution and bargaining power of workers as impact factors. In a study on different types of workers' income; Mueller and Quisumbing (2011) pointed out that the real wage of casual and salaried agricultural workers declined only in the short-term with significant but temporary reduction in salaried income between 34.3 percent and 45.6 percent. Dercon (2004) found out that a 10 percent lower rainfall about 4–5 years earlier had an impact of one percentage point on current consumption growth rates. After controlling for heterogeneity, the paper identified a substantial impact of about 16 percent lower growth when comparing groups that suffered significantly with those being moderately affected. Also in Ethiopia, Foltz et al. (2013) concluded that both food and non-food consumption is directly related to rainfall. Similar evidence has also been identified by Skoufias and Vinha (2013) in the Mexican case where temperature shocks along with rainfall affect both food and non-food consumption. This effect is more nuanced, as Hou (2010) finds that after a drought-related negative income shock occurs, households tend to buy cheaper calories resulting in a net increase in total calories consumed.

Asiimwe and Mpuga (2007) point out that the timing of the rainfall shock appears to matter. In their examination of Uganda, positive rainfall shocks experienced during planting or harvest times actually result in lower household consumption expenditure. Analyzing data on Indonesian rice farmers, Skoufias et al. (2012) argue that although a delayed monsoon does not have a significant impact on average, farmers located in low rainfall exposure areas following the monsoon are negatively affected. Agricultural year and regional climate are also found influential in effecting households' ability to protect consumption as shown by Skoufias and Vinha (2013) in the Mexican case. A study on Indian agricultural labour markets by Mahajan (2012) reported that low rainfall years affect male-female wage gap adversely in rain-fed rice growing regions. Rainfall, of course, matters much more in rural/agricultural communities, than in the urban ones (at least directly).

Variations in rainfall influence households in rural Bangladesh in making crucial occupational choices. In flood-prone areas, less productive employment diversification choices, at the cost of skill-swap and reduced consumption, has been identified by Bandyopadhyay and Skoufias (2015). Employment diversification has also been identified, in the same paper, as an *ex-ante* adaptation strategy in the presence of stable local rainfall variability. The authors further highlighted that with comparison to credit and safety nets, access to markets provides better coping opportunities in protection against costly occupational diversification within households.

Even more nuanced observations about the way different conditions lead to different outcomes in the face of similar shocks were proposed by Reardon and Taylor (1996). They compared the impact of similarly adverse drought shocks over two regions in Burkina Faso (the semi-arid Sahel, and the wetter Guinean region); they find the impacts of drought appear to be very different, in some cases leading to increases in poverty, and in others the opposite.

1.5 THE INDIRECT IMPACTS OF SUDDEN-ONSET EVENTS

The direct impacts are only a part of the economic significance of natural disasters. In general, we do not understand the indirect impacts as well, though they are potentially more severe. These impacts may result from direct damage to the inputs used in production, to infrastructure, or from the fact that reconstruction and rehabilitation pull resources away from other sectors. Further on, the indirect impacts can manifest themselves in a new equilibrium steady-state in which the economy/society are in a different position to what they were pre-disaster. Anttila-Hughes and Hsiang (2013), for example, find that for Philippine households, the indirect impacts are almost an order of magnitude larger than the direct damages wreaked by typhoons.

While it is clear that the poor are more exposed, more vulnerable and less resilient to the direct impact of natural hazards, Baez and Mason (2008) find low levels of income to be the prime limiting factor towards damage mitigation response of households. In a range of studies, the impact of disasters on income and consumption levels of the poorest households is found to be disproportionately strong (Rentschler, 2013).

In contrast to these adverse consequences, reconstruction spending can provide a boost to the domestic economy and specifically employees and employers in that sector. Both government funding and privately funded reconstruction from insurance payments, accumulated saving, or from other sources, is bound to provide some temporary stimulus to the local economy (Cavallo and Noy, 2011). In the longer-run, there is a potential to 'build-back-better;' reconstruction can, at least in theory, be a reconstruction to better standards, newer, more advanced and more innovative infrastructure including better housing for the poor.

Post-disaster realignment of interest groups may even facilitate a new political equilibrium that enables better policies (whatever 'better' means in practice).[4] Equally plausible is the scenario

[4] One can already observe this possibility in the aftermath of what is sometime considered the first international modern natural disaster, the Lisbon earthquake of 1755. Sebastião José de Carvalho e Melo, the prime minister of

that the new political equilibrium will actually be less beneficial to the poor, if the external shock removed what John Kenneth Galbraith called the 'countervailing forces' that prevented elites from capturing specific assets.[5]

Most recent research suggests that aggregate adverse short-run effects, at the national level can be observed in middle- and low-income countries experiencing catastrophic disasters. These countries have difficulty financing reconstruction; as they generally face difficulties conducting counter-cyclical fiscal policy and their insurance and re-insurance markets are significantly shallower (see Noy, 2009; von Peter et al., 2012 and Strobl, 2012).[6] The same financing constraints that seem to prevent middle- and low-income countries from adequately paying for and implementing successful reconstruction are also the ones that typically inhibit lower-income households.

Analyzing the impacts of several types of natural disasters at the municipal level in Mexico, Rodriguez-Oreggia et al. (2013) argue that natural disasters reduce human development and increase measures of poverty (food, capacity and asset). They further conclude that floods and droughts are associated with more significant adverse effects when compared to frost, extreme rainfalls and other types of natural hazards. Similarly, Lal, Singh and Holland (2009) identify evidence indicating a negative relationship between HDI and disasters, and leading to higher poverty levels in Fiji.

Two UNDP projects explored the relationship between natural hazards and poverty in Latin American countries (Baez and Santos, 2008 and Glave et al., 2008). Baez and Santos (2008), on El Salvador, reported that the combined effects of two earthquakes in 2001 led to reduction of household income by one-third of the pre shock average. Evidence from Peru, in Glave et al. (2008), suggests that the effect of disasters on poverty rates ranges between 0.16 and 0.23 percentage point increase in poverty. From a distributional point of view, the authors concluded that an

Portugal, appointed to run the relief operations after the earthquake, wrote: "Politics is not always the cause of revolutions of State. Dreadful phenomena frequently change the face of Empires...We could say that it is necessary that across the land provinces are wasted and cities ruined in order to dispel the blindness of certain nations." (quoted in Shrady, 2008).

[5] Some realizations of this possibility are described in Naomi Klein's book-length investigation in *The Shock Doctrine.*

[6] Most of the research on high-income countries fails to find much aggregate impact of even large disasters (e.g., Doyle and Noy, 2015).

increase in average shocks reduce the median of monthly per capita consumption in the bottom 25^{th} and 50^{th} of the distribution by 3.85 percent and 2.68 percent respectively.[7]

Baez and Santos (2007) investigated the impact of hurricane Mitch in Nicaragua, and found a range of distinct adverse medium-term effects; in particular, they focus on topics that are more relevant for the poor and identified increased probability of undernourishment and a significant increase in labour force participation among children (though this increase did not correspond with a decline in school enrolments). As in Baez and Santos (2007), most research has not attempted to isolate separately the impact of these sudden shocks on the poor versus other income groups. However, most of the mechanisms and impact they identified are more likely to be specifically relevant to low-income households. Evidence from Vietnam, for example, revealed that riverine floods and hurricanes caused welfare losses up to 23 percent and 52 percent respectively inside cities with a population over 500,000 (Thomas et al., 2010); flood-prone urban areas are typically associated with lower-income households.

The importance of credit in facilitating recovery is well documented. Sawada and Shimizutani (2008) report that in the aftermath of the 1995 Kobe earthquake in Japan, households that were credit constrained did not manage to regain their consumption levels while households that had better access to credit restrictions were more successful in recovering. In an attempt to identify a causal relationship between credit access and welfare, Morse (2011) finds that the presence of payday lenders reduce about the frequency of foreclosures by about 1 unit (out of 4.5 units) per 1000 homes in the US in regions hit by a natural disaster. Credit constraints may also lead households to sub-optimally sell productive assets in order to smooth consumption after a major but temporary income shock (Mueller and Osgood, 2009a). Anttila-Hughes and Hsiang (2013) also find similar dynamics for Philippine households. In their case, while both low- and high-income households experience similar level of damages in the initial impact following an exceptionally strong typhoon, it is only the lower-income households whose consumption does not recover in the years that follow.

[7] Comparing impacts of El-Niño shocks to the financial crisis in 1998, Datt and Hoogeveen (2003) show that the largest share of the overall impact on poverty is attributable to the El-Niño shock, ranging between 47% and 57% of the total impact on measures of incidence, depth and severity of poverty relative to the 1998 shock that only accounts for 10–17% of the total poverty impact.

Impacts on the poor in the aftermath of a natural disaster are also being observed through migration and remittances pattern (see Gray and Mueller, 2012; Boustan et al., 2012; Attzs, 2008; Clarke and Wallsten, 2003; Dillon et al., 2011 and Halliday, 2012). A household panel dataset for Jamaica after hurricane Gilbert reveals that remittances increased by only about 25 cents for every dollar of damage (Clarke and Wallsten, 2003). However, Attzs (2008) observes an increase in migration after a hurricane and an increased inflow of remittances (which constitutes 87 percent of income for the poorest deciles in Jamaica). Intriguingly, in El Salvador, Halliday (2012) identified that the 2001 catastrophic earthquake resulted in a large negative effect on female migration with absolutely no effect on male migration.[8] As we have seen with the direct impact, these studies further emphasized that women and the poor are more exposed and dealt with the aftermath of a disaster more directly.[9]

Using unique long time-series data on internal migration in Nigeria, Dillon et al. (2011) distinguish along genders when examining the impact of weather variation on migration. They find that male migration appear to be a coping mechanism for households facing temperature variation; in particular to *ex post* variation but with some evidence also suggesting households are responding to *ex ante* risk as well. Women, they argue, are more exposed to *ex post* covariate risks. They highlight differences in expected male and female labour market returns from migration as the rationale for explaining households' preference for male migration. On the issue of migratory income, Mueller and Osgood (2009b) find that, in Brazil, precipitation shocks have long-term adverse impacts on rural out-migrants' income once they arrive in urban areas. Their finding that urban poverty may be associated with rural climatic pressures to migrate is indicating that the absence of worthy alternatives may be a likely reason for migration, a reason that is more powerful than the damage from migration itself.

Another group of projects had examined the evidence on the impacts of natural shocks on household assets and on consequent income distribution (see Carter et al., 2007; Mogues, 2011; Anttila-Hughes and Hsiang, 2013; Morris et al., 2002; Jakobsen, 2012 and Masozera et al., 2007). Most of these studies point out that, conditional on the severity of the shock, most households

[8] In El Salvador, over 90% of all households do not allocate any males to domestic activities, so the need for domestic labour in the disaster's aftermath may explain this pattern (Halliday, 2012).
[9] Boustan et al. (2012) adds another layer of complexity by identifying ways in which disaster mitigation efforts may interact with individual migration decisions.

suffer a depletion of assets (wealth) beyond the previously documented reduction in current income. Morris et al. (2002) reveals that, after hurricane Mitch, assets of households in the lowest wealth quintile were reduced by 18 percent compared to 3 percent for the upper wealth quintile. Lopez-Calva and Ortiz-Juarez (2009) examine distributional impacts in Peru, and find that a one unit increase of the occurrence of shocks leads to a reduction of 2 percent in household per capita consumption in the lowest quartile compared to only 1.2 percent in the richest quartile.

Another important and policy-relevant question is whether disasters can push households down into poverty trap. Carter et al. (2007) examined two different outcomes in two different case studies. In Honduras, in the medium-term, relatively wealthy households were able to partially rebuild their lost assets unlike the lowest wealth quintiles. However, in Ethiopia, the poorest households (in wealth) try to hold on to their few assets despite consumption possibilities shrinking during drought periods and severe losses in agricultural production/income. Van den Berg (2010) adds more nuance about the ability of households at various income levels to pursue possible strategies that allow them to maintain their capital. She concludes that, in the case of Hurricane Mitch, there is little evidence of changes in the transitions between various income levels, suggesting permanent poverty traps.

Several studies analyzed the impacts of natural disasters on population dynamics and fertility response (e.g. Martine and Guzman, 2002; Lin, 2004 and Finlay, 2009). Martine and Guzman (2002) identified a reduction in population growth in some Honduran provinces by 92 percent-40 percent, depending on the province, due to the effects of Hurricane Mitch. Lin (2004) also reaches similar conclusions. However, Finlay (2009) argues that a large scale natural disaster may have a positive effect on fertility under the assumption that a child could be used as an insurance mechanism to compensate for income and asset loss. We can speculate that these dynamic incentives may affect poorer households differently than richer ones; for example that increasing fertility will only be observed for poorer households that do not have access to other ways of financing retirement. The evidence on these possible differences, however, does not yet exist.

1.6 COPING RESPONSES OF THE POOR

A significant body of research has attempted to shed some light on possible coping mechanisms of dealing with natural disasters, typically focusing on the rural poor in low-income countries. Baez and Mason (2008) argue, for example, that rural households possess limited capacity to fully and efficiently adjust to weather related shocks. This limited capacity is associated with a lack of access to formal financing and other tools that can facilitate optimal coping strategies (such as re-training). In line with this argument, Bandyopadhyay and Skoufias (2015) also provided evidence on effects of occupational choice as *ex ante* adaptation strategy.

Sawada (2007) provides an earlier survey of some of the potential coping mechanisms in the local, regional, and global contexts, while Ghorpade (2012) provides a more recent version. Helgeson et al. (2012) provides a recent example of a careful study identifying the possible coping mechanisms and evaluating their prevalence with a large survey of Ugandan farmers. Patnaik and Narayanan (2010) examine similar questions with data from two districts in rural India. Yet, an evaluation of the differences among income groups in their coping mechanisms is less common.

Khandker (2007) finds that sixty percent of sampled households adopted some form of what appears to be sub-optimal coping mechanism during a sudden shock. These involved borrowing (often at high interest), skipping meals, selling productive assets or migrating away from affected areas.

The use of livestock as a buffer stock in terms of reducing the probability of being 'always poor' in the aftermath of a natural disaster has also been examined. Fafchamps et al. (1998) argue that livestock sales offset at most 30 percent and probably closer to 15 percent of income loss resulting from village level rainfall shocks in West Africa. In Uganda and India, in contrast, livestock are held as a form of liquid savings and selling livestock had been used as the most frequent form of coping strategy after a weather disaster (Helgeson et al., 2012, and Patnaik and Narayanan, 2010).

Formal insurance policies are typically unaffordable or unsuited to conditions in rural low-income regions/countries. Thus other insurance products to deal with weather risks have been developed, with a recent enthusiasm for index insurance. Equally important, are other recent methods and ideas for disaster coping strategies such as disaster micro-insurance or contingent-repayment in microfinance loans (see Jensen, 2000; Barnett and Mahul, 2007; Mechler et al., 2006;

Shoji, 2010 and Janzen and Carter, 2013). Yet, the introduction of insurance tools for the poor is still in its infancy; and the poor often rely on accumulated savings, mortgaging available assets, donations, remittances, emergency loans from microcredit institutions or traditional moneylenders, and if these fail, direct support from family, neighbours, and friends (Mechler et al., 2006).

Estimating an acceptable and affordable premium for disaster insurance specifically for the poor seems to be extremely difficult not only due to multiple risks on life, health and property but also due to the 'fat-tailed' nature of catastrophic natural hazards. However, index- or micro-insurance products could potentially be effective mechanisms in transferring covariate weather risks for the rural poor as has been (provisionally) observed in Mexico and India (Barnett and Mahul, 2007).

Shoji (2010) employed a unique dataset and examined the impact of rescheduling of savings and repayment installments in microfinance (i.e., contingent repayment) for affected members during a natural disaster. The paper pointed out that rescheduling decreased the probability of avoiding meals by 5.1 percent during negative shocks with larger impact on the poor and particularly more on females. Another study on drought impacts in Kenya by Janzen and Carter (2013) reveals that insured households are 8-41 percentage points less likely to reduce meals and 18-50 percentage points less likely to sell productive assets during the recovery process. Yet, identifying whether targeted programs in microfinance and micro insurance are able to compensate the losses adequately and prevent households from resorting to sub-optimal strategies remains to be seen.

The evidence suggests that insurance substantially reduces the probability of selling livestock during a drought improving the chances of advancement in the recovery process (Janzen and Carter, 2013). Drawing a gender distinction on this issue, Hoddinott and Kinsey (2000) suggests that women in poor households are heavily affected by drought shock and *ex ante* private coping strategies. In the region they examine, the accumulation of livestock proves to be more effective in comparison to *ex post* public responses to protect women against adverse consequences.

Silbert and Pilar Useche (2012) find that although male-headed households are less vulnerable and therefore reduce their total consumption to a lesser extent, education can still lead female-headed households to better coping decisions. As already noted, *ex ante* income diversification has also been demonstrated to be an important coping mechanism for consumption smoothing (Wong and Brown, 2011).

Several projects have looked at vulnerability and coping strategies in selected South and South east Asian countries (see Hallegatte et al.,2010; Zoleta-Nantes, 2002; Few, 2003; Patnaik and Narayanan,2010; Takashi et al., 2012 and Israel and Briones, 2013). Zoleta-Nantes (2002) showed the differential impacts of flood hazards on three vulnerable groups - street children, the urban poor and residents of wealthy neighborhoods - in metro Manila, the Philippines. She concluded that spatial isolation and lack of participation in decision-making intensified present and future vulnerability at the household and community levels.[10] A study on the Indian State of Mumbai by Hallegatte et al. (2010) assess the risk and benefits of adaptation due to flood exposure and provides evidence of potential sensitivity and vulnerability to heavy precipitation signifying that improving drainage as part of disaster risk management and extended insurance could reduce the indirect effects of flooding on marginalized groups. Another study by Takashi et al. (2012) on household level recovery after floods in North Pakistan concluded that although households with fewer assets did struggle in the recovery process, the speed of recovery was slower for the richer households later on; leaving an income distribution that was characterized by a mass of households around the income poverty line.

Most researches have focused on first moment impacts of disasters, on the impact of disasters on average levels (of income, of wealth, of health, etc.), but it is also important to point out that disasters can also be an important source of damaging fluctuations (second moments). This generated fluctuations might trigger responses as these may lead to chronic or intergenerational poverty (Sinha et al., 2002).

[10] Another study in Metro Manila, on the impacts of typhoon-related floods by Israel and Briones (2013), found that the occurrence and intensity of aforementioned disasters have a significant negative effect on household income.

1.7 LONG-TERM SCENARIOS IN DISASTERS' AFTERMATH

It is perhaps of even greater importance to determine the long-term effects of catastrophic disasters on various income groups, rather than only their direct and indirect short-term impacts. The limited empirical evidence suggests that large natural shocks can have important regional consequences that may persist for decades. The population of New Orleans, for example, is unlikely to recover from the dramatic exodus of people from the region after Hurricane Katrina - in July 2012, seven years after the hurricane; the population of the city was still 20 percent lower than the week before the storm hit. Emigration, as in Katrina's case, is one possible long-term consequence, and at least in Katrina's case, it seems that the poor and the disenfranchised were disproportionally more likely to emigrate in the storm's aftermath.[11] This evidence, however, is only anecdotal; we have no direct evidence that disasters' long-term impact affect the poor any differently than other segments of society, nor do we have substantial evidence on the distributional consequences, in the long-term, of disaster events.

Analyzing the case of Indonesia, Silbert and Pilar Useche (2012) pointed out that larger households are 16 percent more vulnerable to future poverty in the presence of shocks, and holding all else equal, larger households are likely to be poorer. Similarly, evidence from Brazil suggests that exposure to drought can reduce rural wages by 9 percent in the longer term (defined as 5-10 years; Mueller and Osgood, 2009a). To shed light on distributional impacts, a recent study by Yamamura (2013) concluded that although natural disasters have increased income inequality in the short-term, this effect however, decays over time and disappears in the medium term.[12]

From the macroeconomic/aggregate literature, we know that certain economic conditions and policies may lead to increased resilience in the aftermath of disaster, but on the other hand, its negative impact may be exacerbated significantly by others. Relevant factors include the existence or absence of *ex-ante* disaster management plans, the flexibility to re-allocate resources

[11] Coffman and Noy (2012) describe the impact of a hurricane on a small Hawaiian island, and conclude that the long-term impact of the disaster was a 15% population decline enduring at least two decades after the event. Lynham et al. (2012) provide similar evidence for a tsunami in another Hawaiian island. Hornbeck (2012) examines the long-term impact, at the county level, of the American Dust-Bowl during the 1930s. Hornbeck finds that while there was some adjustment in agricultural activities, there were still substantial declines in productivity and land prices that lasted for many decades. The main adjustment mechanism he describes is emigration.

[12] Narayanan and Sahu (2011) investigate climate related disaster in the Indian state of Orissa, and find deteriorating health conditions due to these events that reduce the ability of the poor to participate in income generating economic activities.

efficiently for disaster relief and reconstruction, the expected access to extra-regional funds from the central government or from other sources (foreign aid, re-insurance payments, etc.), and the ability of the region's dominant economic sectors to rebound. Institutional, cultural and social factors may also play an important constructive role.[13] Whether these differences also matter, in the long-run, at the household level, and differentiate between the poor and others, or have any distributional impacts are all still open questions.

One issue that may turn out to be the most important in determining post-disaster outcomes is not the degree and level of destruction, or the degree of preparedness, but the adjustment in expectations with regard to future events that catastrophes often prompt. Kobe, for example, was not perceived to be a high-risk area for earthquakes before 1995, an assessment which unsurprisingly changed in the disaster's aftermath. In contrast, the devastation wrought by war, even a very destructive one, may be perceived as a one-off event and therefore not lead to long-term shifts in economic activity (see Davis and Weinstein, 2002). The perceived increased risk of future catastrophic events, however, may inhibit human and capital saving and investment in an affected region for decades (see Aizenman and Noy, 2013).

This may be especially important as these changes in the subjective probabilities assigned to plausible hazards may well matter differently for people from different socio-economic backgrounds, given the additional exposure of the poor to risk and given the possibility of decreased investment leading into poverty traps. Once again, however, this is still an open empirical question, like so many of the other issues highlighted in this paper.

[13] For evidence on the importance of social capital, see Aldrich (2012).

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APPENDIX: EMPIRICAL STUDIES ON THE IMPACTS OF NATURAL DISASTERS ON POVERTY

No.	Study Description	Data/Time period	Sample/Methods	Results/Outcomes
1	**Author:** Carter et al. (2007) **Publication:** *World Dev.* **Study area:** Ethiopia, Hondurus **Natural Disaster:** Hurricane Mitch, Drought	**Database used:** Naturally occurring experiments **Time period:** 7 year: Pre-drought (1996-97), drought (1998-2000), recovery (2001-03)	**Sample size:** 416 rural Ethiopian HH, 850 rural Honduran HH **Modeling technique:** Linear regression	*Honduras:* medium-term effects of the shock differ by initial wealth; the relatively wealthy were able to partially rebuild their lost assets. For the poorer households, asset losses lasted longer and were more acute. *Ethiopia*: poorest households try to hold on to their few assets despite decreases in income and consumption possibilities during the period of severe losses in agricultural production.
2	**Author:** Hoddinott and Kinsey (2001) **Publication:** *Oxford Bulletin of Econ. and Stat.* **Study area:** rural Zimbabwe **Natural Disaster:** Drought	**Database used:** Random panel data set **Time period:** 1983 (Jul-Sep), 1984 (Jan-Mar), re-interview in 1997	**Sample size:** 243 children aged 12-24 months **Modeling technique:** Linear regression	This shock lowered annual growth rates for children between 1.5-2cm, and these children remained shorter after four years. This impact has been greater among children living in poor households.
3	**Author:** Glave et al. (2008) **Publication:** UNDP Research paper **Study area:** Peru **Natural Disaster:** Combined Natural Shocks	**Database used:** INDECI-SINPAD database, National Household Survey (ENAHO) **Time period:** 2002-2006	**Sample size:** 2000 rural HH **Modeling technique:** Multinomial regression	The effect of disasters on poverty rates ranges between 0.16 and 0.23pp; an increase in the average number of disasters by one s.d. from the mean would increase poverty rates by at least one percentage point.
4	**Author:** Mogues (2011) **Publication:** *Econ. Dev. and Cultural Change* **Study area:** North-eastern Ethiopia **Natural Disaster:** Rainfall shocks	**Database used:** Panel survey data **Time period:** Jun 2000-Jul 2003 HH survey, livestock holdings data 1996-99	**Sample size:** 448 HH **Modeling technique:** Linear regression; model controls for HH heterogeneity	Analyzed community-level coping mechanisms; found that covariant shocks impacted more on grain stocks than livestock and the impact is greater on total livestock compared to cattle only.
5	**Author:** Dercon (2004) **Publication:** *J of Dev. Econ.*	**Database used:** panel data **Time period:** 1989 - 1997	**Sample size:** 350 HH **Modeling technique:** log	A 10 percent lower rainfall 4–5 years earlier had an impact of one percentage

	Study area: rural Ethiopia **Natural Disaster:** Rainfall shocks		linear model, ML estimation	point on current consumption growth rates.
6	**Author:** Tesliuc and Lindert (2002) **Publication:** World Bank **Study area:** Guatemala **Natural Disaster:** Bunched shocks (D, Fl, H, Q)	**Database used:** Pilot LSMS survey module, QPES, ENCOVI Data **Time period:** 2000	**Sample size:** N = urban-2609, rural-3706, Guatemala city-921 **Modeling technique:** log linear multivariate regression model	The poor are disproportionately more exposed to natural disasters and agriculture related shocks and less to financial shocks. Moreover, as a result of shocks; income inequality increased by 16 percent, consumption inequality by 11 percent and total poverty by 20 percent.
7	**Author:** Datt and Hoogeveen (2003) **Publication:** *World Dev.* **Study area:** Philippines **Natural Disaster:** Drought / El Nino	**Database used:** House Hold survey APIS data **Time period:** Year 1998	**Sample size:** 38,710 **Modeling technique:** log-linear regression	El Nino shock, ranging between 47 percent and 57 percent of the total impact of economic and weather shocks on measures of incidence, depth and severity of poverty.
8	**Author:** Jakobsen (2012) **Publication:** *World Dev.* **Study area:** rural Nicaragua **Natural Disaster:** Hurricane Mitch	**Database used:** Three Nicaraguan Living Standard Measurement Survey (LSMS) panel data **Time period:** 1998, 1999 and 2001	**Sample size:** 3000HH (50 percent rural) **Modeling technique:** Multi-step methodology including difference in difference, single equilibrium model, asset index and OLS	The hurricane did not have an adverse impact on the ownership of productive assets among the affected households on average. Non-productive asset holdings seem to have significantly reduced affecting the poorest households disproportionately.
9	**Author:** Anttila-Hughes and Hsiang (2013) **Publication:** SSRN **Study area:** Philippines **Natural Disaster:** Typhoons / Tropical cyclones	**Database used:** Combine Storm data with FIES and DHS panel data; EM-DAT **Time period:** 1993, 1998, 2003, 2008	**Sample size:** 142,789 **Modeling technique:** Time series non-linear regression	Typhoons causes' large losses to households' economic well-being, destroy durable assets and depress income. Female infant mortality increases substantially in the years following storm exposure. The delayed deaths among female infants outnumber typhoon deaths by a factor of 15.
10	**Author:** Rodriguez-Oreggia et al. (2013)	**Database used:** Poverty panel	**Sample size:** 2,454 municipalities	Natural disasters reduce human development and

	Publication: *J of Dev. Studies* **Study area:** Mexico (municipal level) **Natural Disaster:** ND (Fl, Fr, R,L,Os)	dataset (municipalities); DESINVENTAR; HDI **Time period:** 2000, 2005	**Modeling technique:** Difference-in-Difference regression	increases poverty. Floods and droughts have more significant adverse effects compared to frost, rains, and other natural disasters.
11	**Author:** Lopez-Calva and Ortiz-Juarez (2009) **Publication:** UNDP Research for Public Policy papers **Study area:** Mexico, El Salvador, Peru, Bolivia, Ecuador **Natural Disaster:** Bunched natural shocks	**Database used:** DESINVENTAR, Household and Municipality level data (longitudinal), Census **Time period:** Mexico: 2000-2005,El-Salvador: 2001,Peru: 2002-2006,Bolivia: 1992-2001	**Sample size:** El-Salvador: 700 HH, Peru: 2091HH **Modeling technique:** Fixed Effect and Difference-in Difference	In Bolivia, poverty increased by 12 pp after the flood in 2007. In Peru, given that households have experienced a natural event, they are 2.3-4.8 times more likely to be *always poor* rather than to be *never poor*. All cases suggest that sufficiently large or persistent natural events are likely to have both a short term and a potential long term and inter-generational adverse impact on poverty.
12	**Author:** Baez and Santos (2007) **Publication:** *J of Dev. Econ.* **Study area:** Nicaragua **Natural Disaster:** Hurricane Mitch	**Database used:** Nicaraguan Living Standards Measurement Studies (LSMS), Nicaraguan Demographic Health Surveys (DHS) **Time period:** 1998, 1999, 2001	**Sample size:** 2,764 HH **Modeling technique:** Difference-in Difference approach	Children were 8.7 percentage points more likely to be undernourished due to hurricane Mitch; no significant effect on school enrolment. Child labour force participation increased by 58 percent and the proportion of children simultaneously in school and working increased from 7.5 percent to 15.6 percent.
13	**Author:** Auffret (2003) **Publication:** World Bank **Study area:** 16 countries **Natural Disaster:** Catastrophic shocks	**Database used:** Dynamic Panel Data **Time period:** 1963-1997	**Sample size:** Total Panel Observation: 540 **Modeling technique:** GMM	Catastrophic events lead to a substantial decline in output and investment growth and a moderate decline in consumption growth.
14	**Author:** Giesbert and Schindler (2010) **Publication:** German Institute of Global and Area Studies Paper	**Database used:** Panel survey data of Trabalho de Inquérito Agrícola (TIA) in Mozambique	**Sample size:** 4,104 HH **Modeling technique:** Probit regression	Drought has a significant impact on asset accumulation in the short term with preliminary evidences of households at various wealth

	Study area: Rural Mozambique **Natural Disaster:** Agricultural shocks and earthquakes	**Time period:** 2002, 2005		distributional levels found applying different shock coping strategies.
15	**Author:** Morris et al. (2002) **Publication:** *World Dev.* **Study area:** Hondurus **Natural Disaster:** Hurricane Mitch	**Database used:** Integrated House Hold Survey data **Time period:** Interview: 1999, municipalities up to March 1997	**Sample size:** 2398 rural HH **Modeling technique:** Alternate Logistic Regression	The rural extreme poor were seriously damaged by the hurricane; experienced a reduction in income, depletion of assets and a number of other costs. Assets of households in the lowest wealth quintile reduced by 18 percent compared to 3 percent in upper wealth quintile.
16	**Author:** Asiimwe and Mpuga (2007) **Publication:** AERC Research Paper 168 **Study area:** Uganda **Natural Disaster:** Rainfall Shocks	**Database used:** HH survey data **Time period:** 1992-93, 1999-2000, 2002-2003	**Sample size:** 1992-93 (9900 HH), 1999-2000 (10,696 HH), 2002-2003 (9711 HH) **Modeling technique:** Regression	The impact of rainfall shocks is significant in the first and second planting seasons (March–May, September–November), where positive rainfall shocks result in lower household income and consumption expenditure.
17	**Author:** Maccini and Yang (2009) **Publication:** *American Econ. Rev.* **Study area:** Indonesia **Natural Disaster:** Early life Rainfall	**Database used:** IFLS (Indonesian Family Life Surveys), GHCN (precipitation and temperature data) **Time period:** 2000	**Sample size:** Men - 4277, Women - 4615 **Modeling technique:** Reduced-form Linear Relationship	Women experiencing 20 percent more rainfall are 3.8pp less likely to self-report poor or very poor health. They attain 0.57cm greater height, 0.22 more grades of schooling, and live in HH that score 0.12SD higher on an asset index.
18	**Author:** Narayanan and Sahu (2011) **Publication:** RePEc **Study area:** Orissa, India **Natural Disaster:** Flood	**Database used:** Primary data collection at the household level (CARICOM) **Time period:** 2009	**Sample size:** 150 rural HH **Modeling technique:** Linear regression	Smaller family size, migration income share, caste structure are the major contributors of household health post-disaster.
19	**Author:** Khandker (2007) **Publication:** *Agricultural Economics* **Study area:** Bangladesh	**Database used:** Panel households survey in 1998/99 **Time period:** 1998	**Sample size:** 2,600 HH **Modeling technique:** Regression	Half of rural households were able to mitigate the impact of the 1998 Flood. The flood had no lasting impact on consumption and assets. This is mostly due to a subsequent bumper crop,

	Natural Disaster: Flood			flood relief, or borrowing from micro-credit.
20	**Author:** Tiwari et al. (2013) **Publication:** World Bank **Study area:** rural Nepal **Natural Disaster:** Rainfall shocks	**Database used:** Demographic and Health Survey (DHS), DHM (171 rainfall stations) **Time period:** 2001, 2006, 2011	**Sample size:** 2001 (8602 HH), 2006 (9036 HH) and 2011 (10,826 HH) **Modeling technique:** OLS	A 10 percent increase in rainfall leads to a 0.15 SD increase in weight-for-age for children (0–36 months). Excess monsoon rainfall also enhances child stature iff in the second year of life. This transitory child height effect completely dissipates by age 5.
21	**Author:** Silbert and Pilar Useche (2012) **Publication:** Working Paper, Univ. of Florida **Study area:** Indonesia **Natural Disaster:** ND (Fl, Q, MMw)	**Database used:** IFLS (Indonesian Family Life Surveys); EM-DAT **Time period:** 1997, 2000, 2007	**Sample size:** 3269 HH **Modeling technique:** Estimation of Ligon and Schechter (LS) measure, Housing Quality Index (income)	Disasters between 1992-1997 significantly increase vulnerability to future poverty (by nearly 68 percent) whereas households experiencing a disaster between1995-2000 are 36 percent less vulnerable to poverty.
22	**Author:** Wong and Brown (2011) **Publication:** *B.E. J of Economic Analysis & Policy* **Study area:** Indonesia **Natural Disaster:** Forest Fire	**Database used:** EM-DAT; IFLS (1993, 1997) **Time period:** 1997 fire, HH - 1993, 1997	**Sample size:** 7224 HH **Modeling technique:** Ligon and Schechter(LS) measure, Estimation of OLS Model	Farm households face a 32.4 percent increase in vulnerability in food consumption relative to non-farm. HH who own farm businesses face 49.2 percent more vulnerability than non-farm. Male-headed households are less vulnerable.
23	**Author:** Mahajan (2012) **Publication:** Indian Statistical Institute **Study area:** 14 States, India **Natural Disaster:** Rainfall shocks	**Database used:** 1993/94, 1999/00, 2004/05, and 2007/08 of National Sample Surveys (NSS). Rainfall Data: Univ. of Delaware **Time period:** 1993-2007	**Sample size:** 416 HH, random selection **Modeling technique:** Log-linear regression and Difference analysis	Rainfall shocks do not affect gender wage gap. In rain-fed rice growing regions, females suffer greater loss in terms of wages compared to men due to lower rainfall. Greater demand for women in crop cultivation makes them more vulnerable to labour market losses during low rainfall.
24	**Author:** Lal , Singh and Holland (2009) **Publication:** SOPAC Report 678, UNISDR **Study area:** Fiji	**Database used:** NDMO, EM-DAT, GLIDE, FMS and Pacific Disaster Net;	**Sample size:** 835,869 **Modeling technique:** Regression	A negative relationship between HDI and disasters implying higher poverty levels with decrease in HDI.

	Natural Disaster: Cyclones and floods	HIES, HDI, HPI and IFS database **Time period:** 1990 – 2002		
25	**Author:** Reardon and Taylor (1996) **Publication:** *World Dev.* **Study area:** Burkina Faso **Natural Disaster:** Severe drought	**Database used:** HH Farm survey (ICRISAT) **Time period:** 1983-84, 1984-85	**Sample size:** 150 HH, 25 per vill. **Modeling technique:** Income source decomposition, Foster-Greer-Thorbecke poverty index	In the *Sahelian* zone, inequality decreases but poverty increases after drought. In the *Guinean* zone (superior agro climate), poverty and inequality are positively related.
26	**Author:** Jha (2006) **Publication:** South Asia Research Centre, ANU **Study area:** Fiji, Kyrgyz Rep., PNG and Vanuatu **Natural Disaster:** Earthquakes, Slides, Floods and Windstorms	**Database used:** WDI, EM-DAT **Time period:** Fiji (1960-85,1997-99), Kyrgyz Rep.(1990-2003), PNG (1961-1999), Vanuatu (1983-1995)	**Sample size:** Fiji (.84 mill.), Kyrgyz Rep. (5.1 mill.), PNG (5.5 mill.) and Vanuatu (.21 mill.) **Modeling technique:** Certainty-Equivalent Consumption Growth, macroeconomic aggregates	If consumption continued at an average pace, Fiji would experience a net drop in per capita consumption of 22.74 percent. In Kyrgyz Rep. the drop would be 17.14 percent. In PNG, there would be a rise in per capita consumption of 33.03 percent; in Vanuatu, per capita consumption would grow by 2.67 percent for the period 1995–2015.
27	**Author:** Hou (2010) **Publication:** *Econ. Dev. and Cultural Change* **Study area:** Mexico **Natural Disaster:** Drought	**Database used:** Panel data from PROGRESA **Time period:** 1998-1999	**Sample size:** 24,000HH in 506 localities **Modeling technique:** First Difference model	Drought reduces total expenditure and total food expenditure while increasing total calories available by reducing consumption of expensive calories (vegetables, fruits, and animal products).
28	**Author:** Hoddinott (2006) **Publication:** *J of Dev. Studies* **Study area:** Zimbabwe **Natural Disaster:** 1994-95 Drought	**Database used:** Annual longitudinal data on households and individuals **Time period:** 1994-1999	**Sample size:** 400 HH **Modeling technique:** Fixed Effect estimation and First Difference	Drought causes some households to draw down assets; adult men and older preschoolers were not adversely affected. However, young preschoolers (12–24 months) were adversely affected along with adult women (who recovered quickly).
29	**Author:** Mueller and Osgood (2009a)	**Database used:** HH Surveys, Climate: Research Institute	**Sample size:** 300,000	A decrease of one SD of precipitation can have an 18 percent effect on rural

	Publication: *J of Dev. Studies* **Study area:** Brazil **Natural Disaster:** Drought	for Climate and Society **Time period:** 1992,1993, 1995	individuals, 13,197 weather stations **Modeling technique:** Reduced-form regression	wages within 5 years and a 9 percent effect on rural wages within 5-10 years.
30	**Author:** Mueller and Quisumbing (2011) **Publication:** *J of Dev. Studies* **Study area:** Bangladesh **Natural Disaster:** Flood	**Database used:** Flood Impact panel household survey **Time period:** 1998 – 2004	**Sample size:** 757 HH (126 villages) **Modeling technique:** Regression	Real wages of agricultural workers declined only in the short-term, while magnitude of the salaried income losses was high (34.3-45.6 percent) with wages stabilized over time.
31	**Author:** Shah and Steinberg (2012) **Publication:** University of California, Davis **Study area:** India **Natural Disaster:** Rainfall shocks	**Database used:** Rainfall data: Univ. of Delaware Schooling and Health: Annual Status of Education Report (ASER) Wages: National Sample Survey (NSS) **Time period:** 2005-2009	**Sample size:** 3 million rural children **Modeling technique:** Regression	Children and parents work less and have lower wages in drought years and the reverse for positive rainfall shocks. Early-life exposure to droughts has deleterious effects on health, schooling and later-life wages.
32	**Author:** Foltz et al. (2013) **Publication:** AAEA conference presentation **Study area:** Ethiopia **Natural Disaster:** Drought, Rainfall and Temperature	**Database used:** Ethiopia Rural Household Survey (ERHS) **Time period:** 1995-2009	**Sample size:** 15 collection of villages **Modeling technique:** Logit regression	Food and non-food consumption are a direct function of weather; being in a vulnerable area may not result in being worse-off relative to being poor in a non-vulnerable area.
33	**Author:** Thomas et al. (2010) **Publication:** World Bank **Study area:** Vietnam **Natural Disaster:** Droughts, Floods and Cyclones	**Database used:** Geo-referenced meteorological data, National Living Standard Measurement Surveys **Time period:** 2002, 2004, 2006	**Sample size:** Over 500,000 **Modeling technique:** Regression	Short-run losses from natural disasters can be substantial, with riverine floods causing welfare losses up to 23 percent and hurricanes reducing welfare by up to 52 percent in cities (population>500,000).
34	**Author:** Skoufias et al. (2012) **Publication:** *Bulletin of Indonesian Econ. Studies*	**Database used:** IFLS2 and IFLS3, 32 weather stations **Time period:** 1997-1998, 2000	**Sample size:** 267 communities **Modeling technique:** Regression	A delay in monsoon onset does not have a significant impact on the welfare of rice farmers; HH located in areas exposed to low rainfall following the

	Study area: Indonesia **Natural Disaster:** Rainfall shocks			monsoon are negatively affected.
35	**Author:** Mueller and Osgood (2009b) **Publication:** *Ag. Econ.* **Study area:** Brazil **Natural Disaster:** Short-term precipitation shocks	**Database used:** HH survey, NOAA, National Center for Environmental Prediction, Climate Prediction Center **Time period:** 1995	**Sample size:** 45,370 rural HH, 40,005 urban HH **Modeling technique:** Regression	Large precipitation shocks have long-term negative impacts on rural out-migrants' incomes; observed decline is likely from the loss of worthy alternatives as opposed to damage from migration itself.
36	**Author:** Baez and Santos (2008) **Publication:** UNDP Public Policy paper **Study area:** El Salvador **Natural Disaster:** Earthquake	**Database used:** BASIS El Salvador Rural Household Surveys **Time period:** 1996-2002	**Sample size:** 700 HH **Modeling technique:** Double-Difference analysis	Effect of both earthquakes is a reduction in household income of one-third of the pre shock average for households in the upper half of the ground shaking distribution; also an increase in the depth and severity of poverty.
37	**Author:** Hoddinott and Kinsey (2000) **Publication:** IFPRI Discussion Paper **Study area:** Zimbabwe **Natural Disaster:** 1994-95 Drought	**Database used:** panel data set of households **Time period:** 1994-1997	**Sample size:** 400 HH **Modeling technique:** Fixed Effect estimation	Poor women are more severely affected by drought. *Ex ante* private coping strategies (e.g. accumulation of livestock) protect women against adverse consequences compared to *ex post* ineffective public responses.
38	**Author:** Jensen (2000) **Publication:** *American Econ. Rev.* **Study area:** Cote d'Ivoire **Natural Disaster:** Rainfall shocks	**Database used:** Cote d'Ivoire Living Standards Survey. Rainfall data: Agence Nationale des Aerodromes et de la Meteorologie **Time period:** 1985-1988	**Sample size:** 352 **Modeling technique:** OLS and fixed-effect regression	School enrolment rates decline 33-50 percent and malnutrition doubles in the presence of adverse rainfall shocks. HH are slightly more likely to send children to live elsewhere during an adverse weather shock.
39	**Author:** Cunguara et al. (2011) **Publication:** *Ag. Econ.* **Study area:** Southern Mozambique **Natural Disaster:** Drought	**Database used:** panel survey data **Time period:** 2002 (TIA02), 2005 (TIA05), 2008 (TIA08)	**Sample size:** TIA02 and TIA05: 1154 HH; TIA08: 1196 HH **Modeling technique:** log linear regression	Participation in nonfarm income-generating activities increases during drought. HH are unlikely to generate a higher mean net income necessary to compensate for the shortfall in income from

				crops. Relatively poorer HH often earn less from nonfarm activities than wealthier ones.
40	**Author:** Van den Berg (2010) **Publication:** *Ecological Econ.* **Study area:** Nicaragua **Natural Disaster:** Hurricane Mitch	**Database used:** Living Standard Measurement Survey (LSMS) panel data **Time period:** 1998-2001, 2005	**Sample size:** 3352 **Modeling technique:** multinomial logit regression	Annual farming and farm employment generate low incomes, whereas non-farm wage employment and livestock farming result in relatively high incomes. Poverty traps identified among HH that followed low-welfare coping strategies.
41	**Author:** UNISDR (2012) **Publication:** UNISDR Regional Office, Cairo **Study area:** Jordan, Syria, Yemen **Natural Disaster:** D, Fl, Fr, W-c and h, Q, Lq, Epi, Ss	**Database used:** DESINVENTAR **Time period:** Jordan: 1981-2010; Syria: 1980-2009; Yemen: 1971-2011	**Sample size:** Jordan: 454; Syria: 7326; Yemen: 8945 **Modeling technique:** Descriptive	Poverty is most severe in rural non-diversified regions where agriculture is severely limited by low rainfall, degraded lands, erosion and desertification. Climate variability and water shortage leads to stagnating rural incomes and increased poverty in Syria and Yemen.
42	**Author:** Lal, Rita and Khatri (2009) **Publication:** IUCN **Study area:** Fiji **Natural Disaster:** Floods	**Database used:** 2009 Flood Economic Survey **Time period:** 2009	**Sample size:** 15-20 percent of each category of firm **Modeling technique:** ECLAC Disaster Assessment Method	The total economic cost of floods in the sugar belt is about $24 million. 77 percent of the flood affected sugarcane families will fall below the poverty line, compared to 54 percent of families, if no flooding.
43	**Author:** Kim (2012) **Publication:** *Disasters* **Study area:** Global **Natural Disaster:** Composite Natural Disasters	**Database used:** WDI poverty data, EM-DAT **Time period:** Poverty (2008), EM-DAT (1970-2006)	**Sample size:** 208 countries **Modeling technique:** Disaster Exposure indicator	The total net increase of exposure between 1970-2000 is determined by the increased concentration of the poor (26 percent) in disaster-prone areas. With varying time trend across regions, poor people in East Asia and Pacific are more exposed to natural disasters.
44	**Author:** Halliday (2012) **Publication:** *European Econ. Rev.*	**Database used:** BASIS panel data **Time period:** 1997-2002	**Sample size:** 689 (2001), 1365 (1999,2001), 2008 (1997,1999,2001)	The 2001 earthquake resulted in a large negative effect on female migration, but had absolutely no effect

	Study area: El Salvador **Natural Disaster:** Ag. shocks and earthquakes		**Modeling technique:** Regression	on male migration. A dramatic increase in the number of women's domestic labour hours.
45	**Author:** Attzs (2008) **Publication:** UNU-WIDER Paper **Study area:** Jamaica **Natural Disaster:** Floods, Earthquake and Hurricanes	**Database used:** EM-DAT, poverty assessment studies (CARICOM) **Time period:** 1990s	**Sample size:** CARICOM member states - 17 countries **Modeling technique:** Descriptive stats.	An increase in migration after hurricane and an increased flow of remittances that constitutes 87 percent of total income among the poorest deciles. Women are found more vulnerable (40 percent of HH are headed by females).
46	**Author:** Masozera et al. (2007) **Publication:** *Ecological Econ.* **Study area:** New Orleans **Natural Disaster:** Hurricane Katrina	**Database used:** Census, American Community Survey 2004 **Time period:** 2005-6	**Sample size:** New Orleans (2002 population - 484,674) **Modeling technique:** GIS, vulnerability analysis	Lower income groups suffered disproportionately during the response and recovery phases.
47	**Author:** Little et al. (2006) **Publication:** *J of Dev. Studies* **Study area:** South Wollo, Ethiopia **Natural Disaster:** Drought	**Database used:** 7-rounds of interviews **Time period:** Between 2000 and 2003, 62 cases; recall data 1997-99	**Sample size:** 416 HH **Modeling technique:** Empirical analysis of larger sample and in-depth of smaller sample.	The 1999–2000 droughts had a devastating short-term impact on HH, particularly among the poorest, but did not increase overall rates of poverty in medium term. The greater the dependence on rain fed agriculture-based incomes and less diversification, the greater the risk of poverty.
48	**Author:** Neumayer and Plumper (2007) **Publication:** *Annals of the Association of American Geographers* **Study area:** Global **Natural Disaster:** D, Q, Epi, Ext. temp, Fam, Fir, Fl, Ins. Infes, L, V, S, Ws	**Database used:** EM-DAT; International Data Base of US Census, WB **Time period:** 1981 - 2002	**Sample size:** 141 Countries, 4605 Natural Disasters **Modeling technique:** Regression	Disasters lower life expectancy of women and in certain cases at an earlier age compared to men. Disaster strength is positively related with gender gap in life expectancy; this effect deteriorates with higher level of women's socioeconomic status.

49	**Author:** Boustan et al. (2012) **Publication:** *American Econ. Rev.* **Study area:** 467 SEA (State Economic Area) **Natural Disaster:** Fl, Q,H,T	**Database used:** American Red Cross –circulars**.** Migration data- from two panel datasets (1920-30 and 1935-40). **Time period:** 1920-1940	**Sample size:** 15000 randomly selected men **Modeling technique:** Conditional Logit regression	In the 1920s and 1930s population exited from tornado-prone areas with a larger effect on potential in-migrants than on existing residents, while flood events were associated with net in-migration.
50	**Author:** Shoji (2010) **Publication:** *J of Dev. Studies* **Study area:** Bangladesh **Natural Disaster:** Floods	**Database used:** IFPRI survey **Time period:** 2004-2005	**Sample size:** 326 HH **Modeling technique:** Recursive Bivariate Probit model	Rescheduling plays the role of safety net by decreasing the probability that people skip meals during negative shocks by 5.1 percent; the effect is higher on the landless and females.
51	**Author:** Patnaik and Narayanan (2010) **Publication:** RePEc **Study area:** Uttar Pradesh, India **Natural Disaster:** Floods	**Database used:** Primary HH Survey; EM-DAT **Time period:** 1950-2007	**Sample size:** 600 villages **Modeling technique:** Multivariate Probit model	HH adopt a wide variety of risk coping measures (monetary transfers, relief, selling of livestock and borrowing). Monetary transfers were the most effective but unlikely to be used to cope with health shocks.
52	**Author:** Janzen and Carter (2013) **Publication:** University of California, Davis **Study area:** Kenya **Natural Disaster:** Drought	**Database used:** Index-based Livestock pilot project **Time period:** 2009, 2011	**Sample size:** 924 HH **Modeling technique:** Difference-in-Difference	Insured HH are 18-50 pp less likely to draw down assets and 8-41 pp less likely to reduce meals compared to uninsured households.
53	**Author:** Yamamura (2013) **Publication:** RePEc **Study area:** Global **Natural Disaster:** Disasters in general.	**Database used:** Standardized Income Distribution Database (SIDD); EM-DAT **Time period:** 1965-2004	**Sample size:** 86 countries **Modeling technique:** Regression	Natural disasters lead to increased income inequality in the short-term. Intriguingly, it has further been reported that this effect disappears in the medium-term.
54	**Author:** Baez and Mason (2008) **Publication:** SSRN **Study area:** Lat Am. and the Caribbean **Natural Disaster:** Ws/Fl (clim. ch impacts)	**Database used:** EM-DAT, climate data, social vulnerabilities and public health data. **Time period:** 1970-2007	**Sample size:** Latin America and the Caribbean countries **Modeling technique:** Synthesis of evidences	Weather inconsistencies are expected to have negative short-run and long-run consequences on the well-being of rural populations. Agricultural incomes are likely to be negatively affected due to weather variability.

55	**Author:** Banerjee (2007) **Publication:** *World Dev.* **Study area:** Bangladesh **Natural Disaster:** Flood	**Database used:** District-wise monthly real agricultural wage **Time period:** 1979-2000	**Sample size:** 20 Districts **Modeling technique:** An autoregressive distributed lag process, Difference-in-difference	Floods have positive implications for wages in the long-run; magnitude depends on relative flood-proneness of a district and relative severity of floods.
56	**Author:** De La Fuente (2010) **Publication:** *Well-Being and Social Policy* **Study area:** Lat Am Countries **Natural Disaster:** Hurricane Mitch and floods afterwards	**Database used:** Panel data from nationally representative household surveys, satellite rainfall records **Time period:** 1998-2001	**Sample size:** HH surveys 1998-2001. **Modeling technique:** difference-in-difference	HH having suffered a flood (caused by Mitch) had an income growth rate 20 percent lower than other households. No significant medium-term effect on HH located in municipalities affected by the hurricane.
57	**Author:** Dillon et al. (2011) **Publication:** *American Journal of Ag. Econ.* **Study area:** Nigeria **Natural Disaster:** Extreme temperature	**Database used:** HH survey (2008) on individuals who migrated from villages originally sampled in 1988, temperature data **Time period:** 1988, 2008	**Sample size:** 200 HH (four villages) **Modeling technique:** linear probability model	Males migrate in response to *ex post* risk.
58	**Author:** Hallegatte et al. (2010) **Publication:** OECD Working Paper No.27 **Study area:** Mumbai, India **Natural Disaster:** Flood and climate change	**Database used:** Rainfall observations (Indian Meteorological Department), Affected Exposure Map from Indian Remote Sensing Satellite **Time period:** 2005	**Sample size:** 700,000 HH **Modeling technique:** Cost-Benefit Analysis	Total losses (direct plus indirect) associated with a 1-in-100 year event could triple compared to current scenario. By improving the drainage system in Mumbai, losses could be reduced by as much as 70 percent. Extending insurance to 100 percent penetration could halve the indirect effects.
59	**Author:** Rabassa et al. (2012) **Publication:** World Bank **Study area:** Nigeria **Natural Disaster:** Rainfall shocks	**Database used:** Nigeria Demographic and Health Survey, rainfall data **Time period:** 2003, 2008	**Sample size:** 11,500 child-level records that includes birth dates and detailed child health. **Modeling technique:** Regression	Rainfall shocks have an impact on child weight-for-height and height-for-age, and on the incidence of diarrhoea. No evidence of nonlinear impacts. No gender-based discrimination in resources allocation.

60	**Author:** Bandyopadhyay and Skoufias (2015) **Publication:** *Rev. of Econ. of the Household* **Study area:** Bangladesh **Natural Disaster:** Rainfall variability	**Database used:** Household Income Expenditure Survey (2010), rainfall data (BMD and CRU), flood data (BWDB) **Time period:** 2010, January 2011 (HIES), 1948-2010 (rainfall)	**Sample size:** 7,840 rural HHs **Modeling technique:** Regression	Rural households are found to adopt occupational diversification that comes at a cost of lower consumption. Access to market appears to be more effective compared to access to credit and safety nets in reducing the likelihood of costly occupational diversification.
61	**Author:** Rentschler (2013) **Publication:** World Bank **Study area:** Global **Natural Disaster:** Q, Fl and Ws	**Database used:** MunichRE, nationally representative household income surveys **Time period:** 1980-2012	**Sample size:** Global **Modeling technique:** survey analysis	Low-income countries incur disproportionately large damages relative to assets. The poor are significantly more vulnerable and exposed to the economic and human capital losses.
62	**Author:** Mendiratta (2012) **Publication:** Published online (www. isid.ac.in) **Study area:** India **Natural Disaster:** Rainfall	**Database used:** Global monthly rainfall data, DHS **Time period:** 1998-99	**Sample size:** 436 districts, children aged 13-36 months **Modeling technique:** Reduced-form regression	Height and weight-for-age for both girls and boys are neg. impacted by adv. rainfall while increase the risk of termination of breastfeeding during pos. rainfall.

Source: Authors' elaborations.

Notes: The acronyms used above are explained as follows: TIA (Trabalho de Inqu´erito Agr´ıcola – National Agricultural Survey), LSMS (Living Standard Measurement Survey), QPES (Qualitative Poverty and Exclusion Field Study), ENCOVI (Encuesta Nacional de Condiciones de Vida), APIS (Annual Poverty Indicators Survey), FIES (Family Income and Expenditure Survey), DHS (Demographic and Health Survey), EM-DAT (Emergency Events Database), DESINVENTAR (Disaster Information Management System), HDI, UNDP (United Nations Development Programme), UNISDR (United Nations International Strategy for Disaster Reduction), IUCN (World Conservation Union), ECLAC (Economic Commission for Latin America and the Caribbean), BASIS (fielded by the Ohio State University and the Fundacio´n Salvadoren˜a para el Desarollo Econo´ mico y Social (FUSADES)), IFLS (Indonesian Family Life Survey), GHCN (Global Historical Climatology Network), CARICOM (Caribbean Community Secretariat), DHM (Department of Hydrology and Meteorology), NDMO (National Disaster Management Office), GLIDE (Global Identifier Number), FMS (Fiji Meteorological Service), HIES (Household Income Expenditure Survey), HPI (Human Poverty Index), IFS (International Financial Statistics), BMD (Bangladesh Meteorological Department), CRU (Climate Research Unit of University of East Anglia), BWDB (Bangladesh Water Development Board), ICRISAT (International Crops Research Institute for the Semi-Arid Tropics), WDI (World Development Indicators), WB (World Bank), dc (data card), G (governorates), OLS (Ordinary Least Squares), ND (Natural Disaster) - (D-Drought, , H-Hurricane, Fl-Flood, Fr-Frost, R-Rainfall, L-Landslide, Lq-Liquefaction, W-Wave-cold and heat, Q-Quakes, Ss-Snowstorms, MMw-Mass Movement wet, Epi-Epidemics, Ext.temp-Extreme Temperature, Fir-Fires, Fam-Famines, Ins. Infes – Insect Infestations, V-Volcano, S-surges, Ws-Windstorms, T-Tornado, Os-Others), HH (Household).

CHAPTER TWO

POVERTY AND NATURAL DISASTERS: A REGRESSION META-ANALYSIS

2.1 INTRODUCTION

Natural disasters - earthquakes, typhoons, hurricanes, floods, cold and heat waves, droughts and volcanic eruptions - are a constant presence in all our lives, but especially so for the poor. Disasters are especially prevalent in the most populous region of the world (Asia) and most catastrophic in the destruction they wreak in the poorest countries (e.g., Haiti in 2010). Disasters, however, occur everywhere, and their direct financial costs have been increasing for the past several decades.

The poor, both in low- and higher-income countries are especially vulnerable to the impact of disasters, so that disasters are not only of interest to social scientists because of society-wide economic impact, their impact on the public sector which bears the costs of reconstruction, or because of their environmental impact, but also because of their importance in the processes of development, income growth, and income distribution. The World Bank, for example, devoted its 2014 *World Development Report* to the risk faced by poor households, poor regions, and poor countries, with a special emphasis on risks that are associated with natural events. The need to understand the role of disasters and their impacts on the poor, in creating and sustaining poverty, and in generating poverty traps, is even more acute as the changes due to human-induced climate change are predicted to be more extreme in poorer countries and will thus place additional barriers to poverty alleviation.[14]

The empirical and theoretical research on disasters has been evaluating the impacts of natural disasters on a diverse range of social and economic issues: the economic growth impact of disasters in the short and long terms, the fiscal impact of disasters, the impact on international trade and financial flows, the impact on populations through migration and fertility choices, the impact on human capital accumulation, the importance of political economy in shaping the disasters' aftermath, and other related topics. The research on the impact of disaster shocks specifically on the poor is one branch of this wider 'disaster' literature that has not yet been adequately summarized, nor has there appeared to be any attempt to reach any general

[14] There is little certainty regarding the impact of climate change on the occurrence of natural disasters, though the most recent assessment by the IPCC concludes that the frequency of days with extreme temperature, of floods, and of droughts, is likely to increase (IPCC, 2012). In addition, the spatial distribution of extreme events is likely to change leading to further impact as these will affect areas that are less prepared for them.

conclusions from the numerous case studies (country-specific, disaster-type-specific, or disaster-event-specific) that constitute the bulk of this research stream.

This lacuna is at least in part attributable to the complex nature of the inter-relationship between disaster impacts and poverty and welfare outcomes, and the consequent diversity of impacts across the investigated case studies. An additional difficulty, given this diversity of outcomes, is in identifying the precise channels - both direct and indirect - that describe the causal mechanisms. We aim to fill this lacuna using meta-regression analysis.

For readers who are not familiar with this methodology, meta-regression analysis is a statistical method, a regression that is used to evaluate a body of empirical research that is itself typically regression-based. It is especially appropriate for questions for which there are multiple studies using similar methodologies, but different datasets, different regression specifications, or different time-periods. Meta-regression analysis is a companion method to a narrative survey of the literature. It identifies empirical regularities in the investigated body of work that are more difficult to spot or to rigorously establish. It further establishes what characteristics of the data, the method, or the studies' designs are most closely associated with the observed empirical regularities. Stanley (2001) provides further details about the justification and the theoretical underpinning of the meta-regression method.

Here, we embark on an attempt to provide some generalizations about this literature through the use of a meta-regression analysis of this literature. Two strands of literature constitute our primary focus in this study. The first strand investigates the immediate (direct or first-order) effect of disasters on household welfare, on the poor specifically, and on society-wide incidence of poverty. The second strand explores the consequent indirect (higher-order) effects that have an impact on the lives of the poor, in generating additional poverty, or in the creation and sustenance of poverty traps.[15] Given the nature of our quantitative meta-analysis, we restrict our investigation

[15] Cavallo and Noy (2011), following the ECLAC (1991) methodology, distinguish between the direct impact of sudden-onset disasters (the immediate mortality, morbidity, and physical damage) and the indirect impact that affects the economy in the aftermath of the actual damage caused (including secondary mortality and morbidity, and on economic activity). The World Bank, in its survey *Natural Hazards Unnatural Disasters* (2010), employs a different terminology that makes essentially the same distinction: first-order and higher-order effects.

to research projects that are empirical in nature, and thus exclude qualitative assessments, theoretical analyses, and work that relies on calibration of structural models.[16]

The diverse foci of these empirical studies and the multitude of different empirical findings clearly demonstrate the importance of synthesizing these research results formally in meta-regression analysis. According to guidelines suggested by Stanley et al. (2013), a statistical meta-regression analysis is explicitly designed to integrate econometric estimates, typically regression coefficients or transformation of regression coefficients. To put differently, a meta-analysis is a quantitative summary of statistical indicators reported in a series of similar empirical studies; previous well-known examples include Card and Krueger (1995), Smith and Huang (1995), Brander et al. (2006), and Disdier and Head (2008). We essentially provide an exploratory synopsis of the empirical literature analyzing the direct and indirect relationship among poverty, household welfare and natural disasters attempting to generalize from the contextual idiosyncrasies of each case-study.

Our contribution here is the synthesis of the microeconomic literature examining the heterogeneity of impact of disasters on the poor, using regression meta-analysis methodology. Two recently published papers, Lazzaroni and van Bergeijk (2014) and Klomp and Valckx (2014), both conducted regression meta-analysis of the macroeconomic literature. They both focus on the impact of natural disasters on aggregate growth and conclude that while the average indirect short-term impact is largely negative, there is significant heterogeneity across countries, time periods, and types of events. Our contribution, therefore, provides useful microeconomic detail complementing the macroeconomic insights derived from this previous work.

The empirical studies utilized to conduct the quantitative analysis here illustrate the geographical coverage of this research: Asia (36.8 percent of research projects) and Africa (34.2 percent) are the most studied regions compared to Central America (23.7 percent), South America (18.4 percent) and Oceania (15.8 percent). Regarding the types of natural disasters studied, hydro-meteorological events (mainly floods, rainfall and tropical cyclones) are studied in 21 studies (55.2 percent) followed by geo-climatological events (i.e. droughts and earthquakes) in 13 studies (34.2

[16] A companion narrative review of the literature that also describes the projects that employ other methodological approaches is Karim and Noy (2016).

percent). The rest constitute seven studies that investigate multiple types of natural shocks (18.4 percent).

The organization of this paper is as follows: Section 2.2 details the data construction procedure. We first identify the algorithm that led to the choice of studies to include, and then providing detailed explanation of the specific categories of variables we included as both the independent and dependent variables in our regression analysis. This section follows closely the meta-analysis protocol outlined in Stanley et al. (2013). This section also includes the relevant descriptive and summary statistics. Section 2.3 presents the methodological framework with the specifications we use and the functional form of the meta-regression. Section 2.4 examines the regression output and provides interpretation of results comparing it with the results outlined in the existing literature we analyze. We describe robustness checks with restricted samples in Section 2.5 and end up with some conclusions and a further research agenda in Section 2.6.[17]

2.2 DATA CONSTRUCTION

The empirical literature on poverty and natural disasters is relatively new with a substantial inflow of new studies during the past decade. This may be the case because of the availability of new data, the increasing media reporting of natural catastrophes, and/or the potential link to the changing climate. This short history assists us in as much as almost all the studies we found were completed using rigorous statistical/econometric approaches. In order to make sure our results are less biased than a more informal qualitative survey, we include every single paper that we found by following a well-defined procedure, and which includes all the relevant variables/measures we require for our statistical analysis. In our final sample of 38 papers, 28 had gone through a peer-reviewing process. In order to attenuate any publication bias we also included working papers and other unpublished work we found while following our search procedure described below.[18]

[17] Goodman et al. (2013) describe the steps that are dictated in a standard meta-analysis protocol: "1) a thorough literature search; 2) clear and transparent eligibility criteria for selecting studies to include in the analyses; 3) a standardized approach for critically appraising studies; 4) appropriate statistical calculations to assess comparisons and trends among study findings; and 5) evaluations of potential sources of heterogeneity and bias." In this section, we describe steps (1)-(3), in the next section we describe step (4), while the last two sections include detailed descriptions of the evaluations we undertook (step 5).

[18] Unlike practice in some other research disciplines, in economics most research projects are posted online as working papers long before they are accepted for publication anywhere. Thus, by relying also on search engines that identify working papers we overcome much of the publication bias that could be a bigger concern had we not been able to access unpublished research.

Our base sample constitutes English-language papers identified through an extensive search using the main relevant search engines and electronic journal databases deploying combinations of keywords and terminologies. Papers have been collected between April and June, 2013. We searched in: EconLit, Google Scholar, JSTOR, RePec, Wiley Online Library, and the World Bank working paper series. The keywords we used in these searches were: poverty and natural disasters, inequality and natural disasters, impacts of natural disasters on household, weather shocks and household welfare, and impacts of natural shocks on the poor. We followed this by examining the existing bibliographies within these papers we already identified to further widen our sample. The studies we collected range from journal articles, to project reports, book chapters and working papers.

Out of 62 studies we identified, we were able to extract 161 separate observations from 38 studies of direct and indirect impacts on poverty and welfare indicators impacted through different types of sudden and slow on-set naturally occurring events.[19] The maximum number of observations taken from a single study is 20 and the average number is 4.2. Table 1 details the list of studies we analyzed and reports the number of observations derived from each study in the finalized sample of 38 papers.

2.2.1 DISASTER TYPES AND OUTCOME VARIABLES: BROAD AND SUB-CATEGORIES

Due to diverse range of foci within the available literature, we have accumulated the measures of poverty and welfare outcomes under several broad categories: income, consumption, poverty, wealth, health, education and labour. Within each category, we further sub-divided the measures into separate indicators, to enable us to examine whether the type of poverty/welfare measure used affects the results. The classification of types of natural disasters and the methodologies used were also recorded and classified for further analysis. Table 2 presents the lists of categories of variables and their descriptions. The frequency distribution of observations

[19] We could not use 24 studies for our statistical analysis either because of the methodology they used (e.g., calibrated modelling), some of the data was missing in their reporting (e.g., number of observations in sample), or their focus was on evaluation of alternative coping strategies rather than impact analysis. In a companion paper (Karim and Noy, 2016), we summarize some general information from all 62 studies including a study description (author, year of publication, study area and specification of natural disaster), data sources and time period used, sample size and methodology, and the results and main conclusions of each study.

and the descriptive statistics of for each of nine (9) types of outcome variables is described in Table 3. Among the outcome values (in percentage changes), consumption1 displays the maximum number of observations (39) followed by health (29), poverty (20), and labour (20). Interestingly, the number of negative outcomes in these categories are 16 (consumption1), 19 (health), 12 (poverty) and 15 (labour). This skewness of the observations suggests the presence of heterogenous impacts among the poverty-disaster outcome measures in this literature.

The direct and indirect impacts of disasters have mostly been defined from the perspectives of income, consumption (for direct impact) and poverty and wealth indicators (for indirect or longer-term). We have further sub-divided income and consumption into two sub-categories while leaving wealth and poverty under one broad category. The direct and indirect impacts of shocks on health, education and labour outcomes have also been investigated in some of the studies in our sample; we classified health, education, and labour in one category each.

In order to conduct our analysis, without assuming that 'all disasters are created equal', we classified three different types of disasters: disaster 1 (hydro-meteorological), disaster 2 (geo-climatological) and disaster 3 (grouped natural shocks). Table 2 provides additional information. Information on our procedure for standardizing the dependent variables is available in the appendix.

2.2.2 CONTROL VARIABLES

We recorded a set of control variables for the observations in our sample. The control variables are included in a binary format based upon their usage in the selected studies; i.e., when a particular control variable had been used in a paper we have recorded 1 and when the specified model failed to control for a specific variable, we recorded 0. The set of control variables whose inclusion we recorded are household/community characteristics (i.e. household heterogeneity including characteristics regarding household head), year and seasonal effects, regional characteristics (i.e., district dummies), demographics (population and labour force characteristics), socio-economic indicators (occupation, land ownership and access to safety net) and features indicating geographical and natural-environmental features. Comprehensive descriptions of all these controls are provided in table 2. In Appendix Table 1 we document the descriptive statistics of all the variables used to conduct this meta-analysis.

2.3 METHODOLOGICAL FRAMEWORK

Our main objective here is to generalize the direct and indirect impacts of natural disasters on households, poverty and welfare measures. We employ the following general econometric specification: $y_i = \alpha C_i + \beta D_i + \delta x_i + \mu_i$. The dependent variable in our regression equation is a vector of percentage change of disaster-impact indicators, labeled y_i. C_i is the vector of outcome variables that are potentially examined in each paper i. D_i is the set of shock variables (disaster and methodology) variables in binary format measured in each study i, while x_i is the set of control variables included in the regressions of the original studies, all these are also in binary format. μ_i represent the error term; we assume the error terms are clustered by study. α , β, and δ are the vectors of estimated coefficients.

Heterogeneity in the precision of estimates is likely to be present due to between-study variation. Possible reasons could be differences in sample size or population, study design and methodologies employed. We therefore estimate the model with standard errors clustered by study.[20]

We start with the most basic specification, estimated using ordinary least squares (OLS) with standard errors clustered by study. We continued with weighted least squares (WLS) estimation using the same control variable specifications as in the OLS regressions. The weights are determined by the square root of the number of observations in each of the original papers we investigated. Basing the weights on the square root of the sample size allows us not to place undue weight on the few studies with very large number of observations.[21]

[20] Cipollina and Salvatici (2010), in their meta-analysis on reciprocal trade agreements, used clustered standard errors (by study). We also estimated the model without the clustered errors; results are very similar and are available upon request.

[21] Longhi et al. (2010), in their meta-study on the impact of immigration on employment and wages, adopted the technique of weighted least square with weights based on the square root of the sample size.

2.4 ESTIMATION RESULTS

Our meta-regression results are reported in tables 4 and 5. We formulated three groups to obtain four different model specifications. Model (1) includes all variables[22], Model (2) the outcome and shock variables, Model (3) the outcome and the control variables and finally Model (4) includes only the outcome variables.[23]

We first examine the outcome variables in table 4. Generally, we find little statistical significance in the coefficients of these outcome variables. For income, for example, we mostly obtain a negative coefficient in most specifications. In this case, a negative coefficient is interpreted to mean that the impact of disasters on income (rather than on other outcome measures) is more negative. When compared to the average impact on other outcome measures, income is impacted more adversely, by 2.5 percentage point. That is, income declines by more. Disasters appear to decrease incomes more (in percentage terms) than other impact measures such as consumption. While the coefficient on income is mostly negative and the coefficient on consumption is generally positive, they are not statistically different from zero (not statistically significant). It is important to note, however, that the coefficients are at times quite large, even if they are imprecisely estimated. The largest coefficient we estimate point to an increase of consumption of 5.4 percentage points, *ceteris paribus*, relative to other variables of interest. The average decrease of an outcome variable was 2.0 percentage points (see Appendix Table 1).

This finding of a larger decrease in income, relative to consumption, in a post-disaster environment is the explicit conclusion arrived in several of the empirical case studies that are part of our sample.[24] In general, this finding of decreased income that is larger than any impact on consumption is suggestive that, at least in part, households and individuals are able to realize (partial) consumption smoothing through the supply of *ex post* credit (formal or informal), relief support, tax relief, or other mitigation policies. More results about the types of income and consumption that are impacted are available in Table 5.

More intriguingly, the longer-term welfare measures that are sometime investigated—poverty indicators, wealth and labour market measures—do not yield unambiguous results in the

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[22] Model 1 excludes the education control as it is dropped because of multicollinearity.
[23] The fit (R^2 and adjusted-R^2) of some of the models, especially in table 5, appears to be better for OLS compared to WLS estimations; see Willett and Singer (1988).
[24] See Carter et al, 2007; Tesliuc and Lindert, 2002; Anttila-Hughes and Hsiang, 2013; Giesbert and Schindler, 2012; Morris et al, 2002; Asiimwe and Mpuga, 2007; Mueller and Osgood, 2009b; and Baez and Santos, 2008.

benchmark regressions in table 4. In the un-weighted regressions, poverty and wealth indicators are consistently negative, but these coefficients are not statistically significant, so we are reluctant to attach much importance to these estimates.

Two variables appear to be consistently estimated to be statistically significant. These are the controls for household heterogeneity, and for socio-economic characteristics. This finding endorses a theme that is found in several research projects. They typically point to differential access to recovery funding and/or credit as a major determinant of the post-disaster economic dynamics (e.g., Sawada and Shimizutani, 2008, at the microeconomic level, and Noy, 2009, at the aggregate macro level). We can conclude here that disaster impacts are not 'an equal opportunity menace' and that disasters exact a differential impact on households with different characteristics belonging to different socio-economic strata. While we do not know the exact general pattern of differential impacts, prior evidence suggests that the poor are more adversely affected by disasters than groups from more privileged socio-economic backgrounds; especially when these affects are measured by poverty indicators or by health and labour outcomes (e.g. Noy and Patel, 2014).[25]

Finally, when comparing the different columns in table 4, we observe that the weighted models, and the ones that include controls for the community, time, region, demographic, socio-economic and geographical characteristics—models (1) and (3)—have a significantly higher fit (higher adjusted R^2).

A separate research agenda, whose methodology did not allow us to include many of the projects within this stream in the corpus of papers we examine, focus on the role of social cohesion in the affected communities and the various types of social capital (bonding, linking, bridging) in determining post disaster recovery. Aldrich (2012) includes a thorough investigation of this literature and a summary of the evidence.[26] For example, Aldrich and Sawada (2015) provide a recent investigation of the importance of social capital in determining mortality due to the tsunami wave generated by the Sendai earthquake of 2011. So, it might be the case that the variables we interpret as proxies for access to resources (credit or otherwise) are also correlated with the presence of social capital in the affected communities. Given our method, we are unable to

[25] We thank Stephane Hallegatte for suggesting this interpretation of the evidence.
[26] Kage (2011), Klinenberg (2002) and Chamlee-Wright (2010) are all book-length investigations of the role of social capital in specific case-studies.

differentiate between the two channels (nor do we think these are mutually exclusive interpretations of the evidence).

In table 5, we investigate the impact of disasters on the various outcome variables in more detail, now distinguishing between the different types of income and consumption. We observe, for example, that while initially we concluded that indeed there is an exceptionally adverse impact of disasters on income in general, this result appears to be driven by a negative impact on per capita or household income (income_2) rather than aggregate measures of total, urban, or rural income. We note that agricultural income (income_1) increases, relative to other measures, in the post-disaster period.

For consumption, the relatively milder impact of disasters on consumption focused on per capita consumption (consume_1) compare to aggregate measures of food and non-food consumption (consume_2). It is impossible to robustly compare the impacts of food and non-food consumption measures in further disaggregation due to limited number of observations.

Human capital (education) and health outcomes appear to be especially adversely affected by disasters. This is more explicit in the models (models 1 and 3) that include household and socio-economic controls (as in table 4, these are also the models with a higher adjusted R^2). This decline in health and educational outcomes could potentially explain the observed and relatively milder impacts on consumption; though the methodology does not allow us to precisely identify that.[27] The results on labour market indicators also portray the adverse (negative) impact of disasters particularly in models 1 and 3.[28] However, the impacts on wages and labour force participation rates could not be differentiated due to less variation in the disaggregated data.

As before, we still observe negative and statistically significant coefficients for household heterogeneity and the socio-economic characteristics – again supporting the hypothesis of differential impact of disasters. In this case, the coefficient for household heterogeneity in Table 4 (column 1 in OLS regression) indicates that if the estimated model does not control for household heterogeneity in the impacted households, this will mean that the estimated effect of disasters on income will be higher by 5.12 percentage points. That is, the impact on income would have been

[27] This result corresponds with the findings of Tiwari et al. (2013) on children's weight and adult women's outcomes of Maccini and Yang (2009).

[28] This result corresponds with the findings of Mueller and Osgood (2009a), Mueller and Quisumbing (2011), Mahajan (2012) and Shah and Steinberg (2012).

larger than 2.5 percentage point if not controlled for household heterogeneity in our estimated model. We find no statistically consistently observable difference in estimation results for the poverty, wealth, and health, labour, and education indicators, and across the various methodological approaches adopted in this literature. Finally, the estimates regarding the disaster indicators mostly illustrates the comparison between hydro-meteorological events—primarily floods, rainfall and tropical cyclones—and geo-climatological ones. We find no robust evidence that different types of disasters have a differential impact.

2.5 ROBUSTNESS CHECKS

As robustness checks, in Table 6, we split our sample to samples focused on consumption and non-consumption outcome measures, and conducted meta-regression analysis with our baseline model and these samples separately.[29] We do not observe any systematic difference on poverty-disaster impact outcomes. The controls for household heterogeneity and socio-economic characteristics appear to be statistically significant in most cases as was the case previously. However, the coefficients for household characteristics are found positive and significant in consumption outcomes. This demonstrates consumption smoothing through cutting non-food consumption (e.g. education and health) and spending more on food consumption in the aftermath of a natural disaster. The coefficients for household characteristics and socio-economic controls are negative and significant in non-consumption outcome measures suggesting their presence would further worsen the impact of disasters on this category.

2.6 CONCLUSIONS

Natural disasters affect households adversely, and they do so especially for people with focusing especially on the poor and on poverty measures. We find lower incomes and wealth that are less able to smooth their consumption. We conducted a meta-regression analysis of the existing literature on the impacts of disasters on households, much heterogeneity in these impacts, and this is most likely the most important insight gleaned from our analysis. There is no 'one-size fits all' description of the ways disasters have an impact on poverty, and the poor.

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[29] This is due to having fewer observations in non-consumption outcome categories of interest.

Yet, several general patterns that are observed in individual case studies also emerge. Incomes are clearly impacted adversely, with the impact observed specifically in per-capita measures (so it is not due to the mortality caused by the observed disaster). Consumption is also reduced, but to a lesser extent than incomes. Importantly, poor households appear to smooth their food consumption by reducing the consumption of non-food items; the most significant items in this category are spending on health and education. This suggests potentially long-term adverse consequences as consumption of health and education services is often better viewed as long-term investment.

There are limits to what we can conclude using our methodology, especially since this meta-analysis is covering a fairly large and diverse literature. These limits are especially obvious as we note that we observe no robust insight on the impact of disasters in the longer term. It might be the case that only very large disasters impose long-term consequences on the affected, but it may also be the case that our measurements are not focused enough to enable us to identify what these outcomes are. There is, after all, significant evidence that adverse but short-term shocks can imply long term adverse consequences, especially within the context of under-development and poverty traps (World Bank, 2014).

The literature on the impact of disasters—both intensive and extensive—on the welfare of households, is growing daily. A remaining important task is to identify the channels through which the shocks impose more costs than the immediate impacts, so that policy intervention may mitigate those, while also trying to prevent the initial losses. The observation that we consistently find; non-food spending decrease in the aftermath of natural disasters is especially of concern, as it implies the possibility that disasters prevent long-term investment and therefore trap households in cycles of poorer education and health outcomes and persistent poverty.

The general pattern of post-shock dynamics is established with the meta-regression analysis we conducted here, and the need to develop the policy instruments that can deal with these dangers is clearer. One potentially promising tool for transferring this risk, and protecting households from the indirect impact of disasters is the provision of insurance. The distribution of insurance products, especially within the context of urban poverty in low-income countries, is facing significant challenges. This appears to be one potential tool that needs to be examined further.

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TABLE 1: NUMBER OF OBSERVATIONS FROM THE SELECTED STUDIES

PAPER IDENTIFICATION	PAPER SOURCE	NO. OF OBSERVATIONS
1	Rodriguez-Oreggia et al. (2013)	16
2	Mogues (2011)	2
3	Morris et al. (2002)	2
4	Datt and Hoogeveen (2003)	2
5	Carter et al (2007)	1
6	Hoddinott and Kinsey (2001)	4
7	Reardon and Taylor (1996)	1
8	Lal et al. (2009)	1
9	Jha (2006)	5
10	Wong and Brown (2011)	2
11	Silbert and Pilar Useche (2012)	3
12	Tiwari et al. (2013)	4
13	Maccini and Yang (2009)	6
14	Asiimwe and Mpuga (2007)	7
15	Dercon (2004)	3
16	Glave et al. (2008)	4
17	Tesliuc and Lindert (2002)	20
18	Anttila-Hughes and Hsiang (2013)	13
19	Jakobsen (2012)	2
20	Lopez-Calva and Juarez (2009)	3
21	Baez and Santos (2007)	7
22	Auffret (2003)	1
23	Skoufias et al. (2012)	6
24	Mueller and Osgood (2009b)	4
25	Mueller and Quisumbing (2011)	2
26	Giesbert and Schindler (2012)	1
27	Narayanan and Sahu (2011)	1
28	Khandker (2007)	1
29	Mahajan (2012)	2
30	Foltz et al. (2013)	4
31	Shah and Steinberg (2012)	10
32	Thomas et al. (2010)	4
33	Hou (2010)	2
34	Hoddinott (2006)	4
35	Hoddinott and Kinsey (2000)	4
36	Jensen (2000)	4
37	Baez and Santos (2008)	2
38	Mueller and Osgood (2009a)	1

Source: Authors' calculations.

TABLE 2: LISTS OF CATEGORIES OF VARIABLES AND THEIR DESCRIPTIONS

CATEGORIES	DESCRIPTION OF VARIABLES
Income 1	Farm/Agricultural/Rural income
	Non-Farm/Entrepreneurial/Urban income
Income 2	Total Household Income
	Per Capita Income
	Total Income Loss
Consumption 1	Household Consumption/Expenditure
	Per Capita Consumption/Expenditure
	Rural Consumption /rural per capita consumption
	Urban Consumption
	Consumption Growth/CECG
Consumption 2	Food Consumption/Expenditure
	Non-Food Consumption/Expenditure
Poverty	Poverty Incidence
	Food Poverty Incidence
	Asset Poverty Incidence
	Capacities Poverty Incidence
	Poverty Rate
	Human Development Index
Wealth	Total livestock asset
	Asset Index
	Agricultural Productive Asset Index
	Non-Productive Asset Index
	Asset Growth
	Asset Loss
Health	Child Height (cm), cohort 1 - 12-24m
	Child Height (cm), cohort 2 - 24-36m
	Child Height (cm), cohort 3 - 36-48m
	Child Height (cm), cohort 4 - 48-60m
	Child Weight (kilo), cohort 1 - 12-24m
	Child Weight (kilo), cohort 2 - 24-36m
	Child Mortality , CM (female)
	Malnourishment/malnutrition (by gender), MAL (rural HH)
	Adult (women) height (cm)
	Body Mass Index (men)
	Body Mass Index (women)/mother

	Health Expenditure
Education	Completed Grades of Schooling
	School Attendance, SA (rural HH)
	School Enrolment by gender
	Educational Expenditure
Labour	Agricultural/Farm/Rural wage
	Non-Farm/Urban wage
	Male wage
	Female wage
	Labour Force Participation-male
	Labour Force Participation-female
	Child Labour Force Participation/ CLFP (rural HH)
Household / Community Characteristics	Household heterogeneity
	Community/ village level heterogeneity and characteristics (e.g. access to roads, markets)
	Head of HH's education, age, gender, marital status, employment status
	HH size
	HH composition (e.g. number of adult male/female members, no. of children)
	Control regarding HH level data limitation
	Ethnicity
Time variant characteristics	Time fixed effect
	Seasonal Fixed effect
	Survey year fixed effect
	Birth year-season, birth district-season and season specific linear time trends
Regional characteristics	Region /District/Province fixed effect
	Municipality fixed effect
Demographic	Life-cycle age of Households
	Population characteristics in general
	Labour force characteristics
Socio-Economic	HH ownership of business, land, animals
	Occupation (e.g. farm/non-farm)
	Asset (e.g. access to electricity, water, sanitation, healthcare, credit, banks, savings)

	Pre-shock HH income/asset value
	Post-shock inheritance
Geography / Nature	Natural and geographical characteristics (e.g. measures of latitude, altitude, surface length, avg. temp. and rainfall (max/min))
	Precipitation rate
	Earth shaking distribution
Disaster 1	Flood / riverine flood
(Hydro-Meteorological)	Rains / rainfall shocks
	Positive rainfall including seasonal deviation
	Negative Rainfall including variability (e.g. delay of monsoon / post on-set low rainfall)
	Hurricane/Storms/Cyclone/Tornado/Typhoon
	Tsunami
Disaster 2	Frost
(Geo-Climatological)	Drought / dry spell including time horizons (1-5 years ago/6-10 years ago)
	Earthquake
	Forest Fire
	Volcanic eruptions
Disaster 3	Bunched natural shocks
(Groups)	
Method	Linear regression
	Logistic regression
	Multinomial /multivariate (logit) regression
	Time series non-linear regression
	Difference in difference regression
	Reduced-form linear regression / reduced form log-linear regression
	Log linear regression
	Dynamic model using regression
	Multivariate Probit regression
	Recursive bivariate Probit model
	Foster-Greer-Thorbecke (FGT) poverty index
	Macroeconomic aggregates corresponding to ND
	Income source decomposition
	Case study analysis, group interviews
	Cluster analysis

Source: Authors' elaborations.

TABLE 3: FREQUENCY DISTRIBUTION OF OBSERVATIONS IN OUTCOME VARIABLES

OUTCOME VARIABLES	NO. OF OBSERVATIONS	MEAN	STD. DEV	NUMBER OF NEGATIVE OUTCOME	MIN	MAX
INCOME 1	11 (6.8)	5.53	6.96	1	-6.76	22.2
INCOME 2	10 (6.2)	-9.90	9.24	9	-32.23	.477
CONSUMPTION 1	39 (24.2)	0.83	6.66	16	-11.66	22
CONSUMPTION 2	13 (8.0)	-2.11	6.81	7	-15.04	10.3
(NON)POVERTY [b]	20 (12.4)	-2.47	4.58	12	-16.1	1.28
WEALTH	9 (5.6)	-4.81	6.06	6	-17.6	3
HEALTH	29 (18.0)	-2.47	5.95	19	-22.98	7.1
EDUCATION	10 (6.2)	-1.40	14.06	6	-21.8	24.96
LABOUR	20 (12.4)	-5.64	7.58	15	-17.9	11

Source: Authors' calculations.
Note: [a] The numbers in parenthesis shows the percentage of number of observations against the corresponding variable.
[b] As we have changed the sign due to standardization, we use non(poverty) for ease of reading.

TABLE 4: META-REGRESSION RESULTS A: THE DIRECT AND INDIRECT IMPACTS

		(1)		(2)		(3)		(4)	
	VARIABLES	OLS	WLS	OLS	WLS	OLS	WLS	OLS	WLS
OUTCOME VARIABLES	INCOME	-2.503	-1.228	-2.753	-6.739	1.856	0.995	-1.818	-4.761
		(5.417)	(3.026)	(5.504)	(6.315)	(4.972)	(4.120)	(4.704)	(4.100)
	CONSUMPTION	2.365	3.663	-0.193	-3.149	6.081	5.451*	0.0956	-0.999
		(4.372)	(3.081)	(4.201)	(5.273)	(3.750)	(2.972)	(1.448)	(2.262)
	POVERTY	-1.677	1.167	-3.378	-4.768	2.651	3.955	-2.475	-2.241
		(5.158)	(4.855)	(4.638)	(6.080)	(4.188)	(4.555)	(1.651)	(1.479)
	WEALTH	-5.398	-3.270	-5.704	-4.949	-0.632	0.165	-4.808**	-2.942
		(5.180)	(5.122)	(4.743)	(5.680)	(4.152)	(3.885)	(2.145)	(2.053)
	HEALTH	0.711	2.248	-3.112	-4.951	5.251	4.409	-2.466**	-3.142***
		(4.329)	(3.968)	(4.404)	(5.360)	(3.837)	(4.411)	(1.116)	(0.907)
	LABOUR	-3.459	-1.610	-6.368	-7.356	0.725	0.589	-5.642***	-5.242***
		(4.811)	(4.565)	(4.784)	(5.735)	(5.171)	(5.152)	(1.468)	(1.527)
	EDUCATION			-1.998	-3.799	4.313	2.267	-1.401	-1.986
				(6.751)	(5.754)	(6.116)	(4.791)	(5.620)	(4.045)
CONTROL VARIABLES	HHCOMMUNITY	-5.115*	-4.392**			-4.936*	-3.899**		
		(2.998)	(2.062)			(2.732)	(1.767)		
	TIME	0.0902	2.371			0.409	3.024		
		(1.609)	(1.750)			(1.691)	(1.950)		
	REGION	2.839	1.732			3.612*	3.796		
		(2.261)	(2.661)			(2.034)	(2.486)		
	DEMOGRAPHIC	-2.668	-2.362			-2.731	-2.151		

		(1.893)	(1.496)			(1.960)	(1.560)		
	SOCIOECONOMIC	-4.402***	-8.062***			-3.921**	-7.327***		
		(1.503)	(1.352)			(1.460)	(1.475)		
	GEOGNATURE	-2.616	-4.012*			-2.662	-4.180		
		(1.900)	(2.180)			(1.956)	(2.670)		
SHOCK VARIABLES	**METHOD**	4.779	6.880	1.752	2.533				
		(4.949)	(5.203)	(4.387)	(5.057)				
	DIS_1	0.658	-1.282	-1.283	-0.737				
		(6.294)	(5.862)	(1.575)	(2.288)				
	DIS_2	1.467	-1.096						
		(6.039)	(5.394)						
	DIS_3	-0.499	-0.997	-2.712	1.488				
		(5.997)	(4.464)	(4.577)	(5.356)				
	OBSERVATIONS	161	161	161	161	161	161	161	161
	R-SQUARED	0.267	0.311	0.128	0.162	0.250	0.296	0.116	0.159
	ADJUSTED R-SQUARED	0.186	0.235	0.0705	0.107	0.184	0.234	0.0760	0.121
	F-TEST (OUTCOME VARIABLES)	2.06 (0.0818)	4.21 (0.0025)	1.71 (0.1377)	0.73 (0.6463)	2.64 (0.0256)	5.83 (0.0001)	4.14 (0.0019)	7.60 (0.0000)
	F-TEST(CONTROL VARIABLES)	4.07 (0.0031)	11.79 (0.0000)			3.26 (0.0112)	6.65 (0.0001)		
	F-TEST (SHOCK VARIABLES)	1.47 (0.2312)	1.73 (0.1651)	0.87 (0.4666)	0.14 (0.9337)				

Source: Authors' calculations.

Notes: [a] Robust standard errors (clustered by studies) in parentheses *** p<0.01, ** p<0.05, * p<0.1.

[b] The numbers in parentheses under each set of F-test result shows P-value (Prob>F).

TABLE 5: META-REGRESSION RESULTS B: THE DIRECT AND INDIRECT IMPACTS

		(1)		(2)		(3)		(4)	
	VARIABLES	**OLS**	**WLS**	**OLS**	**WLS**	**OLS**	**WLS**	**OLS**	**WLS**
OUTCOME VARIABLES	INCOME_1	4.714	3.481	10.25***	5.060	8.519**	5.040	5.531***	2.129
		(4.451)	(3.018)	(2.753)	(5.012)	(3.215)	(3.621)	(1.643)	(4.460)
	INCOME_2	-8.548	-3.797	-5.087	-6.388**	-5.170	-2.945	-9.901***	-9.365***
		(5.833)	(3.637)	(4.415)	(2.875)	(4.463)	(4.383)	(3.623)	(2.014)
	CONSUME_1	3.075	4.732	6.829**	3.475	5.779	4.996	0.829	0.193
		(4.462)	(3.435)	(2.563)	(3.078)	(3.525)	(3.169)	(1.615)	(1.809)
	CONSUME_2	1.449	0.390	2.713	-2.905	5.163	2.341	-2.106	-5.848
		(4.897)	(3.280)	(2.802)	(4.681)	(4.111)	(4.771)	(1.800)	(4.170)
	POVERTY	-1.933	1.011	2.633	0.573	1.424	2.808	-2.475	-2.241
		(5.003)	(4.830)	(2.536)	(2.790)	(3.531)	(4.432)	(1.662)	(1.489)
	WEALTH	-4.909	-2.945			-1.061	-0.313	-4.808**	-2.942
		(5.185)	(4.978)			(3.811)	(3.684)	(2.159)	(2.066)
	HEALTH	0.706	1.833	2.427	-0.173	4.592	3.074	-2.466**	-3.142***
		(4.371)	(4.104)	(2.303)	(2.113)	(3.446)	(4.447)	(1.123)	(0.913)
	LABOUR	-3.626	-1.749	-0.777	-2.314	-0.0277	-0.598	-5.642***	-5.242***
		(4.851)	(4.648)	(2.702)	(2.543)	(4.796)	(5.163)	(1.477)	(1.537)
	EDUCATION			3.508	0.982	3.723	1.299	-1.401	-1.986
				(5.042)	(3.871)	(5.919)	(4.994)	(5.657)	(4.071)
CONTROL VARIABLES	HHCOMMUNITY	-5.377*	-4.182*			-5.447**	-3.466*		
		(2.788)	(2.189)			(2.572)	(1.996)		
	TIME	1.290	2.712			1.402	3.619*		
		(1.523)	(1.898)			(1.571)	(2.022)		

	REGION	2.169	0.0695			2.792	2.733		
		(2.166)	(2.731)			(1.820)	(2.328)		
	DEMOGRAPHIC	-2.623	-1.954			-2.766	-1.829		
		(1.766)	(1.605)			(1.855)	(1.730)		
	SOCIOECONOMIC	-2.889*	-7.065***			-2.574*	-6.399***		
		(1.580)	(1.549)			(1.467)	(1.518)		
	GEOGNATURE	-2.441	-3.310			-2.487	-3.604		
		(1.854)	(2.060)			(1.865)	(2.433)		
SHOCK VARIABLES	**METHOD**	1.899	7.111	-0.0782	2.685				
		(4.360)	(5.139)	(3.926)	(4.963)				
	DIS_1	2.375	-1.622	-4.874	-5.656				
		(5.985)	(6.125)	(4.639)	(5.414)				
	DIS_2	2.591	-1.911	-4.441	-5.557				
		(5.717)	(5.651)	(4.366)	(5.523)				
	DIS_3	0.0378	-2.227	-8.380***	-5.060				
		(5.733)	(4.947)	(2.631)	(3.070)				
	OBSERVATIONS	161	161	161	161	161	161	161	161
	R-SQUARED	0.338	0.339	0.255	0.242	0.328	0.323	0.242	0.240
	ADJUSTED R-SQUARED	0.254	0.256	0.195	0.181	0.259	0.253	0.197	0.195
	F-TEST (OUTCOME VARIABLES)	2.29 (0.0417)	4.82 (0.0004)	3.72 (0.0028)	2.46 (0.0302)	2.98 (0.0090)	6.23 (0.0000)	6.57 (0.0000)	9.11 (0.0000)
	F-TEST(CONTROL VARIABLES)	2.56 (0.0358)	7.82 (0.0000)			2.57 (0.0348)	5.79 (0.0002)		
	F-TEST (SHOCK VARIABLES)	0.71 (0.5894)	1.66 (0.1804)	2.79 (0.0402)	0.84 (0.5114)				

Source: Authors' calculations.

Notes: [a] Robust standard errors (clustered by studies) in parentheses *** p<0.01, ** p<0.05, * p<0.1.

[b] The numbers in parentheses under each set of F-test result shows P-value (Prob>F) at 95 percent confidence interval.

Table 6: Meta-Regression results with restricted observations

VARIABLES	Consumption		Non-consumption	
	OLS	WLS	OLS	WLS
CONSUME_1	-29.85**	-40.16***		
	(11.85)	(10.51)		
CONSUME_2	-34.14**	-48.18***		
	(12.25)	(11.20)		
INCOME_1				5.71
				(4.18)
INCOME_2			-11.33**	0.95
			(4.48)	(4.15)
POVERTY			-5.27	9.31**
			(5.27)	(4.43)
WEALTH			-8.93**	
			(3.62)	
HEALTH			-2.34	7.13*
			(3.20)	(3.91)
LABOUR			-6.91	4.39
			(4.37)	(4.53)
EDUCATION			-3.32	5.21
			(4.89)	(5.78)
HHCOMMUNITY	23.14***	28.98***	-7.05**	-5.44***
	(6.63)	(6.78)	(2.75)	(1.64)
TIME	0.69	-1.05	0.53	0.44
	(3.70)	(4.24)	(2.82)	(2.56)
REGION	-4.47	-7.77*	3.35	2.36
	(3.17)	(4.03)	(2.83)	(3.26)
DEMOGRAPHIC	-11.89**	-15.27**	-2.60	-3.36**
	(4.84)	(5.36)	(2.00)	(1.56)
SOCIOECONOMIC	-4.42	-4.48	-3.96**	-8.63***
	(3.66)	(4.11)	(1.73)	(1.49)
GEOGNATURE	0.94	1.11	-3.75	-5.35**
	(2.91)	(4.10)	(2.88)	(1.99)
METHOD	15.08*	22.66***	7.35	13.09***
	(7.67)	(7.47)	(5.32)	(3.66)
DIS_1	-0.71	-0.39	2.96	-8.22**
	(1.29)	(1.46)	(5.10)	(3.94)
DIS_2			2.18	-10.10**
			(4.48)	(4.15)
DIS_3	5.08	9.56**	-3.32	-23.45***
	(5.50)	(4.46)	(6.61)	(6.05)
Observations	52	52	109	109
R-squared	0.32	0.36	0.44	0.43
Adjusted R-squared	0.14	0.19	0.34	0.33

Source: Authors' calculations.
Notes: Robust standard errors (clustered by studies) in parentheses *** p<0.01, ** p<0.05, * p<0.1.

Appendix Table 1: Descriptive Statistics of Variables Defined

Variables	Observations	Mean	Median	Std. Dev.	Min	Max
Y	161	-2.01	-0.75	7.89	-32.23	24.96
N	161	28076.38	3823	69540.15	94	446780
INCOME	161	0.13	0	0.34	0	1
INCOME_1	161	0.07	0	0.25	0	1
INCOME_2	161	0.06	0	0.24	0	1
CONSUMPTION	161	0.32	0	0.47	0	1
CONSUME_1	161	0.24	0	0.43	0	1
CONSUME_2	161	0.08	0	0.27	0	1
POVERTY	161	0.12	0	0.33	0	1
WEALTH	161	0.06	0	0.23	0	1
HEALTH	161	0.18	0	0.39	0	1
LABOUR	161	0.12	0	0.33	0	1
EDUCATION	161	0.06	0	0.24	0	1
HH/COMMUNITY	161	0.80	1	0.40	0	1
TIME	161	0.67	1	0.47	0	1
REGION	161	0.76	1	0.43	0	1
DEMOGRAPHIC	161	0.37	0	0.48	0	1
SOCIOECONOMIC	161	0.62	1	0.49	0	1
GEOG/NATURE	161	0.54	1	0.50	0	1
METHOD	161	0.96	1	0.19	0	1
DISASTER	161	1.46	1	0.66	1	3
DIS_1	161	0.63	1	0.48	0	1
DIS_2	161	0.27	0	0.45	0	1
DIS_3	161	0.09	0	0.29	0	1

Source: Authors' calculations.

Appendix Table 2: Meta-Regression Results A: The Direct and Indirect Impacts

		(1)		(2)		(3)		(4)	
	VARIABLES	OLS	WLS	OLS	WLS	OLS	WLS	OLS	WLS
Outcome Variables	INCOME	-2.503	2.042	-2.753	-1.790	1.856	0.995	-1.818	-4.761
		(5.417)	(4.051)	(5.504)	(4.522)	(4.972)	(4.120)	(4.704)	(4.100)
	CONSUMPTION	2.365	6.934*	-0.193	1.799	6.081	5.451*	0.0956	-0.999
		(4.372)	(4.046)	(4.201)	(3.510)	(3.750)	(2.972)	(1.448)	(2.262)
	POVERTY	-1.677	4.437	-3.378	0.181	2.651	3.955	-2.475	-2.241
		(5.158)	(4.835)	(4.638)	(2.958)	(4.188)	(4.555)	(1.651)	(1.479)
	WEALTH	-5.398		-5.704		-0.632	0.165	-4.808**	-2.942
		(5.180)		(4.743)		(4.152)	(3.885)	(2.145)	(2.053)
	HEALTH	0.711	5.518	-3.112	-0.00269	5.251	4.409	-2.466**	-3.142***
		(4.329)	(3.899)	(4.404)	(2.098)	(3.837)	(4.411)	(1.116)	(0.907)
	LABOUR	-3.459	1.660	-6.368	-2.407	0.725	0.589	-5.642***	-5.242***
		(4.811)	(4.570)	(4.784)	(2.618)	(5.171)	(5.152)	(1.468)	(1.527)
	EDUCATION		3.270	-1.998	1.150	4.313	2.267	-1.401	-1.986
			(5.122)	(6.751)	(3.786)	(6.116)	(4.791)	(5.620)	(4.045)
Control Variables	HHCOMMUNITY	-5.115*	-4.392**			-4.936*	-3.899**		
		(2.998)	(2.062)			(2.732)	(1.767)		
	TIME	0.0902	2.371			0.409	3.024		
		(1.609)	(1.750)			(1.691)	(1.950)		
	REGION	2.839	1.732			3.612*	3.796		
		(2.261)	(2.661)			(2.034)	(2.486)		
	DEMOGRAPHIC	-2.668	-2.362			-2.731	-2.151		

		(1.893)	(1.496)			(1.960)	(1.560)		
	SOCIOECONOMIC	-4.402***	-8.062***			-3.921**	-7.327***		
		(1.503)	(1.352)			(1.460)	(1.475)		
	GEOGNATURE	-2.616	-4.012*			-2.662	-4.180		
		(1.900)	(2.180)			(1.956)	(2.670)		
SHOCK VARIABLES	**METHOD**	4.779	6.880	1.752	2.533				
		(4.949)	(5.203)	(4.387)	(5.057)				
	DIS_1	0.658	-4.553	-1.283	-5.686				
		(6.294)	(5.427)	(1.575)	(5.506)				
	DIS_2	1.467	-4.366		-4.949				
		(6.039)	(5.466)		(5.680)				
	DIS_3	-0.499	-4.267	-2.712	-3.460				
		(5.997)	(3.528)	(4.577)	(3.529)				
	OBSERVATIONS	161	161	161	161	161	161	161	161
	R^2	0.267	0.311	0.128	0.162	0.250	0.296	0.116	0.159
	ADJUSTED R^2	0.186	0.235	0.0705	0.107	0.184	0.234	0.0760	0.121
	F-TEST (OUTCOME VARIABLES)	2.06 (0.0818)	4.21 (0.0025)	1.71 (0.1377)	0.82 (0.5648)	2.64 (0.0256)	5.83 (0.0001)	4.14 (0.0019)	7.60 (0.0000)
	F-TEST(CONTROL VARIABLES)	4.07 (0.0031)	11.79 (0.0000)			3.26 (0.0112)	6.65 (0.0001)		
	F-TEST (SHOCK VARIABLES)	1.47 (0.2312)	1.85 (0.1392)	0.87 (0.4666)	0.61 (0.6552)				

Source: Authors' calculations.

Notes: [a] Robust standard errors (clustered by studies) in parentheses *** p<0.01, ** p<0.05, * p<0.1.

[b] The numbers in parentheses under each set of F-test result shows P-value (Prob>F).

APPENDIX TABLE 3: META-REGRESSION RESULTS B: THE DIRECT AND INDIRECT IMPACTS

		(1)		(2)		(3)		(4)	
	VARIABLES	OLS	WLS	OLS	WLS	OLS	WLS	OLS	WLS
OUTCOME VARIABLES	INCOME_1	4.714	1.570	10.25***	-0.497	8.519**	5.040	5.531***	2.129
		(4.451)	(5.193)	(2.753)	(6.271)	(3.215)	(3.621)	(1.643)	(4.460)
	INCOME_2	-8.548	-5.708	-5.087	-11.95**	-5.170	-2.945	-9.901***	-9.365***
		(5.833)	(5.150)	(4.415)	(5.278)	(4.463)	(4.383)	(3.623)	(2.014)
	CONSUME_1	3.075	2.821	6.829**	-2.082	5.779	4.996	0.829	0.193
		(4.462)	(4.817)	(2.563)	(5.005)	(3.525)	(3.169)	(1.615)	(1.809)
	CONSUME_2	1.449	-1.521	2.713	-8.462	5.163	2.341	-2.106	-5.848
		(4.897)	(5.671)	(2.802)	(6.024)	(4.111)	(4.771)	(1.800)	(4.170)
	POVERTY	-1.933	-0.900	2.633	-4.984	1.424	2.808	-2.475	-2.241
		(5.003)	(5.660)	(2.536)	(5.931)	(3.531)	(4.432)	(1.662)	(1.489)
	WEALTH	-4.909	-4.856		-5.557	-1.061	-0.313	-4.808**	-2.942
		(5.185)	(5.248)		(5.523)	(3.811)	(3.684)	(2.159)	(2.066)
	HEALTH	0.706	-0.0778	2.427	-5.730	4.592	3.074	-2.466**	-3.142***
		(4.371)	(5.052)	(2.303)	(5.136)	(3.446)	(4.447)	(1.123)	(0.913)
	LABOUR	-3.626	-3.660	-0.777	-7.871	-0.0277	-0.598	-5.642***	-5.242***
		(4.851)	(5.395)	(2.702)	(5.486)	(4.796)	(5.163)	(1.477)	(1.537)
	EDUCATION		-1.911	3.508	-4.575	3.723	1.299	-1.401	-1.986
			(5.651)	(5.042)	(5.729)	(5.919)	(4.994)	(5.657)	(4.071)
CONTROL VARIABLES	HHCOMMUNITY	-5.377*	-4.182*			-5.447**	-3.466*		
		(2.788)	(2.189)			(2.572)	(1.996)		
	TIME	1.290	2.712			1.402	3.619*		
		(1.523)	(1.898)			(1.571)	(2.022)		

	REGION	2.169	0.0695			2.792	2.733		
		(2.166)	(2.731)			(1.820)	(2.328)		
	DEMOGRAPHIC	-2.623	-1.954			-2.766	-1.829		
		(1.766)	(1.605)			(1.855)	(1.730)		
	SOCIOECONOMIC	-2.889*	-7.065***			-2.574*	-6.399***		
		(1.580)	(1.549)			(1.467)	(1.518)		
	GEOGNATURE	-2.441	-3.310			-2.487	-3.604		
		(1.854)	(2.060)			(1.865)	(2.433)		
SHOCK VARIABLES	**METHOD**	1.899	7.111	-0.0782	2.685				
		(4.360)	(5.139)	(3.926)	(4.963)				
	DIS_1	2.375	0.289	-4.874	-0.0985				
		(5.985)	(1.129)	(4.639)	(1.811)				
	DIS_2	2.591		-4.441					
		(5.717)		(4.366)					
	DIS_3	0.0378	-0.315	-8.380***	0.497				
		(5.733)	(4.963)	(2.631)	(5.071)				
	OBSERVATIONS	161	161	161	161	161	161	161	161
	R^2	0.338	0.339	0.255	0.242	0.328	0.323	0.242	0.240
	ADJUSTED R^2	0.254	0.256	0.195	0.181	0.259	0.253	0.197	0.195
	F-TEST (OUTCOME VARIABLES)	2.29 (0.0417)	4.29 (0.0007)	3.72 (0.0028)	2.34 (0.0335)	2.98 (0.0090)	6.23 (0.0000)	6.57 (0.0000)	9.11 (0.0000)
	F-TEST(CONTROL VARIABLES)	2.56 (0.0358)	7.82 (0.0000)			2.57 (0.0348)	5.79 (0.0002)		
	F-TEST (SHOCK VARIABLES)	0.71 (0.5894)	2.16 (0.1096)	2.79 (0.0402)	0.46 (0.7133)				

Source: Authors' calculations.

Notes: [a] Robust standard errors (clustered by studies) in parentheses *** p<0.01, ** p<0.05, * p<0.1.

[b] The numbers in parentheses under each set of F-test result shows P-value (Prob>F) at 95 percent confidence interval.

APPENDIX: STANDARDIZATION OF DEPENDENT VARIABLES

Following the data collection from the 38 papers included in our sample, we standardized and converted the estimates of different categories of variables taken from each study to a common metric to make them usable for a comparative meta-analysis. We calculated the percentage changes of the major indicators under representation. The literature sometimes uses other methods to standardize the dependent variable; for example, by using t-statistics if the question that is being answered relates to the precision of estimates (e.g., Lazzaroni and van Bergeijk, 2014). Given the diverse nature of our dependent variables, we chose to standardize by calculating the percentage change in the examined indicator. We considered other methods that rely on indicator-specific second moments as less appropriate in this case. In cases where seasonal impacts of disasters (e.g. rainfall) had been reported (e.g., Asiimwe and Mpuga, 2007), index values are used (e.g. Rodriguez-Oreggia et al., 2013), or anthropometric values are being recovered (Hoddinott and Kinsey, 2000 and 2001), we used the following measure as used in Rodriguez-Oreggia et al. (2013) to extract the respective observation: PC = CV/MV *100; where PC = percentage Change, MV = Mean Value and CV = Coefficient Value. For more discussion on the various potential measures of the dependent variable in meta-analysis, see Borenstein et al. (2009, chapter 4). Other recent papers that follow a similar standardization procedure in a meta-regression context are Rose and Dormady (2011) and Mazzotta et al. (2014). In studies where impacts of particular type of disaster (e.g. typhoon) had been documented for various disaster strengths (e.g., Anttila-Hughes and Hsiang, 2013), we calculated the cumulative effect over the investigated horizon of a disaster of average strength. The standardization also includes a sign change (+/-) with a positive sign implying a positive ('favourable' in a normative sense) impact on poverty and welfare outcomes due to natural disaster whereas a negative sign suggesting the opposite.

CHAPTER THREE

THE (MIS) ALLOCATION OF PUBLIC SPENDING IN A LOW INCOME COUNTRY: EVIDENCE FROM DISASTER RISK REDUCTION SPENDING IN BANGLADESH

3.1 INTRODUCTION

A burgeoning literature has emerged investigating the efficacy of public spending in lower income countries. For example, recently Sennoga and Matovu (2013) provided an investigation of public spending in Uganda, Ramirez (2004) investigated public infrastructure spending in Mexico, Kruse et al. (2012) examine public health spending in Indonesia, and Rajkumar and Swaroop (2008) focus on a cross-country statistical analysis of levels of spending, institutional structures, and relevant outcomes. This literature also uses a wide variety of methodologies to approach this efficacy question: Sennoga and Matovu (2013) use general equilibrium modeling, Ramirez (2004) uses a vector error correction empirical model with impulse response functions, and Kruse et al. (2012) use panel data regression techniques.

This literature assumes that public spending is indeed geared towards achieving the relevant favourable outcomes—productivity growth for infrastructure spending, better health service utilization for health spending, or improved literacy for education spending. More importantly, this literature implicitly assumes that funding is allocated optimally given these desired outcomes and the perceived community needs. It is this last assumption that we examine in this paper. We ask whether we can find evidence that public spending is indeed allocated rationally according to perceived needs, or whether we can identify other explanations for the pattern of *de facto* public spending.

We focus on disaster risk reduction (DRR) spending in Bangladesh for several reasons. Disaster risk reduction spending has a clearly defined policy aim, and measurable outcomes. As such, DRR spending is maybe uniquely suited to examine the rationale for the regional allocation of public resources. Bangladesh has a long history with natural disasters due to its geography and its location on the shores of the Bay of Bengal. Natural hazards in Bangladesh range from floods and cyclones to river bank erosion and droughts. Flooding associated with the monsoon season occurs each year. The monsoon rain plays a pivotal role in securing domestic agricultural production, but can also kill and devastate crops and livelihoods. Along the coasts, the most destructive cyclones generate storm surges that can inundate vast land areas, and have in the last few decades killed hundreds of thousands of people. Given all these; it is obvious that disaster planning and government-led disaster risk reduction (DRR) program have been part of the Bangladesh government's economic planning process for a long time.

Bangladesh, it is important to note, is widely perceived as poster-child for successful spending on DRR by a developing country. In particular, Bangladesh is often mentioned for its successful early warning programmes for cyclones, which is frequently favourably contrasted with neighbouring Burma after its catastrophic experience with cyclone *Nargis* in 2008. Most recently for cyclone *Sidr* in 2007, for example, Bangladesh managed to evacuate millions away from the coast and the storm's surge (Paul and Dutt, 2010).[30] Bangladesh's successful disaster risk reduction policies is also mentioned in the context of the management of the annual monsoon floods (del Ninno et al., 2003).

A demonstration of the crucial role that government safety net policies can play in DRR is the comparison of the severe flood of 1998 in comparison to an equally severe flood in 1974.[31] In this case, in 1998, the government's substantial disaster management facilities and emergency food and financial assistance through better management of targeted programs such as Vulnerable Group Feeding (VGF) and Food For work (FFW), it is claimed, helped prevent mass starvation and other associated risks compared with the severe flood impacts of 1974.[32]

Besides the already mentioned ease of determining the aim of DRR spending in the Bangladeshi context, its importance is also well established. *Ex ante* spending choices on disaster risk management has been advocated for by all the international aid multilaterals, as DRR's importance in reducing mortality, morbidity, and risk to livelihoods is undisputed in Bangladesh, and elsewhere. The most recent example of this emphasis is the Philippines' decision to initiate a US$293 million national disaster risk reduction and management fund that is targeted to be used for pre-disaster risk reduction activities. In Bangladesh, as well as in the Philippines, one of the more important decisions the central government consistently needs to make is how to allocate DRR program spending across communities to minimize and mitigate the risks associated with the natural hazards both countries are exposed to.

Our focus here amounts to answering a basic question: 'what determines public spending in disaster risk reduction and mitigation in Bangladesh?' We believe that this particular question has important implications not only for DRR spending in Bangladesh—as

[30] For further data and a comparison of *Sidr* to previous storms, see p. 502 in IPCC (2012).

[31] The severity of the 1998 flood has been identified in terms of area affected (affecting two-thirds of the country) and lasted for a prolonged period (from early July till mid-September) in many areas and direct damages were estimated at US$2 billion (Khandker, 2007).

[32] For discussions and analysis of the impacts of floods in Bangladesh, see Khandker (2007) and Banerjee (2007).

important as that is—but also to DRR spending elsewhere, and more generally for government spending in low income countries and its challenges.

We identify the determinants' of per capita public spending on disaster risk reduction and mitigation at the local government (sub-district/upazila[33]) level in Bangladesh. The objective of this study is to identify the rationale behind the allocation of public spending based on the stated aims of these DRR safety net programs.

After describing the, admittedly very limited, literature that examines the determinants of public expenditure in section 3.4, we discuss our data in section 3.5 in detail. Section 3.6 provides relevant descriptive and summary statistics of the variables we use along with the methodological framework and justifies our use of the Heckman two-step selection model. Section 3.7 examines the estimation results and interprets them. We also add some additional models as robustness checks in section 3.8. Finally, in Section 3.9 we conclude, identify potential caveats, and discuss possible future research.

3.2 THE DETERMINANTS OF FISCAL SPENDING IN DEVELOPING COUNTRIES?

Oftentimes, natural disasters are perceived as an exogenous shock to the economy resulting in additional fiscal expenditure or re-adjustment of existing expenditure to finance rehabilitation and reconstruction activities. The financial aspects of post-disaster fiscal management has been examined in country-specific policy papers (e.g. Bangladesh after the 1998 flood is examined in Benson and Clay, 2002, while Belize is analysed in Borensztein et al., 2009). Several cross-country studies have also attempted to measure the average *ex post* fiscal costs (in lost revenue and increased expenditures) of a proto-typical disaster (e.g. Noy and Nualsri, 2011 and Lis and Nickel, 2010) and a global assessment is provided in Hochrainer-Stigler et al. (2014). Yet, none of these papers examine *ex-ante* disaster risk financing.

As we have already noted in the introduction, we are not aware of any literature that attempts to examine the rationale behind central government's financing to the sub-national level in non-high income countries; neither in the context of disaster risk financing, nor in other contexts.[34] We aim to investigate the determinants of regional financing for DRR

[33] Bangladesh is divided into 7 administrative regions (Divisions), 64 districts (Zila) and 483 sub-districts (Upazila). Our primary focus in this investigation includes all 483 sub-districts.

[34] Vorhies (2012) summarizes the literature on fiscal spending on DRR, and also does not identify any research on the determinants of this spending.

activities and examine whether these flows of funds are conditional upon actual (or perceived) regional hazards, vulnerabilities, other socio-economic regional attributes, and political affiliations at the local government level.[35] Aldrich (2010) and Takasaki (2011) identify the ability of elites to capture post-disaster reconstruction spending in India and rural Fiji, respectively.

The research project most closely related to our own work is Miller and Vela (2014). They examine the allocation of disaster funding (both preventative and for recovery) for Peruvian regions (districts in the Bangladesh context), and focus on whether distribution of public expenditure in both recovery and prevention categories is conditional upon the occurrence of natural disasters in the recent past and on exposure and vulnerability. The data they use, their empirical approach, and the questions they ask are all quite different, but ultimately they also find it difficult to correlate the spending they examine with measureable risk.

3.3 WHAT WE DEFINE AS DRR?

We interpret the term DRR spending fairly broadly, given the often repeated insight that 'an ounce of prevention is worth a pound of cure' and the increased awareness that social and socio-economic vulnerability is as important in determining a disaster's impact as is the natural hazard itself. The need for social protection through the provision of social safety nets has been reiterated in various papers that focus on DRR (e.g. Pelham et al, 2011; Rahman and Choudhury, 2012; and World Bank, 2010). Relevant examples of disaster safety net[36] programs incorporated into a country's DRR policies are Bangladesh's National Disaster Management Prevention Strategy and Ethiopia's Productive Safety Net Program.[37]

An additional type of DRR activity that we include in our analysis is 'Investments in specific infrastructure' whose aim is disaster prevention; again this type of DRR spending is widely recognized in the DRR literature (e.g. World Bank, 2010). For example, the Department of Disaster Management (DDM) in Bangladesh constructs bridges/culverts (up to 12 meters

[35] Indirectly, Hodler and Raschky (2014) identify political favoritism in regional allocations by examining the intensity of nighttime light in regions associated with the political leadership.
[36] In this paper, the term 'Disaster Safety Net' refers to particular social safety net programs that has embedded structural mechanism to participate in disaster risk reduction activities.
[37] See Pelham et al (2011) for discussion of these two programs.

long) under its Annual Development Plan – the main aim for this infrastructure is DRR rather than development or poverty alleviation more broadly.

The connection between the climate and disaster occurrence is obvious, but the causality from climatic change to disasters has only been emphasized in the past few years, and most forcefully by the IPCC in their Special Report on Extreme Events (IPCC, 2012). Another international organization that has emphasized the link between DRR and climate change adaptation is the United Nations International Strategy for Disaster Risk Reduction (e.g. UNISDR, 2009b).[38] We therefore also include an investigation of the US$350 million allocated by the Government of Bangladesh in fiscal years 2009-2013 to tackle climate change impacts.

3.4 THE POSSIBLE DETERMINANTS OF DRR

The future probability of exposure to hazards (and their probable intensity) is proxied in this paper by past experience of this hazard. In this case, we focus on DRR activities that are mostly related to flood exposure, and therefore focus on flood risk. We measure the past exposure to hazards using details of rainfall record in each region.[39]

The two other components of disaster risk, after the hazard itself, is the exposure of the population, and its vulnerability. Socio-economic vulnerability is as important as geographical exposure in order to more fully understand community-level adaptive capacity. The past literature has identified indicators of socio-economic vulnerability to natural hazards and emphasizes the importance of integrating them into national disaster prevention planning (Cutter et al. 2009; Tapsell et al. 2010). This widely discussed need to insert this socio-economic perspective into DRR planning motivates our use of socio-economic indicators.

The political dimension of natural disaster policy has also been receiving attention in recent years with a primary focus on the evident failure of politicians' and voters' to prioritize prevention over post-event response; see for example Healy and Malhotra (2009) and Garret and Sobel (2003) on US post-disaster funding, Cole et al. (2012) on India, and Fuchs and

[38] See also Shamsuddoha et al. (2013).

[39] The risk associated with geological hazards is much more difficult to forecast, and this partly justifies our choice to focus on Bangladesh, where disaster risk is generally only associated with climatological events (unlike, for example, Peru) – see, for example, Kerr (2011).

Rodriguez-Chamussy (2014) on Mexico. When funding is awarded *ex ante*, the evidence seems to suggest that governments favour spending in regions that are politically aligned with the party in power (e.g. Cohen and Werker, 2008), and this is the focus of our investigation into the political economy of fiscal spending on the sub-regions.

3.5 THE DATA

The data for this study were collected from various Bangladeshi government sources described below, both online and in print. Appendix table 1 provides the precise definition of all the variables and their data sources.

3.5.1 DRR PROGRAMS IN BANGLADESH

The disaster risk reduction public spending data at the local government level was collected from publications of Bangladesh's Ministry of Food (former Ministry of Food and Disaster Management) – the information was collected from the Ministry's web portal where sub-district (upazila) disaster risk reduction and mitigation funding allocation data from FY (fiscal year) 2010-11 to FY2013-14 was available. For each year, the dataset records the *'allocation'* (allocated spending) and *'expenses'* (realized spending) for the various disaster safety net programmes - Test Relief (TR), Food For Work (FFW), Gratuitous Relief (GR) and Vulnerable Group Feeding (VGF). It also records the same information for the DRR infrastructure programme (bridges and culvert construction) and the climate change fund (also known as the climate investment fund). These various programs are described below.

The *Test Relief* (TR) program has been implemented every year since 1975 in rural areas. This programme is mainly for repairing roads, damaged infrastructure such as schools and clinics, and other rural activities. It provides employment opportunities by providing 8 kilograms of rice/wheat to every person in return for working 7 hours/day in specific projects related to disaster risk reduction and mitigation. The *Gratuitous Relief* (GR) programme (established in 1973) is designed to provide a maximum of 20 kilograms of rice/wheat to worst affected poor households with no associated work requirements. *Vulnerable Group Feeding* (VGF) is another form of gratuitous relief (i.e. without work requirement) and is normally launched during or after a disaster and attempts to assist people remaining vulnerable to hunger.

The *Food For Work* (FFW) program has been implemented since 1975 and is designed for construction, maintenance, reconstruction and development of rural infrastructure. Based on government food and monetary support, various rural infrastructural projects (many of them aimed at reducing vulnerability) are financed under this program during normal times and in post-disaster scenarios with work requirements. Among these infrastructure projects, the Department of Disaster Management funds construction of bridge/culverts (up to 12 meter long) under the Annual Development Programme of the Bangladesh Government (*Bridges and Culverts programme*).

Data has been aggregated by adding up allocations in general and special categories under each DRR programme for each of the 483 sub-districts. We converted the food allocations in some of these programs into its monetary value using the contemporaneous (average) market price of rice in Dhaka (wholesale price). We aggregate both food and cash amount to get total allocation under each particular DRR activity for each sub-district. We then divide total allocated and realized spending amounts for each program/sub-district by the size of the population of each corresponding sub-district.

3.5.2 RAINFALL HAZARD DATA

Due to its geographical location in the South-Eastern part of Hindu-Kush Himalayan region and being at the confluence of three major rivers – the Ganges, the Brahmaputra and the Meghna, Bangladesh is an extremely flood-prone country. River-bank flooding, occurs mostly during the monsoon period (May-October) is the most frequent case.[40] High rainfall is primarily the reason of river-bank floods. Here, we calculate a rainfall-based flood risk probability index for 483 sub-districts of Bangladesh to examine the sensitivity government DRR spending to flood risks. The index captures historical rainfall variability to determine local (sub-district) flood risks. In as much as this index is based on past experiences, it does not capture the projected future changes that are associated with climatic change.

To develop this index, we collected annual rainfall data of 64 years for 35 weather stations covering the whole country from the Bangladesh Meteorological Department (BMD).[41] The BMD records daily rainfall data since 1948 for all available weather stations across the country. We first calculated total monthly rainfall for each year under each weather

[40] Other, less common types of flooding are the flash floods (in hilly areas) and storm surges (along the coast).
[41] The available data were for the years 1948-2012.

station. We next calculated the mean and standard deviation for each month for each sub-district by matching weather stations with sub-districts.[42] We develop two indexes of low- and high-risk indices. For the low flood risk, we count the number of months over the 64 years for which we have data with extreme rainfall using two thresholds: monthly rainfall exceeding 15 percent of average annual rainfall for this sub-district; and monthly rainfall exceeding one standard deviation above the mean for that month throughout the available time period.[43]

We calculate the average number of months with extreme rainfall to obtain the probability of flooding occurring annually in that particular weather station (and consequently sub-district). The mean probability is 0.93 with 0.16 standard deviation. The second index, high flood risk, is constructed similarly, but in this case the two thresholds are 20 percent of average annual rainfall and more than two standard deviation above the monthly mean. For the high-risk measure, the mean probability is 0.26 with 0.08 standard deviation.

3.5.3 OTHER VARIABLES

Population numbers and poverty rates for each sub-district (annually) were collated from government circular orders of the Department of Disaster Management. Our proxy for 'economic development' for each sub-district is a composite variable averaging the shares of the population with access to basic amenities (electricity, safe drinking water, and sanitation facilities). This data were collected from the 2011 Population and Housing Census of Bangladesh.

To capture the importance of politics in allocation of funding from the central government to the sub-regions, we construct a political binary variable that measures whether the Member of Parliament (MP) representing the sub-district belongs to the main political party in power. To construct this variable, we divide the 300 electoral constituencies with respect to 483 sub-districts based upon the electoral delimitation information on the Bangladesh Gazette (2013). Information regarding election results and the sub-district representatives has been collected from the Bangladesh Election Commission report of 2008.

[42] In cases where a sub-district did not have a rainfall measurement station, we used an average of the three nearest stations.

[43] The historical coverage of rainfall data in BMD weather stations varies depending upon their establishment year. Therefore, we calculate the average number of months with extreme rainfall by dividing with the total number of rainfall years available to calculate the probability of annual flooding in that particular weather station. Guiteras et al. (2015) use satellite data for rainfall, but find that this data is poorly correlated with actual flooding.

According to the Coastal Zone Policy of the Government of Bangladesh (2005), the zone is divided into 'exposed coast' (the area/upazilas that front the sea directly, and 'interior coast' (the area/upazilas that are located behind the exposed coast). Here, we include both groups to create the 'coastal belt binary variable'. Another dummy variable has been created to capture ethnic divisions within the sub-district. Bangladesh, unlike some of its neighbours, is relatively homogenous. We include a dummy variable noting if indigenous ethnic minorities reside in a particular sub-district. To create this ethnicity dummy, we use information from the 2011 Population and Housing Census of Bangladesh. We add two more binary variables. The first identifies the central sub-district in any particular district (in most cases that implies bigger populations, higher degree of urbanization and more industrialized). The other binary measure indicate urban sub-districts associated with the two mega-cities in Bangladesh (Dhaka and Chittagong).

3.6 DESCRIPTIVE STATISTICS AND MODEL SPECIFICATION

Table 1 reports the descriptive statistics of public spending on DRR in Bangladesh, including both allocated and realized spending for the fiscal year 2010-11 to 2013-14 for each of the programmes described earlier. These statistics include mean, standard deviation, maximum and minimum of total DRR allocated and realized spending per capita for only positive observations (when funds were allocated) for Test Relief (TR), Vulnerable Group Feeding (VGF), Food For Work (FFW), Gratuitous Relief (GR), Infrastructure Spending (Bridges and Culvert construction under FFW) and Climate Investment Fund (CIF). The mean for DRR allocated (realized) spending per capita for only positive observations is 51.4 (41.4). On average, TR received the highest amount of funding per capita followed by VGF while the maximum amount in a single sub-district has been distributed through the VGF program.

Table 2 documents the descriptive statistics of all the independent (RHS) variables. The mean population size in each sub-district is 0.26 million. The mean probability of low and high flood-risk assigned to each sub-district is 0.935 and 0.258 respectively. Although the current ethnic population size is just over 2 million people, 46 percent of the sub-districts include some ethnic minorities indicating their dispersal across a wide range of sub-districts. The political risk dummy indicates that fully 77 percent of sub-districts are represented by MPs from the ruling party as a consequence of the 2008 general election. 19 percent of the 483 sub-districts are in the coastal zone.

We also examine the difference, in the Bangladeshi government's accounts, between the allocated vs. realized spending, and whether the two are determined differently. We do not have a pre-conceived notion of the types of influences that affect the regional allocation of public spending, but for DRR spending, we assume that these are determined by the perception of risk, by socio-economic vulnerability, and by political and geographic factors.

Some sub-districts do not receive any funding for some of the DRR programs we investigate over some fiscal years. Figures 1 and 2 demonstrate the number of sub-districts with no DRR funding. Out of 483 sub-districts; 211 sub-districts did not receive any funding at all. Two additional sub-districts were allocated some funding but this was not realised. The funding allocation decision-making process therefore appears to comprise of two questions: The first asks: *should sub-district X be allocated disaster risk reduction funding?* If the answer to the first was affirmative, the second asks*: How much should be allocated?* Due to this two-stage decision-making process, we employ a two-stage Heckman selection model to identify the determinants' of public spending on disaster risk reduction and mitigation. To construct this two-stage Heckman selection model, we start with the following premise:

$$SPEND_{ijt}^{x} = f(risk^{v}, pop_{it}, pov_{it}, dep_{i}, D_{i}) \qquad [1]$$

Public spending (*SPEND*) in sub-district (*i*), for program (*j*), at fiscal year (*t*), is a function of several variables. The perceived risk (*risk*) which is calculated as an index constructed from past exposure, with low and high thresholds (*v*). Spending is also a function of the population (*pop*) and poverty (*pov*) rates in the receiving sub-district, and measures of socio-economic deprivation (*dep*: measured as access to certain assets – see the data discussion earlier in section 3.5). This public spending is also a function of a set of characteristics, measured as binary variables (vector *D*), that include political affiliation with the centre, presence of ethnic minorities, being a district headquarter, belonging to either of the two large metropolitan areas, and a coastal location. The spending variable measures either the allocated or realized equivalent for each sub-district, fiscal year, and DRR programme (indicated by superscript *x*).

Our theoretical prior is that these determinants' should have positive correlation with sub-districts' DRR funding allocation. *Ceteris paribus*, a sub-district with higher perceived risk, more poverty, less access to assets, more deprivation, more political connections, and a coastal location should be receiving more DRR funding (either allocated or realized). We are agnostic regarding several of the other controls, including location as a district headquarter or as part of the two metropolitan agglomerations, and the presence of ethnic minorities.

Given the truncated nature of this allocation (many sub-districts get nothing), we estimate the model in two stages. In the first stage, we estimate the probability of getting funding ($SPEND_{ijt}^{x} > 0$). More formally, the funding selection equation defines the cases where a particular sub-district has received or been allocated funding in any targeted program:

$$z_{ijt} = \begin{cases} 1 \; if \; SPEND_{ijt}^{x} > 0 \\ 0 \; if \; SPEND_{ijt}^{x} = 0 \end{cases} \qquad \text{and} \qquad z_{ijt} = \alpha W_{ijt} + \varepsilon_{ijt} \qquad [2]$$

Where, z_{ijt} is a latent variable indicating funding, and is the dependent variable of the selection equation [2]. W_{ijt} is a vector of covariates, and ε_{ijt} is the random disturbance term. The selection variable z_{ijt} is binary and we therefore use a Probit regression specification to estimate the first stage selection equation [2]. The second stage specifies the outcome (public spending) equation where public spending (allocated or realized) is the dependent variable. The model specification for the second stage equation is as follows:

$$Y_{ijt} = \beta X_{ijt} + u_{ijt} \qquad [3]$$

Where Y_{ijt} is the dependent variable of the outcome equation, X_{ijt} is a vector of covariates, β is a vector of coefficients and u_{ijt} is the random disturbance term. The selection equation (first stage) includes the population variable which is not included in the outcome equation (second stage). Population is excluded from the second stage as the LHS in this stage is the amount of funding available per capita. This exclusion assumption then implies that the decision on quantity is based on per capita considerations (i.e., once the government decided to award funding to a specific sub-district for a specific program, their quantity decision is based on a goal of achieving specific funding target per capita. Thus, the per capita funding amount is not impacted by the size of the population.[44] We estimate our model with robust standard errors clustered by sub-districts.

3.7 ESTIMATION RESULTS

The estimation results for the two-stage Heckman selection model for allocated spending are documented in tables 3-4. The first column show the estimated coefficients of low and high flood risks along with a set of socio-economic and geo-political controls where the column correspond to total allocated spending of disaster risk reduction spending per capita.[45] Columns (2) and (3) present the estimated coefficients for obligatory public funding per capita[46] and non-obligatory public funding per capita[47] for low- and high- flood risks consecutively.

Table 3 reports the results from the first stage selection regression displaying the marginal effects. For the highest low (high) flood risk sub-district, the probability of getting funded is approximately 12 percent (31 percent) higher than for the sub-district with the lowest risk of flooding (although both are statistically insignificant).[48] The only exception in terms of statistical significance is for non-obligatory relief funding in the context of low flood risk. That is, for the highest low flood risk sub-district, the probability of getting non-obligatory funding is approximately 61 percent higher (and is statistically significant) than for the sub-district with the lowest risk of flooding. Among the independent (RHS) variables; poverty rate, socio-economic status, coastal location, and population size are found to be sign consistent with our previous predictions. Note that estimations for the first stage regressions are identical for columns (1) and (2). This is because the group of sub-districts that received non-

[44] Heckman (1979) suggests that the outcome and selection equation are correlated and dependent variable (public spending) of the outcome equation is observed only if the a particular sub-district has received funding in any targeted program which also indicates: $u_i \sim N(0, \sigma)$, $\varepsilon_i \sim N(0, 1)$, $corr(u_i, \varepsilon_i) = \rho$; where ρ denotes the correlation between errors of the two stages been defined.

[45] This refers to the sum of all public funds (per capita) that were allocated for disaster risk reduction in all the previously described programmes except the climate investment fund. We estimated the impacts on the climate fund separately.

[46] Obligatory public funding are dispersed through programmes which include work requirements. Here, the obligatory programmes are Test Relief, Food For Work and Bridges and Culvert construction.

[47] Non-obligatory per capita public funding are dispersed through targeted safety net programs which do not have work requirements in their structural mechanism. Here, the non-obligatory safety net programs are Gratuitous Relief and Vulnerable Group Feeding.

[48] We identify low flood risk sub-district = (highest probability – lowest probability) * 0.10 and high flood risk sub-district = (highest probability – lowest probability) * 0.52.

obligatory funding is a subset of the obligatory ones (in other words, there is no sub-district that received non-obligatory funding but received no obligatory funding). In terms of statistical significance, coastal location is significant at the 1 percent level in all specifications, while economic development is consistently significant and positive at the 5 percent level; suggesting more developed areas receive more funding (per capita). Interestingly; ethnic minority presence, district headquarter and urban centre indicator variables all have negative coefficient estimates in most cases (though these are statistically insignificant). The most striking results are for the risk and political variables. Both low and high flood risk variables (based on past exposure) appear not to have a consistent statistical relationship with the amount allocated for DRR, with sometime even having a counter-intuitive negative sign; without any consistent statistical significance. The political connection to the centre indicator appears to get a negative sign too, though this estimate is statistically insignificant.

Table 4 presents the second stage in the Heckman selection estimation where the dependent variable is DRR per capita allocated funding of the sub-districts which have received funding. The interpretation of the coefficient is a one percentage point increase in low (high) flood risk leads to a decrease of allocated per capita DRR funding by approximately 123 (159) BDT respectively (but is statistically insignificant). The only exception here in terms of statistical significance is the coefficient for obligatory relief funding in the context of low flood risk. That is, a percentage point increase in low flood risk leads to decrease of a sub-district's per capita allocated obligatory funding approximately by 82 BDT. Among the independent variables; the poverty rate, economic development, and coastal effect again show positive signs (consistently with our priors) but with no statistical significance. In contrast to our selection estimation, the outcome for ethnicity and district headquarter showed largely positive association with DRR funding allocation.

Similar to the first-stage regressions, political connections and flood risks showed negative association with allocated spending patterns but with no statistical significance. Taken overall, and in particular this finding about flood risk measure, our findings suggest there is no evident logic to the way the Bangladeshi government allocated its DRR funding.[49]

[49] We obtain very similar results when included interaction terms for the flood risk variable, to examine whether the logic of DRR allocation is different for different groupings of districts (by their geographical location, their poverty rates, or their political connections). None of these interactions terms have a statistically significant coefficient in the second stage regression, further emphasizing our conclusions.

We report the same set of first (showing marginal effects) - and second-stage Heckman selection regressions for realized funding (rather than allocated funding) in appendix tables 2 and 3 respectively. All columns in these two tables represent the same set of variables with the dependent variable being realized per capita funding in DRR. To a large extent, the results are very similar. In particular, we observe a similar pattern for the two variables we singled out earlier: flood risks and political connection. Again, low and high flood risks tend to show statistically insignificant coefficient estimates.

We report Heckman two stage regression results for climate investment fund separately in tables 5 and 6. The first column in table 5 (the marginal effects) display the determinants of sub-district wise allocated per capita public spending on climate change. The second column portrays the impacts on realized per capita public spending for the same set of independent variables as in column (1). Among the independent variables, coastal location, urban centre, and district headquarter again shows signs consistent with our priors with coastal location and socio-economic status being statistically significant in both cases. Ethnicity and population size are not similarly consistent with ethnicity generating statistically significant estimates. As before, the results we are most interested in are the coefficients for the flood risk measures. High flood risk measure has a negative association with both allocated and realized climate fund spending but with no statistical significance, while low flood risk measure showed mixed evidence. None of the other variables seem to adequately explain the climate change funding allocation.

The second stage regression results for the climate investment fund, in table 6, shows an even starker pattern. Among the RHS variables, nothing seem to consistently explain the amount of funding allocated. For the climate investment fund, we no longer observe the counter-intuitive negative coefficients for flood risks (but these results were never statistically significant in the second stage regression).[50]

3.8 ROBUSTNESS CHECKS

Our results to this point largely failed to uncover any rhyme or reason for the way the DRR funding is allocated to sub-districts in Bangladesh. In order to further verify that our results are not dependent on the modelling choice we made (the Heckman two-stage

[50] An exception has been observed in case of low flood risk for allocated spending per capita.

selection model), we re-estimated our models with several other plausible models. We present results of these robustness checks in table 7 for allocated spending per capita. We show the same results in appendix table 4 for realized spending per capita as well. We present results for an OLS estimation, a negative binomial regression, zero-inflated Poisson regression, and a censored Tobit model. The RHS variables in these models are the same as the two stage Heckman selection model. Our original model choice is a combination of linear and non-linear regression framework. As robustness checks; we employ three additional specialized non-linear regression models (i.e. negative binomial regression, zero-inflated Poisson regression, and a censored Tobit model) suitably justified for cases with excess zeros (that is sub-districts receiving no funding at all) and its bounds at 0 and a positive value (Long, 1997). We complemented our non-linear models with the classic OLS linear regression model to justify our findings. Our main result, that flood risk does not explain DRR funding, is consistently presented in all of these different estimations.

3.9 CONCLUSION

Bangladesh is a low-income country. Its natural disaster risk will not change dramatically in the near future, though its risk clearly extends beyond the immediate disaster effects to future impacts associated with climate change. As is true for almost any public programme of fiscal spending, rational allocation of limited public resources is critical to the stated aims of the programmes we examine (i.e., enhance households' coping abilities to reduce and mitigate disasters risks). Clearly, the effectiveness of prevention spending is important, and equally obviously the first pre-condition for any effective spending, not exclusively for DRR, is that this spending is allocated rationally across space.

It is well understood that any government's public spending decision-making processes are affected by other considerations rather than need, but the balance between these competing pressures is not obviously clear. Our objective in this paper is to identify the determinants' of publicly allocated and realized spending at the local government (sub-district) level in Bangladesh. We employ the Heckman two-stage selection model to empirically estimate the covariates where we assume public spending is a function of the probability of flood risks, population size, poverty rate, socio-economic development, political connections, ethnic composition, and details about the geo-location of the sub-district.

While some of our results conform with our priors (where these priors are well formed), it is surprising to note that the presence of the ruling party's elected candidates fails to become a statistically important factor when it is time to attract DRR funding. The most intriguing finding of this study, however, is the response to the sub-district flood risk probabilities as a factor affecting the DRR financing mechanism. This variable is consistently counter-intuitively negative and statistically significant. This result, we should add, is also observed when we do not control for coastal location, when we add other variables, and when we estimate a simpler linear model.

To summarize, we find little evidence (and some counter-evidence) of rationality in the regional funding allocation decisions of the Bangladeshi government. The DRR regional allocations do not seem to be determined by risk and exposure, and only weakly by vulnerability. Even obvious and transparent political economy motivations do not seem to explain much of the variation in inter-regional funding. These funding decisions appear to be much murkier than we expected them to be. This surprised us, as the Bangladesh DRR program is considered a poster-child of DRR investments. Of course, our result are about DRR funding. We do not rule out the possibility that our results are biased because of the absence of long-term data, a possible omitted variable bias and reverse causality. All these justify future research in this area. Whether our conclusions apply to other types of central government funding in Bangladesh, or whether this is indeed typical of regional allocations in lower-income countries, are also all still open questions that require more evidence-based answers.

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FIGURE 1: DISASTER RISK REDUCTION PER CAPITA ALLOCATED SPENDING

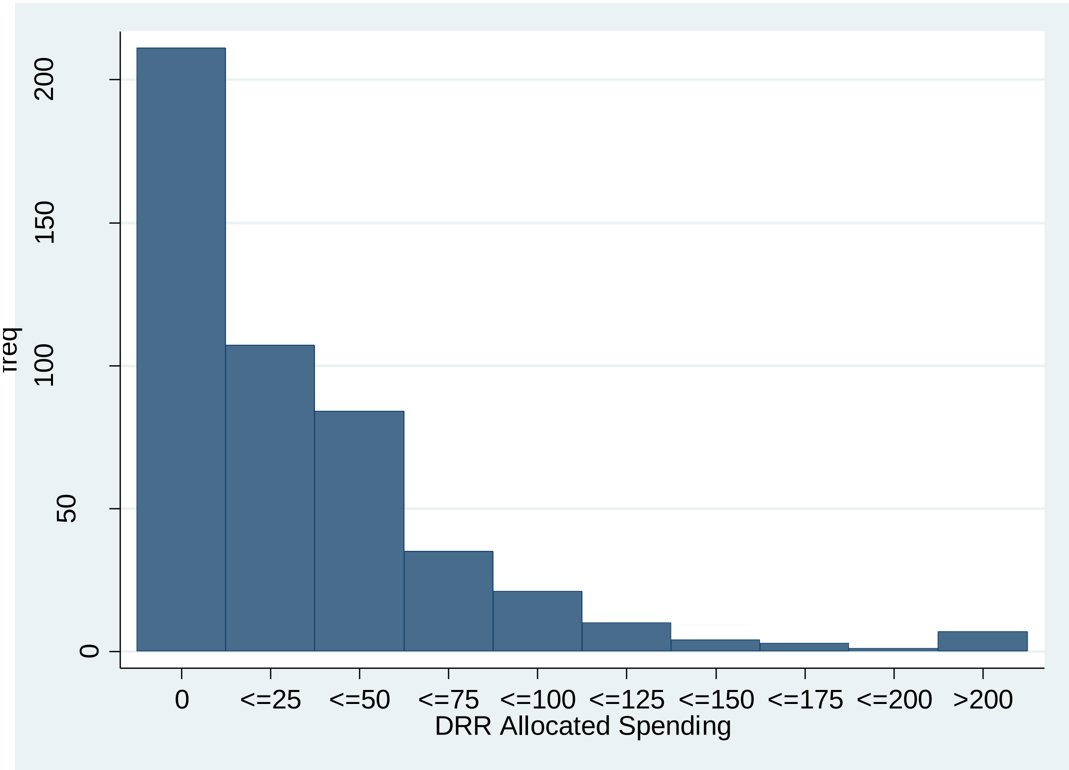

FIGURE 2: DISASTER RISK REDUCTION PER CAPITA REALIZED SPENDING

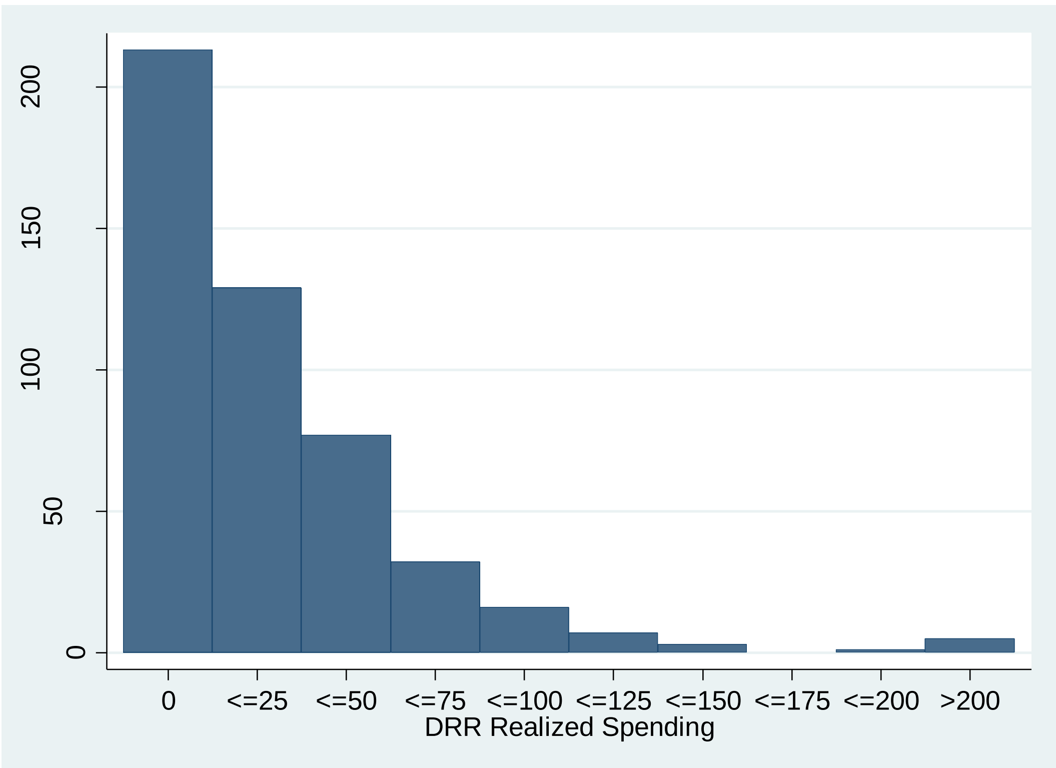

TABLE 1: DESCRIPTIVE STATISTICS A: LEFT-HAND SIDE VARIABLES

VARIABLES	OBSERVATION	MEAN	STANDARD DEVIATION	MINIMUM	MAXIMUM
DRR TOTAL ALLOCATED SPENDING	272 (P)	51.35041	80.69222	0.3851942	968.5986
DRR TOTAL REALIZED SPENDING	270 (P)	41.44611	73.12375	0.231117	966.675
TR_ALLOCATED	483 (A)	12.37298	17.5886	0	137.6302
TR_REALIZED	483 (A)	9.809799	14.28539	0	95.31361
FFW_ALLOCATED	483 (A)	5.443759	13.4828	0	126.3999
FFW_REALIZED	483 (A)	3.819665	9.05842	0	90.41516
INFRA_ALLOCATED	483 (A)	3.15629	9.593239	0	102.8087
INFRA_REALIZED	483 (A)	1.96463	7.554146	0	102.8087
GR_ALLOCATED	483 (A)	2.145435	20.45798	0	374.9262
GR_REALIZED	483 (A)	1.607032	17.19828	0	374.9262
VGF_ALLOCATED	483 (A)	5.799361	42.9692	0	921.9801
VGF_REALIZED	483 (A)	5.967508	43.00797	0	921.9801
CIF_ALLOCATED	483 (A)	1.28391	5.476021	0	58.71323
CIF_REALIZED	483 (A)	0.9925554	4.739405	0	58.46924

Source: Authors' calculations.

Note: The acronyms used here represents Disaster Risk Reduction Allocated and Realized spending, Test Relief, Food For Work, Infrastructure, Gratuitous Relief, Vulnerable Group Feeding and Climate Investment Fund respectively (all in per capita terms). Allocated and realized for each safety net program indicates total (per capita) amount of public fund been allocated and total (per capita) amount of public fund been spent out of total allocation in disaster risk reduction consecutively. P and A represent only positive and all observations, respectively. The currency unit is in BDT (Bangladeshi Taka) [1 USD = 75.79 BDT].

TABLE 2: DESCRIPTIVE STATISTICS B: RIGHT-HAND SIDE VARIABLES

VARIABLES	OBSERVATION	MEAN	STANDARD DEVIATION	MINIMUM	MAXIMUM
POPULATION	483	255833.4	138584.8	17152	941005
FLRISK_LOW	483	0.9347943	0.156718	0.6818	1.909
FLRISK_HIGH	483	0.2577505	0.078411	0.123	0.7272
POVERTY RATE	483	28.3388	13.23799	1.9	68
ECONOMIC DEVELOPMENT	483	52.60449	11.12422	8.1	73.5
ETHNICITY	483	0.4637681	0.499203	0	1
DISTRICT HQ	483	0.1325052	0.339391	0	1
POLITICAL RISK	483	.7763975	.4170906	0	1
URBAN EFFECT	483	0.0393375	0.194598	0	1
COASTAL EFFECT	483	0.1904762	0.393084	0	1

Source: Authors' calculations.

TABLE 3: ALLOCATED SPENDING: HECKMAN FIRST STAGE REGRESSION RESULTS

ALLOCATED SPENDING VARIABLES	FIRST STAGE DISASTER RISK REDUCTION_TOTAL(DY/DX)	RELIEF _OBLIGATORY (DY/DX)	RELIEF _NON-OBLIGATORY (DY/DX)
FLRISK_LOW	-0.10	-0.10	-0.50**
	(0.19)	(0.19)	(0.20)
FLRISK_HIGH	-0.52	-0.52	0.21
	(0.39)	(0.39)	(0.41)
POVERTY RATE	0.25	0.25	0.18
	(0.20)	(0.20)	(0.19)
ECONOMIC DEVELOPMENT	0.42*	0.42*	0.37*
	(0.22)	(0.22)	(0.21)
ETHNICITY	-0.02	-0.02	0.02
	(0.05)	(0.05)	(0.05)
DISTRICT HQ	-0.03	-0.03	-0.02
	(0.08)	(0.08)	(0.08)
POLITICAL RISK	-0.08	-0.08	-0.08
	(0.06)	(0.06)	(0.05)
URBAN EFFECT	-0.04	-0.04	-0.19
	(0.15)	(0.15)	(0.13)
COASTAL EFFECT	0.25***	0.25***	0.22***
	(0.07)	(0.07)	(0.06)
POPULATION	0.26	0.26	0.13
	(0.23)	(0.23)	(0.20)
OBSERVATIONS	483	483	483

Source: Authors' calculations.

Notes: [a] Robust standard errors (clustered by sub-district) in parentheses *** p<0.01, ** p<0.05, * p<0.1.

[b] The regression results in poverty rate and economic development are multiplied by 100 for ease of reading and the population variable is represented in millions.

TABLE 4: ALLOCATED SPENDING: HECKMAN SECOND STAGE REGRESSION RESULTS

ALLOCATED SPENDING VARIABLES	SECOND STAGE DISASTER RISK REDUCTION_TOTAL	RELIEF _OBLIGATORY	RELIEF _NON-OBLIGATORY
FLRISK_LOW	-122.88	-82.44*	-259.32
	(92.63)	(49.72)	(410.96)
FLRISK_HIGH	-159.07	-44.16	44.67
	(260.06)	(107.98)	(288.62)
POVERTY RATE	1.77	0.62	1.80
	(1.48)	(0.60)	(2.06)
ECONOMIC DEVELOPMENT	0.85	0.29	1.17
	(1.80)	(0.83)	(3.22)
ETHNICITY	12.96	-4.75	35.50
	(24.15)	(10.85)	(39.82)
DISTRICT HQ	15.30	11.22	5.08
	(25.80)	(14.54)	(29.41)
POLITICAL RISK	-42.25	-18.26	-49.65
	(40.03)	(15.84)	(73.66)
URBAN EFFECT	-33.19	-12.36	-95.01
	(47.26)	(23.00)	(163.89)
COASTAL EFFECT	87.41	36.03	107.71
	(77.93)	(34.17)	(165.70)
CONSTANT	-35.46	21.00	-104.34
	(188.91)	(86.93)	(296.93)
MILLS			
LAMBDA	221.53	114.83	217.96
	(206.78)	(95.38)	(358.01)
OBSERVATIONS	483	483	483

Source: Authors' calculations.

Note: Robust standard errors (clustered by sub-district) in parentheses *** p<0.01, ** p<0.05, * p<0.1.

TABLE 5: CLIMATE INVESTMENT FUND: HECKMAN FIRST STAGE REGRESSION RESULTS

VARIABLES	CLIMATE INVESTMENT FUND – HECKMAN FIRST STAGE REGRESSION ALLOCATED SPENDING (DY/DX)	REALIZED SPENDING (DY/DX)
FLRISK_LOW	-0.01	0.04
	(0.14)	(0.12)
FLRISK_HIGH	-0.15	-0.21
	(0.34)	(0.32)
POVERTY RATE	-0.09	-0.09
	(0.10)	(0.10)
ECONOMIC DEVELOPMENT	-0.17*	-0.18**
	(0.09)	(0.09)
ETHNICITY	-0.11***	-0.10**
	(0.04)	(0.04)
DISTRICT HQ	0.02	0.02
	(0.04)	(0.04)
POLITICAL RISK	-0.05	-0.03
	(0.03)	(0.03)
URBAN EFFECT	0.01	0.01
	(0.05)	(0.05)
COASTAL EFFECT	0.19***	0.19***
	(0.02)	(0.02)
POPULATION	-0.12	-0.10
	(0.10)	(0.99)
OBSERVATIONS	483	483

Source: Authors' calculations.

Notes: [a] Robust standard errors (clustered by sub-district) in parentheses *** p<0.01, ** p<0.05, * p<0.1.

[b] The regression results in poverty rate and economic development are multiplied by 100 for ease of reading and the population variable is represented in millions.

TABLE 6: CLIMATE INVESTMENT FUND: HECKMAN SECOND STAGE REGRESSION RESULTS

VARIABLES	CLIMATE INVESTMENT FUND – HECKMAN SECOND STAGE REGRESSION ALLOCATED SPENDING	REALIZED SPENDING
FLRISK_LOW	-13.05	7.87
	(22.90)	(38.27)
FLRISK_HIGH	80.36	64.46
	(75.13)	(97.22)
POVERTY RATE	0.20	0.23
	(0.32)	(0.35)
ECONOMIC DEVELOPMENT	-0.21	-0.31
	(0.36)	(0.49)
ETHNICITY	7.42	4.89
	(25.48)	(26.80)
DISTRICT HQ	-6.54	-4.95
	(5.55)	(4.91)
POLITICAL RISK	9.60	8.53
	(11.24)	(10.22)
URBAN EFFECT	3.40	6.05
	(11.78)	(10.69)
COASTAL EFFECT	-22.13	-17.17
	(50.16)	(64.00)
CONSTANT	42.83	23.18
	(47.02)	(70.10)
MILLS		
LAMBDA	-18.68	-15.43
	(27.17)	(34.94)
OBSERVATIONS	483	483

Source: Authors' calculations.

Note: Robust standard errors (clustered by sub-district) in parentheses *** p<0.01, ** p<0.05, * p<0.1.

TABLE 7: ALLOCATED SPENDING: ROBUSTNESS CHECKS

VARIABLES	OLS REGRESSION	NEGATIVE BINOMIAL REGRESSION	ZERO-INFLATED POISSON REGRESSION	TOBIT REGRESSION
FLRISK_LOW	-11929804.42***	-1.77**	-1.75**	-70.62*
	(3,102,041.65)	(0.70)	(0.82)	(40.25)
FLRISK_HIGH	10123486.75	0.34	0.73	-65.70
	(6,210,811.76)	(1.50)	(2.05)	(93.61)
POVERTY RATE	139,125.66***	0.02**	0.01	1.07*
	(45,105.02)	(0.01)	(0.01)	(0.57)
ECONOMIC DEVELOPMENT	54,367.24**	-0.01	-0.02**	0.21
	(24,771.58)	(0.01)	(0.01)	(0.45)
ETHNICITY	4,144,180.70***	0.03	0.20	9.74
	(1,154,026.02)	(0.18)	(0.27)	(13.37)
DISTRICT HQ	644,919.67	0.22	0.11	9.16
	(1,218,619.46)	(0.23)	(0.21)	(12.31)
POLITICAL RISK	-2695571.44***	-0.38**	-0.24	-21.02
	(961,695.17)	(0.18)	(0.22)	(13.74)
URBAN EFFECT	-7050462.68***	-0.72***	-0.97***	-26.15
	(1,621,003.47)	(0.26)	(0.32)	(19.63)
COASTAL EFFECT	6,118,915.26***	0.61***	0.19	45.00***
	(1,174,980.32)	(0.17)	(0.18)	(16.59)
CONSTANT	7,379,671.70***	4.84***	5.80***	38.75
	(2,614,660.81)	(0.78)	(0.85)	(45.28)
LNALPHA		1.57***		
		(0.08)		
SIGMA				92.81***

				(19.47)
INFLATED VARIABLES				
POPULATION			-0.14**	
			(0.73)	
NUMBER OF UPAZILAS (BY DISTRICT)			-0.03	
			(0.03)	
OBSERVATIONS	483	483	483	483

Source: Authors' calculations.

Note: Robust standard errors (clustered by sub-district) in parentheses *** p<0.01, ** p<0.05, * p<0.1.

APPENDIX TABLE 1: DESCRIPTION OF VARIABLES DEFINED AND THEIR SOURCES

No.	Variables	Description	Source
1	**Population**	The total number of people residing in each sub-district.	Department of Disaster Management, Government of Bangladesh.
2	**TR_allocated**	The total (per capita) amount of public fund been allocated in disaster risk reduction through test relief program.	Ministry of Food (Former Ministry of Food and Disaster Management), Government of Bangladesh.
3	**TR_realized**	The total (per capita) amount of public fund been spent out of total allocation in disaster risk reduction through test relief program.	Ministry of Food (Former Ministry of Food and Disaster Management), Government of Bangladesh.
4	**FFW_allocated**	The total (per capita) amount of public fund been allocated in disaster risk reduction through Food For Work program.	Ministry of Food (Former Ministry of Food and Disaster Management), Government of Bangladesh.
5	**FFW_realized**	The total (per capita) amount of public fund been spent out of total allocation in disaster risk reduction through Food For Work program.	Ministry of Food (Former Ministry of Food and Disaster Management), Government of Bangladesh.
6	**Infra_allocated**	The total (per capita) amount of public fund been allocated in bridges and culvert construction under Food For Work program.	Ministry of Food (Former Ministry of Food and Disaster Management), Government of Bangladesh.
7	**Infra_realized**	The total (per capita) amount of public fund been spent out of total allocation in bridges and culvert construction under Food For Work program.	Ministry of Food (Former Ministry of Food and Disaster Management), Government of Bangladesh.
8	**GR_allocated**	The total (per capita) amount of public fund been allocated in disaster risk reduction through gratuitous relief program.	Ministry of Food (Former Ministry of Food and Disaster Management), Government of Bangladesh.
9	**GR_realized**	The total (per capita) amount of public fund been spent out of total allocation in disaster risk reduction through gratuitous relief program.	Ministry of Food (Former Ministry of Food and Disaster Management), Government of Bangladesh.

10	**VGF_ALLOCATED**	The total (per capita) amount of public fund been allocated in disaster risk reduction through vulnerable group feeding program.	Ministry of Food (Former Ministry of Food and Disaster Management), Government of Bangladesh.
11	**VGF_REALIZED**	The total (per capita) amount of public fund been spent out of total allocation in disaster risk reduction through vulnerable group feeding program.	Ministry of Food (Former Ministry of Food and Disaster Management), Government of Bangladesh.
12	**CIF_ALLOCATED**	The total (per capita) amount of public fund been allocated in climate investment fund to combat climate change induced risks.	Ministry of Food (Former Ministry of Food and Disaster Management), Government of Bangladesh.
13	**CIF_REALIZED**	The total (per capita) amount of public fund been spent out of total allocation in climate investment fund to combat climate change induced risks.	Ministry of Food (Former Ministry of Food and Disaster Management), Government of Bangladesh.
14	**FLRISK_LOW**	Also defined as 'low flood risk'. The number of times each sub-district is likely to incur flood risk each year. The threshold is the number of months each sub-district has total rainfall higher than 15 percent of average annual rainfall and more than 1 standard deviation above the mean divided by the number of years' rainfall data has been recorded for each weather station corresponding to each sub-district out of 64 year time span.	Bangladesh Meteorological Department (BMD) rainfall data of 64 years (1948-2012) for 35 weather stations of Bangladesh.
15	**FLRISK_HIGH**	Also defined as 'high flood risk'. The number of times each sub-district is likely to incur flood risk each year. The threshold is the number of months each sub-district has total rainfall higher than 20 percent of average annual rainfall and more than 2 standard deviation above the mean divided by the number of years' rainfall data has been recorded for each weather station corresponding to each sub-district out of 64 year time span.	Bangladesh Meteorological Department (BMD) rainfall data of 64 years (1948-2012) for 35 weather stations of Bangladesh.
16	**POVERTY RATE**	The number of people living below the national poverty line of US$ 2 per day.	Department of Disaster Management, Government of Bangladesh.

17	**ECONOMIC DEVELOPMENT**	This is a composite variable averaging the percentage of population under each sub-district to get access to safe drinking water, sanitation facilities and electricity.	Population and Housing Census of Bangladesh, 2011.
18	**ETHNICITY**	Dummy variable; 1 if indigenous ethnic minorities resides in any sub-district, 0 otherwise.	Authors' elaborations using Population and Housing Census of Bangladesh, 2011.
19	**DISTRICT HQ**	Dummy variable; 1 if the sub-district is central (in most cases, bigger population size and main economic centre) in any particular district, 0 otherwise.	Authors' elaborations.
20	**POLITICAL RISK**	Dummy variable; 1 if the Member of Parliament (MP) is from the main political party in power, 0 otherwise.	Authors' elaborations using Bangladesh Election Commission Report, 2008 and Bangladesh Gazette (2013).
21	**URBAN EFFECT**	Dummy variable; 1 if the sub-district belongs to the bigger urban cities; Dhaka or Chittagong, 0 otherwise.	Authors' elaborations.
22	**COASTAL EFFECT**	Dummy variable; 1 if the sub-district belongs to any districts situated in the coastal belts [a], 0 otherwise.	Authors' elaborations.

Source: Authors' elaborations.

Note: 'Coastal Zone' is most frequently defined as land affected by its proximity to the sea and that part of the sea affected by its proximity to the land (Kamaluddin and Kaudstaal, 2003). According to the Coastal Zone Policy (2005) of the Government of Bangladesh (GOB), the zone is divided into 'exposed coast' (the area/upazilas that embraces the sea directly and is subject to be affected highly by the anticipated sea level rise, also known as *first tier* coastal upazilas) and 'interior coast' (the area/upazilas that are located behind the exposed coast, can also be sub-divided into *second* and *third tier* coastal upazilas). Here, we consider the *first* and *second tier* coastal upazilas to create the 'coastal effect' dummy variable.

APPENDIX TABLE 2: REALIZED SPENDING: HECKMAN FIRST STAGE REGRESSION RESULTS

REALIZED SPENDING VARIABLES	FIRST STAGE DISASTER RISK REDUCTION_TOTAL (DY/DX)	 RELIEF _OBLIGATORY (DY/DX)	 RELIEF _NON-OBLIGATORY (DY/DX)
FLRISK_LOW	-0.12	-0.16	-0.49**
	(0.19)	(0.19)	(0.20)
FLRISK_HIGH	-0.55	-0.39	0.24
	(0.39)	(0.39)	(0.41)
POVERTY RATE	0.27	0.25	0.17
	(0.20)	(0.20)	(0.19)
ECONOMIC DEVELOPMENT	0.39*	0.35	0.42**
	(0.22)	(0.22)	(0.21)
ETHNICITY	-0.01	-0.00	0.02
	(0.05)	(0.05)	(0.05)
DISTRICT HQ	-0.02	-0.03	-0.01
	(0.08)	(0.08)	(0.08)
POLITICAL RISK	-0.08	-0.06	-0.08
	(0.06)	(0.06)	(0.05)
URBAN EFFECT	-0.03	-0.03	-0.18
	(0.15)	(0.15)	(0.13)
COASTAL EFFECT	0.25***	0.27***	0.20***
	(0.07)	(0.07)	(0.06)
POPULATION	0.28	0.30	0.13
	(0.23)	(0.23)	(0.20)
OBSERVATIONS	483	483	483

Source: Authors' calculations.

Notes: [a] Robust standard errors (clustered by sub-district) in parentheses *** p<0.01, ** p<0.05, * p<0.1.

[b] The regression results in poverty rate and economic development are multiplied by 100 for ease of reading and the population variable is represented in millions.

APPENDIX TABLE 3: REALIZED SPENDING: HECKMAN SECOND STAGE REGRESSION RESULTS

REALIZED SPENDING VARIABLES	SECOND STAGE DISASTER RISK REDUCTION_TOTAL	RELIEF _OBLIGATORY	RELIEF _NON-OBLIGATORY
FLRISK_LOW	-90.77	-56.97	-247.05
	(87.37)	(44.77)	(420.40)
FLRISK_HIGH	-201.62	-64.87	70.87
	(255.48)	(83.07)	(311.09)
POVERTY RATE	1.81	0.63	1.78
	(1.43)	(0.49)	(2.13)
ECONOMIC DEVELOPMENT	0.93	0.23	1.63
	(1.64)	(0.62)	(3.79)
ETHNICITY	19.23	-0.23	39.73
	(23.49)	(8.73)	(44.93)
DISTRICT HQ	16.80	10.30	6.34
	(25.49)	(13.22)	(30.42)
POLITICAL RISK	-42.09	-14.96	-54.71
	(37.23)	(11.56)	(80.92)
URBAN EFFECT	-29.49	-8.56	-98.01
	(45.67)	(20.84)	(170.21)
COASTAL EFFECT	85.61	36.56	102.20
	(74.42)	(29.89)	(164.07)
CONSTANT	-69.44	-2.10	-152.93
	(172.11)	(68.87)	(347.18)
MILLS			
LAMBDA	214.95	103.02	224.97
	(194.80)	(78.54)	(378.41)
OBSERVATIONS	483	483	483

Source: Authors' calculations.
Note: Robust standard errors (clustered by sub-district) in parentheses *** p<0.01, ** p<0.05, * p<0.1.

APPENDIX TABLE 4: REALIZED SPENDING: ROBUSTNESS CHECKS

VARIABLES	OLS REGRESSION	NEGATIVE BINOMIAL REGRESSION	ZERO-INFLATED POISSON REGRESSION	TOBIT REGRESSION
FLRISK_LOW	-7791982.56***	-1.37**	-1.05	-46.93
	(2,421,626.26)	(0.68)	(0.78)	(33.39)
FLRISK_HIGH	5,849,044.78	-0.24	0.01	-79.72
	(5,063,921.41)	(1.47)	(2.16)	(86.38)
POVERTY RATE	117,208.63***	0.02**	0.02	1.00*
	(36,059.99)	(0.01)	(0.01)	(0.52)
ECONOMIC DEVELOPMENT	34,715.24	-0.01	-0.01*	0.20
	(21,105.00)	(0.01)	(0.01)	(0.42)
ETHNICITY	3,858,568.79***	0.12	0.33	12.69
	(926,362.99)	(0.19)	(0.30)	(12.11)
DISTRICT HQ	539,520.72	0.23	0.11	8.65
	(990,918.02)	(0.24)	(0.24)	(10.68)
POLITICAL RISK	-2606937.39***	-0.40**	-0.35	-20.76
	(840,510.66)	(0.19)	(0.24)	(13.26)
URBAN EFFECT	-6522802.53***	-0.71**	-1.06***	-23.56
	(1,490,083.88)	(0.29)	(0.37)	(18.23)
COASTAL EFFECT	5,581,593.30***	0.63***	0.24	40.18**
	(1,065,229.21)	(0.18)	(0.20)	(16.33)
CONSTANT	5,231,897.22**	4.29***	4.94***	19.26
	(2,137,943.79)	(0.75)	(0.81)	(38.94)
LNALPHA		1.55***		
		(0.08)		
SIGMA				82.29***
				(21.08)

INFLATED VARIABLES				
POPULATION			-0.15**	
			(0.73)	
NUMBER OF UPAZILAS (BY DISTRICT)			-0.03	
			(0.03)	
OBSERVATIONS	483	483	483	483

Source: Authors' calculations.
Note: Robust standard errors (clustered by sub-district) in parentheses *** p<0.01, ** p<0.05, * p<0.1.

CHAPTER FOUR

THE HOUSEHOLD RESPONSE TO PERSISTENT NATURAL DISASTERS: EVIDENCE FROM BANGLADESH

4.1 INTRODUCTION

Bangladesh has a long history with natural disasters due to its geography and its location on the shores of the Bay of Bengal. Climate change models predict Bangladesh will be warmer and wetter in the future.[51] This changing climate induces flood risk associated with the monsoon season each year (Gosling et al. 2011). It is now widely understood that climate induced increasingly repeated risks threaten to undo decades of development efforts and the costs would be mostly on developing countries impacting existing and future development (OECD, 2003; McGuigan et al., 2002; Beg et al., 2002). Recent literatures examine the short-run effects of natural disasters on household welfare and health outcomes (Arouri et al., 2015; Lohmann and Lechtenfeld, 2015; Silbert and Pilar Useche, 2012; Rodriguez-Oreggia et al. 2013, Lopez-Calva and Juarez, 2009). However, less advancement has been observed in the use of self-reported data to capture the short-run disaster-development nexus in least developed countries with high climatic risks.[52] In this paper, we ask: 'what are the impacts on household income, expenditure, asset and labour market outcomes of recurrent flooding in Bangladesh?'

We examine the short-run economic impacts of recurrent flooding on Bangladeshi households surveyed in 2000, 2005 and 2010. In 2010 Household Income and Expenditure Survey (HIES), households answered a set of questions' on whether they were affected by flood and its likely impacts. Therefore, this paper makes two key contributions in the 'disaster-development' literature: First, we develop a difference-in-difference (DID) model and estimate the impacts of recurrent flooding through identification of two different treatment (affected) groups using self-reported information and historical rainfall data based flood risk index for Bangladesh. We further extend our analysis using a quantile regression and quantify the impacts on the 'ultra' (extreme) poor.[53] The development responses of the climatic disasters may therefore depend on the novel approach i.e. accuracy in identifying the treatment groups using self- and non-self-reported data. Second, we show that there is

[51] See Bandyopadhyay and Skoufias (2015).

[52] Poapongsakorn and Meethom (2013) looked at the household welfare impacts of 2011 floods in Thailand (an upper-middle income country by World Bank definition) and Noy and Patel (2014) further extended this to look at spill over effects.

[53] The term 'ultra-poor' was coined in 1986 by Michael Lipton of the University of Sussex and is defined as 'a group of people who eat below 80% of their energy requirements despite spending at least 80% of income on food'. In this paper, we refer to the households who belong to the bottom 15[th]quintile of per capita income/expenditure brackets.

inconsistency between self- and non-self-reported information based estimates with literature outcomes questioning the designation of survey questions (related to natural shocks) and their usefulness to capture development impacts.

The paper is designed as follows: Section 4.2 reviews the 'new' macro-micro literature highlighting recent insights to explore the nexus between climate disasters and economic development. Section 4.3 portrays our identification strategy while Section 4.4 describes the data, provides detailed breakdown of our methodological framework, identifies the key variables and justifies the choice of the covariates with added descriptive statistics. In Section 4.5, we present and analyse the estimation results with previous literature along with some robustness checks in Section 4.6. Finally, in Section 4.7 we conclude with relevant policy implications and also some insight for further advancements.

4.2 Climate Disasters and Development: The New 'Macro-Micro' Literature

The last few years have seen a new wave of empirical research on the consequences of changes in precipitation patterns, temperature and other climatic variables on economic development and household welfare. Climate-related natural disasters are expected to rise as the earth is getting warmer with prospect of significant negative economic growth mostly affecting the poor countries (Felbermayr and Gröschl, 2014; Acevedo, 2014). Vulnerable economies for example, the Pacific islands could expect a growth drop by 0.7 percentage points for damages equivalent to 1 percent of GDP in the year of the disaster (Cabezon et al., 2015). On the causality between catastrophic events and long-run economic growth using 6,700 cyclones, Hsiang and Jina (2014) find robust evidence that national incomes decline compared to pre-disaster trends and the recovery do not happen for twenty years for both poor and rich countries. This finding contrasts with the earlier work of Noy (2009) and Fomby, Ikeda and Loayza (2009)[54] to some extent and carry profound implications as climate change induced repeated disasters could lead to accumulation of income losses over time. Therefore, climate disasters have become a development concern with likelihood of rolling back years of development gains and exacerbate inequality.

Climate resilience has become integral in the post-2015 development framework and recent cross-country 'micro' literatures explore the channels through which climate disasters

[54] These studies focus on the short-run effects of natural disasters.

impacted poverty.[55] Two recent studies on rural Vietnam looked at the impacts on climate disasters such as floods, storms and droughts on household resilience and health outcomes (Arouri, Nguyen and Youssef, 2015 and Lohmann and Lechtenfeld, 2015). Arouri et al. (2015) pointed out that micro-credit access, internal remittance and social allowances could strengthen household resilience to natural disasters. However, high resilience might not necessarily reflect low vulnerability as evident in a study conducted on tropical coastal communities in Bangladesh (Akter and Mallick, 2013). Moreover, another study on the Pacific island of Samoa by Le De, Gaillard and Friesen (2015) suggests that differential access to remittances could increase both inequality and vulnerability. Bandyopadhyay and Skoufias (2015) show that climate induced rainfall variability influence employment choices impacting lower consumption in flood-prone sub-districts in rural Bangladesh. Assessing relationship between household heterogeneity and vulnerability to consumption patterns to covariate shocks as floods and droughts, Kurosaki (2015) identified landownership to be a critical factor to cope with floods in Pakistan. A recent study on the Indian state of Tamil Nadu by Balasubramanian (2015) estimates the impact of climate variables (i.e. reduction in ground water availability at higher temperature than a threshold of 34.31^0 C) on agricultural income impacting small land owners to get low returns to agriculture. In one particular examination on occurrence and frequency of typhoons and/or floods in Pasay City, Metro Manila by Israel and Briones (2014) reveals significant and negative effects on household per capita income.

This growing 'Climate-Development' literature further explores empirical patterns in risk, shocks and risk management by using shock modules in questionnaire-based surveys to complement existing risk management tools. This usage of self-reported information on natural shocks motivated researchers to develop different dimension of identification strategies and compare impact findings using econometric models. Two recent studies by Noy and Patel (2014) and Poapongsakorn and Meethom (2013) investigate household welfare and spill over effects of the 2011 Thailand flood identifying self-reported affected (treatment) group in a difference-in-difference modelling framework. Nevertheless, evidences suggest careful use of self-reported data in identifying the true impacts which is also one of the highlights in this paper.[56]

[55] Karim and Noy (2016) provide a qualitative survey of the empirical literature on poverty and natural disasters.
[56] See Guiteras, Jina, and Mobarak (2015) and Heltberg, Oviedo and Talukdar (2015).

4.3 IDENTIFICATION STRATEGY

Our objective in this paper is to analyse the short-run impacts of recurrent flooding on household income, expenditure, asset and labour market outcomes through identification of treatment (affected) groups using both self- and non-self-reported data (historical rainfall data based flood risk index). We use the term 'persistent natural disasters' to refer to repeated natural disasters (e.g. flood) that occurs almost every year and possess increase risks of occurrence due to rainfall variability.[57] Our estimation strategy compares households surveyed on and before year 2010 (in which shock module was introduced with questionnaire related to natural disasters). Therefore, we define year 2010 as post. Although there was no major flood event in 2010, we identified those sub-districts that were surveyed with shock questionnaire in 2010 and compared them in the earlier years (i.e. 2000 and 2005). The key assumption in our identification strategy is that in the absence of 2010 treatment (self-identified flood impact), the evolution of the outcome of interest (e.g. income, expenditure, asset and labour market outcomes) would have followed the same trend as the control group (i.e. common trend assumption).

We identify two treatment groups using self- and non-self-reported data as a) shock module was introduced in the 2010 Household Income and Expenditure Survey (HIES) and no new surveys have been conducted at the national level since then[58] and b) self-reporting in terms of being affected could be subjective and might bring biased results due to sorting or selective reporting.[59] Self-reported data could not only be a subject of recall error, but also to other forms of cognitive bias like reference dependence (Guiteras, Jina and Mobarak, 2015).The module on shocks and coping responses was first introduced in HIES 2010 to identify households affected by various idiosyncratic and covariate shocks. As our focus in this paper is on covariate shocks i.e. flood, we identify households who have self-reported to be affected by floods only in 2010 survey. The earlier surveys – 2000 and 2005 did not have any shock module and hence identification of self-reported affected groups were not possible. However, Bangladesh as a disaster-prone country, disasters particularly flood is a repeated phenomenon every year. Therefore, a comparison control group could be those households

[57] See Bandyopadhyay and Skoufias (2015) and Gosling et al. (2011).

[58] The decision process of 2015 survey is currently underway according to the information provided by the current Project Director of HIES.

[59] See Heltberg, Oviedo and Talukdar (2015) for a discussion on how survey modules falls short of expectations in several ways.

who are not affected by specific natural disasters, if any, in the survey regions in that particular year. Here, we took flood as persistent natural disaster due its repeated occurrence every year mostly during the monsoon period (May-October). Due to absence of shock modules in the dataset in years 2000 and 2005, we identify two 'treatment' groups – treatment group A and treatment group B.

To identify our first treatment group i.e. treatment group A, we use a rainfall-based flood risk probability index using historical rainfall dataset from the Bangladesh Meteorological Department (BMD) to identify upazilas/thanas (in particular, the survey areas) which are affected by excessive rainfall more than average rainfall over a long period (1948-2012).[60] The rule of thumb is the survey areas which experienced more than average rainfall compared to the benchmark of average rainfall of 64 years in the corresponding weather station in respective survey years (e.g. 2000, 2005 and 2010), the surveyed households' falls under treatment group A. The control (not affected) group i.e. control group A are those households who resided in survey areas that did not experience excessive rainfall compared to the average rainfall of 64 years in the corresponding weather station in respective survey years (here, 2000, 2005 and 2010). Figures 1 and 3 presents the evolution of per capita total income and expenditure for treatment and control group A, respectively. These figures were created by averaging the residuals of income and expenditure after controlling for covariates by year and separately for the treatment and control group A. It can be seen that the trajectories in both groups (treatment and control) are quite similar in 2000 and 2005 (pre-treatment years), an indication that the common trend assumption holds in these periods.

The second treatment group i.e. treatment group B is identified through a combination of both self-reported and non-self-reported information due to absence of shock modules before 2010 and prevalence of flooding every year. From 2010 survey, the treatment group is the respondents who have said 'Yes' as being affected by natural disasters such as flood. The benefits of using a rainfall-based flood risk criterion are twofold. First, it justifies homogeneity among affected households in terms of a common natural shock i.e. flood. Second, we can compare the development impacts with two different treatment groups and

[60] See Karim and Noy (2015) for a detailed breakdown of the index construction.

the differences could refer to discrepancies in capturing the true impacts using shock modules. The second control group i.e. control group B is also identified through a combination of both self-reported and non-self-reported information due to absence of shock modules in years 2000 and 2005. In 2010, the controls are those households who have responded 'No' to being affected by flood. We use the rainfall-based flood risk measure to identify the control households for 2000 and 2005 in control group B. To check for the validity of the common trend assumption using treatment and control group B, we show the evolution of per capita total income and expenditure in figures 2 and 4 respectively. These figures were created by averaging the residuals of income and expenditure after controlling for covariates by year and separately for the treatment and control group B. The trajectories here again validate the common trend assumption in pre-treatment years (e.g. 2000 and 2005).

4.4 DATA AND METHODOLOGY

4.4.1 DATA DESCRIPTION

We use Household Income and Expenditure Survey (HIES) of the Bangladesh economy spanning over a time period of 10 years and consists of three (3) waves: 2000, 2005 and 2010. The HIES is the nationally representative dataset conducted by the Bangladesh Bureau of Statistics (BBS) (in affiliation with the Ministry of Planning, Government of Bangladesh and technical and financial assistance from the World Bank) that records information regarding income, expenditure, consumption, education, health, employment and labour market, assets, measures of standard of living and poverty situation for different income brackets in urban and rural areas. The BBS conducts this survey every five (5) years. The latest HIES conducted in 2010 added four (4) additional modules in which one refers to 'Shocks and Coping' (Section 6B) in the questionnaire. The BBS HIES is a repeated cross-section dataset with randomly selected households in designated primary sampling units (PSUs). Therefore, the strength of the dataset is large sample size covering a broad range of households. However, limitations are there in capturing the impacts over time. The number of households in year 2000 is 7,440 with 10,080 and 12,240 in year 2005 and year 2010 respectively. We also use the Bangladesh Meteorological Department (BMD) rainfall dataset from 1948-2012 (i.e.

64 years) for 35 weather stations across the country to identify flood-affected treatment group in respective survey years under consideration.

4.4.2 METHODOLOGICAL FRAMEWORK

We employ the difference-in-difference (DID) estimation framework to estimate the development impacts on affected households due to flood. We start with the following specification:

$$y_{it} = \beta_0 + \beta_1 \text{post}_{2010} + \beta_2 \text{treated}_i + \beta_3 \text{post}_{2010}.\text{treated}_i + \beta_4 X_{it} + \beta_5 \text{year}_{2005} + \beta_6 \text{year}_{2005}.\ \text{treated}_i + \text{u}_{it} \qquad (1)$$

Where post = 1 if the observation is from 2010, β_2 is the difference between treatment and control groups on the baseline, X_{it} denotes the covariates indicating household (i) and socio-economic characteristics and infrastructural features, β_5 is time fixed effect for year 2005, β_6 is the interaction term and u_{it} indicate the error term. The β_3 coefficient measures the difference-in-difference (DID) impact of a natural shock on outcome variables (development impact indicators), y_{it}. We use robust standard errors for our hypothesis tests.

We further conduct quantile regression (estimating five different quintiles e.g. 15th, 25th, 50th, 75th and 85th quintiles) using the same DID framework to compare our results for different income and expenditure brackets.[61]

$$\text{Q}y_{it} = \beta_{0(\alpha)} + \beta_{1(\alpha)} \text{post}_{2010} + \beta_{2(\alpha)} \text{treated}_i + \beta_{3(\alpha)} \text{post}_{2010}.\text{treated}_i + \beta_{4\,(\alpha)} X_{it} + \beta_{5(\alpha)} \text{year}_{2005} + \beta_{6(\alpha)} \text{year}_{2005}.\ \text{treated}_i + \text{u}_{it} \qquad (2)$$

Where Q refers to quantile regression, α denotes selected quintiles (0.15, 0.25, 0.50, 0.75 and 0.85) and all other variables are as previously defined (as the treatment groups are not randomly assigned in our context).[62] We also estimate the following semi-logarithmic

[61] See Khandker, Bakht and Koolwal (2009).
[62] We also regress equation (2) without the control variables and the results are presented in the appendix.

regression model by log-transformation of the dependent and continuous independent variables as robustness checks for our main results:[63]

$$\log y_{it} = \alpha_0 + \alpha_1 \text{post}_{2010} + \alpha_2 \text{treated}_i + \alpha_3 \text{post}_{2010}.\text{treated}_i + \alpha_4 X_{it} + \alpha_5 \text{ year}_{2005} + \alpha_6 \text{year}_{2005}.\text{ treated}_i + \text{u}_{it} \qquad (3)$$

4.4.3 OUTCOME VARIABLES AND CHOICE OF COVARIATES

Appendix tables 1 and 2 show the list of key outcome variables and the covariates (continuous and categorical) and their descriptive statistics for two different sets of treatment and control groups. Our outcome variables of interest include four sets of development indicators. They are: income (income by category), expenditure (expenditure/consumption by category), asset types and labour market outcomes. Income and expenditure are divided into various sub-groups with statistics shown in per capita household measures. Asset and labour market outcomes are also sub-divided into various categories (also described in appendix tables 1 and 2). The continuous (monetary) variables in each category are inflation-adjusted using consumer price index (CPI) data from the Bangladesh Bank to allow for comparisons across different years.

Alleviating poverty is a fundamental challenge for Bangladesh with the majority of the extreme poor living in rural areas with considerable flood risk bringing annual agricultural and losses to livelihoods (JBIC, 2007; Fadeeva, 2014; Ferdousi and Dehai, 2014). Hence, we control for 'rural' that takes the value 1 if the household resides in a rural area and 0 if otherwise reported. The male member as household head is generally considered as 'bread earner' and a good amount of literature also highlighted the positive association between female-headed households and poverty especially in developing countries (Mallick and Rafi, 2010; Aritomi et al., 2008; Buvinic and Rao Gupta, 1997). Therefore, a dummy variable has been created indicating 1 if the household head is male and 0, if reported otherwise. Household characteristics such as age structure and number of dependents is critical to analyse poverty status and one might expect larger number of dependents leads to greater poverty (Kotikula et al., 2010; Haughton and Khandker, 2009; Lanjouw and Ravallion, 1995). Education is also related with lower poverty (Kotikula et al., 2010). Community-level characteristic such as

[63] Since this type of transformation closely follows normal distribution. See Sugiyarto (2007) for more discussion.

access to sanitation and access to safe drinking water is clearly associated with better health outcomes improving poverty status (World Bank, 2014; Duflo et al., 2012) of households with access to electricity also showing a positive trend in living standards (Kotikula et al., 2010). Therefore, three (3) binary variables are created indicating 1 to imply access to these services, 0 otherwise. Ownership status of households such as house and land has also been argued as important determinant of poverty with owners of a dwelling place are found to be less vulnerable to flood risk (e.g. Khatun, 2015; Tasneem and Shindaini, 2013; Gerstter et al., 2011; Meinzen-Dick, 2009; Rayhan, 2010). A description of these variables including summary statistics is also provided in appendix tables 1 and 2.

4.4.4 Descriptive statistics

We provide two sets of descriptive statistics for two different treatment and control groups (treatment group A and treatment group B) in appendix tables 1 and 2 respectively. We present mean and standard deviation for various outcome categories and covariates for both rainfall-based and self-reported treatment (affected) and control (not affected) groups. Most of the income categories especially agricultural (crop and non-crop) income seems to be much higher for the control group compared to treatment for treatment group A with exception in 'other income' category. The total income per capita for the control group is on average, almost 80 percent higher compared to the treatment group. The other treatment group i.e. treatment group B intriguingly does not show too much variation in terms of mean income by categories. However, mean of 'other income' turns out to be almost 11 percent lower for the controls compared to treatment in treatment group B. The expenditure categories also show almost similar patterns i.e. larger variations between treatment and control groups for treatment group A compared to smaller variation for treatment group B. The expenditure per capita for the control group A is, on average, almost 82 percent higher compared to the treatment group (rainfall-based). Moreover, the education and health expenditure measures show considerably less variation in self-reported treatment group compared to non-self-reported one. The control group A displays on average, almost 76 percent more educational expenditure compared to the treatment group. The proportion of household members in control group A getting access to formal education is around 30 percent more compared to treatment group A. There are substantial variations in terms of total change in agricultural and other business asset categories between treatment and control groups using both rainfall-based and self-reported identifications. This variation is 27 percent higher for the rainfall-based control group compared to the self-report control group. Observable variations can also be seen in labour market outcomes between treatment and control groups. Both daily and salaried wage for the control group A (rainfall-based) seems to be almost 76 percent higher compared to the treatment group. The self-reported identification (treatment group B) does not seem to vary considerably with respect to labour market outcomes. There are interesting parallel trends in the mean results of the covariates (independent variables) between the two treatment groups. The affected households in treatment group A have more working adults i.e. fewer dependents (around 25 percent) compared to treatment group B. However, the self-reported treatment group owns more land (16.3 percent more) compared to non-self-reported one. Proportion of household members getting access to formal education is almost 16 percent higher in self-reported treatment group compared to rainfall-based treatment identification. Community characteristics such as access to sanitation, safe drinking water and electricity also show parallel trends in their mean outcomes in both treatment group – A and B.

4.5 ESTIMATION RESULTS

We start by estimating our benchmark difference-in-difference (DID) model with two treatment groups: treatment group A and treatment group B for four development outcomes: income, expenditure, asset and labour market. We compare the results for each category (in terms of aggregate and disaggregated outcome measures) and show the robustness under various income and expenditure brackets.

4.5.1 INCOME

We report impacts of recurrent-flooding on different income categories i.e. crop, non-crop, business and other income for rainfall-based flood affected and self-reported treatment groups in tables 1 and 2 respectively. We find both treated (affected) households experience negative impacts on total income being consistent with previous disaster literatures (e.g. Asiimwe and Mpuga, 2007; Thomas et al., 2010; De La Fuente, 2010). Our results indicate that total income reduces by almost 11 percent more (estimated to be approximately BDT 17,807) for treatment group A compared to the mean.[64] A decline in crop income is higher for treatment group A (by BDT 7,428) whereas treatment group B observe comparatively greater reduction in non-crop income (by BDT 26,644) being consistent with evidences that show decline in agricultural income due to rainfall shocks (e.g. Skoufias et al., 2012; Baez and Mason, 2008; UNISDR, 2012). We do not observe any significant negative impacts on business income (non-agricultural enterprise) and other income in both treatment cases. These results could also be justified by previous works done by Attzs (2008) and Patnaik and Narayanan (2010). Among the covariates; male-headed households and formal education seems to have a stronger positive association with total income in addition to community variables such as access to sanitation and access to electricity. Ownership of land show moderate to strong impact on total income. Intriguingly, both average age of households and the number of dependents show a positive association with total income. This might be due to the fact that there exists a relationship between household head and household members who are over 65 years old.[65] It is more likely that the senior members are household heads and possess control over ownership of land and house.[66]

The impact on various categories of income - such as crop, non-crop, business and other income - also varies across different time horizons i.e. short- and medium to long-run impacts. The rainfall-based affected group (treatment group A) experiences a fall in both crop and non-crop income (although coefficient of crop income is significant). Similarly, the self-reported affected group also observes a significant fall in both crop and non-crop income. The interesting thing to note here is that treatment group A (rainfall-based) experienced a significant drop of almost BDT 4,559 more in crop income compared to treatment group B (self-reported). However, self-reported impact is of higher magnitude (difference of BDT 14,944) with regards to non-crop income compared to non-self-reported one. The other two categories of income we analyse are more indirect and have medium to long-run impacts on households. Business income in both of these treatment groups are found to be positive (and significant in the self-reported group) with an increase of approximately BDT 13,706 in the self-reported case. The other income category show negative sign (not significant) in both

[64] 1 US Dollar = 77.88 Bangladeshi Taka (BDT).
[65] We define household members who are less than 15 and greater than 65 years old as 'dependents'.
[66] See Zaman (1999).

treatment cases with less variation. The coefficients of the covariates do not vary substantially in terms of sign and significance between the two treatment groups.

To observe the income distributional effects of repeated-flooding on household income, we estimate both conditional and unconditional quantile regression model at various quintiles (0.15, 0.25, 0.50, 0.75 and 0.85). Tables 9 and 10 displays the quantile treatment effects for income categories conditional on all the covariates as in our baseline model and time fixed effect for both treatment groups – A and B. We observe a contrast in terms of the impacts of repeated-flooding on the ultra-poor (i.e. the bottom 15 percent) between both treatment groups. Total income for the extreme poor are found to be negatively affected for self-reported treatment group (treatment group B) whereas income effect is much stronger for the middle 50 percent for treatment group A.[67] However, the richer households are not found to be negatively affected in treatment group B compared to a significantly negative effect for richer households (i.e. the top 15 percent) for rainfall-based treatment group (treatment group A). Nevertheless, crop income show significantly negative impact (drop by BDT 3,198) on the bottom 15th quintile for treatment group A while treatment group B revealing a much stronger impact for the middle to higher income brackets (in per capita measures). We observe significant negative impacts (by BDT 319,522) on business income for the ultra-poor for self-reported treatment group (treatment group B). Households also experience significant negative impacts in other income category in both treatment cases. However, we also estimate an unconditional quantile regression as traditional estimators might be more appropriate when identified without control variables (Powell, 2016).[68]

4.5.2 CONSUMPTION / EXPENDITURE

We report impact estimates of various expenditure categories i.e. food, non-food, crop, non-crop, agricultural input, education and health for non-self- and self-reported treatment groups in tables 3 and 4 consecutively. Our results show a significant decline of

[67] According to Tesliuc and Lindert (2002); the poor are disproportionately more exposed to natural disasters and agriculture related shocks and income inequality increased by 16% as a result of shocks. Yamamura (2013) also conclude an increase in income inequality in the short-term due to disasters in general.

[68] We present our results for unconditional quantile regression in appendix tables 9 and 10 for treatment groups A and B respectively. The difference across various quintiles among income categories between the two treatment groups could possibly be explained through the presence of household heterogeneity issues in our benchmark quantile estimation (equation 2).

around 14 percent compared to the mean for total expenditure (i.e. drop by BDT 22,007) for treatment group A (non-self-reported) being consistent with previous literatures (e.g. Dercon, 2004; Auffret, 2003; Asiimwe and Mpuga, 2007; Jha, 2006; Shoji, 2010; Foltz et al. 2013). Interestingly, treatment group B (self-reported) reveal a positive impact on total expenditure due to flooding. This result could also be justified by coping strategies, safety net and micro-credit borrowing by households.[69] Our focal categories i.e. crop expenditure and agricultural input expenditure (as we assume these categories are directly related to rainfall shocks and flood) show negative impacts in both treatment cases. However, although both categories show sign consistencies, agricultural input expenditure is found statistically significant in treatment group A while treatment group B display statistical significance in crop expenditure. In accordance with income estimates for two treatment groups, the covariates in the expenditure categories also reveal almost similar types of relationship with expenditure outcome categories. In both treatment cases, in addition to male-headed households and formal education, all three community characteristics (e.g. access to electricity, sanitation and pure drinking water) demonstrate strong positive association with total expenditure. We also anticipate similar reasoning for positive outcomes of average age and number of dependents for both treatment group – A and B.

The various categories of expenditure - food, non-food, crop, non-crop, agricultural input, educational and health expenditure - could also be categorized based upon their time horizons e.g. short- and medium to long-run impacts. Expenditure categories as food, non-food and agricultural consumption indicate the short-term impacts whereas education and health expenditures may lead to long-term impacts. The treatment households (A and B) experienced significant contrast in terms of the direct impacts (food and non-food) where the self-reported treatment group observed positive and significant impacts. Both affected groups show contrasting estimates in education and health spending as well. However, the self-reported households experience a rise in educational expenditure (approximately by BDT 2,189) accompanied by a significant decline in health expenditure (approximately by BDT 689). Interestingly, the total expenditure in the self-reported treatment group (B) increases (although not significantly) compared to a significant decline for the non-self-reported group.

[69] See Khandker (2007); Demont (2013); Vicarelli (2010).

Similar to income categories, we further extend our analysis by looking at various quintiles for expenditure categories. Tables 9 and 10 also displays the quantile treatment effects for expenditure categories conditional on all covariates and time fixed effect for both treatment groups – A and B. We observe a contrast in estimation results for different quintiles for non-self and self-reported treatment groups. We find significant negative impacts for the bottom 15 percent with a much stronger impact for the middle 50 percent for treatment group A. Intriguingly, we find a significant positive outcome for the bottom 15 percent for treatment group B (also justified by previous work)[70] which however demonstrate significantly negative impact for the bottom 25 percent (by BDT 301,632) and for the top 15 percent (drop by BDT 47,967). Again, crop expenditure reveals significantly negative impact for the ultra-poor (i.e. the bottom 15th quintile) in treatment group A and B. However, although agricultural input expenditure show negative impacts for treatment group A, it reveals a positive outcome for treatment group B with statistical significance in both cases. We also observe a contrast in educational and health expenditure outcomes for non-self and self-reported treatment groups as well. Furthermore, we also estimate an unconditional quantile regression in expenditure categories. Appendix tables 9 and 10 portrays the unconditional quantile treatment effects for expenditure categories for treatment groups A and B. [71]

4.5.3 ASSET

Tables 5 and 6 demonstrate the impacts of repeated-flooding on three asset categories: changes in agricultural and other business asset, agricultural input asset value and consumer durable asset value for both affected (treatment) groups. We do not observe much contrast in these categories though. The rainfall-based flood affected group (treatment group A) observe negative impacts (although not statistically significant) on change in agricultural and other business asset (by BDT 6,144) while self-reported treatment group (treatment group B) reveal significant negative impacts (by BDT 103,611) in similar category quite consistent with previous evidences on asset categories (e.g. Mogues, 2011; Anttila-Hughes

[70] Ibid.

[71] The difference across various quintiles among expenditure categories between the two treatment groups could again possibly be explained through the presence of household heterogeneity issues in our benchmark quantile estimation (equation 2).

and Hsiang, 2013). The noticeable aspect to note here is that the impact on the self-reported group is BDT 97,467 more compared to the non-self-reported one. Nevertheless, treatment group B reveals significant positive impact on agricultural input asset value compared to a negative value for treatment group A in this category.

4.5.4 LABOUR MARKET

We present impacts on labour market for both treatment group – A and B in tables 7 and 8 sequentially. Daily wages are not found to be severely affected in both treatment groups (positive impact) with statistical significance for self-reported treatment case (by BDT 101). This somewhat been justified in some previous empirical researches (e.g. Shah and Steinberg, 2012; Banerjee, 2007).[72] Interestingly, salaried wage seems 7 percent higher compared to the mean (i.e. by BDT 3,894) in treatment group B with 1 percent drop (compared to the mean) for treatment group A (but in this case without statistical significance). This result is also partially found consistent with the findings of Mueller and Quisumbing (2011). We also observe a contrast in estimates of yearly benefits for both treatment group.

4.6 ROBUSTNESS CHECKS

As robustness checks, we further examine these impacts by estimating a semi-logarithmic regression model (as specified in equation 3) and compare the results with our benchmark estimation results. In the income category, we observe significantly negative impact on total income (drop by BDT 28,078 compared to the mean) for treatment group A (rainfall-based). The interesting thing to note here is that treatment group B (self-reported) experiences an additional total income decline of BDT 52,581 more (and is significant) compared to the non-self-reported one. Most of this excess decline (approximately BDT 29,442) resulted from crop income for the self-reported treatment group B. However, treatment group A experience a significant drop of BDT 6,572 on average in the non-crop

[72] Banerjee (2007) find that floods have positive implications for wages in the long run. Interestingly, Mueller and Osgood (2009) reveal that droughts have significant negative impacts on rural wages in the long run. We are quite agnostic on the general implications of natural disasters on wages due to limitations in this study.

income category. Business income in both treatment groups reveals positive impact (with statistical significance in treatment group A) being consistent with our prior estimations. We observe a significant increase of BDT 13,030 on average for treatment group A in business income category. The other income category also reveals a significant increase of BDT 4,146 more (compared to the mean) for rainfall-based treatment group A compared to the self-reported one (treatment group B).

We find consistent patterns in total expenditure category in the semi-logarithmic regression results compare to our baseline model specifications. Similar to total income patterns, the self-reported treatment group B experience an average decline in total expenditure by BDT 46,551 more compared to treatment group A (rainfall-based). The self-reported treatment group reported an additional decline of BDT 8,694 on average in non-crop expenditure due to flood compared to the non-self-reported one. The difference in our focal categories (i.e. crop expenditure and agricultural input expenditure) is strikingly more in agricultural input expenditure for treatment group B (drop by BDT 25,761 on average) compared to treatment group A. Although educational and health expenditure reveals a significantly positive impact, the difference is not too high between the two treatment groups compared to the mean. The food and non-food expenditure categories display significantly declines for both rainfall-based and self-reported treatment cases. Despite households experience significant decline in food and non-food expenditure, flood impacts are reported much higher by the self-reported treatment group B (drop by BDT 15,288 more on average) in non-food expenditure category compared to rainfall-based treatment group A.

The impacts on agricultural input asset value show significantly negative impacts for both treatment cases in our semi-logarithmic regression results. The noticeable aspect here is that the self-reported treatment group reveals an excess decline of BDT 31,626 in agricultural input asset value compared to the non-self-reported one. The category on consumer durable asset value also illustrate significant negative impacts in both treatment cases. Treatment group A experience a significant average decline of BDT 16, 0108 which is comparatively higher than for treatment group B (self-reported).

4.7 CONCLUSION

Our objective in this paper is to estimate the impacts of recurrent flooding on income, expenditure, asset and labour market outcomes. We start with identification of the treatment (affected) groups with setting two benchmarks i.e. using self- and non-self-reported (historical rainfall data based flood risk index) information. We employ a difference-in-difference estimation model to understand the impacts of disaster on households surveyed on and before year 2010 (defined as post). Our results suggest a sharp decline in agricultural income (crop and non-crop) for both treatment group – A (rainfall-based) and B (self-reported). This significant decline in agricultural income, being consistent with previous literatures reveals a clear message on timely adoption of insurance in the context of increased climatic threat to achieve sustainable poverty goals for the ultra-poor especially in agriculture-based economy like Bangladesh. As per expenditure in concerned, we also observe a negative response to crop and agricultural input expenditure consistent with our theoretical prior in both treatment cases.

We extend our analysis for income and expenditure categories for households of various socio-economic backgrounds. We find a contrast in terms of impact for the ultra (bottom 15 percent) poor in total income and expenditure between treatment group – A and B. We also observe a contrast in educational and health expenditures for both non-self and self-reported treatment group. We further strengthen our results using semi-logarithmic regression model as robustness checks and observe consistencies in most cases with our benchmark estimation results.

The ‘disaster-development’ literature has made considerably less progress on the use of shock modules to empirically estimate the impacts of natural disasters on development outcomes. The recent addition of shock questionnaires in nationally representative household income and expenditure surveys provides an ample scope to identify the self-reported affected groups in repeated natural disasters. This self-identification in the questionnaire could be advantageous to capture the disaster impacts on households’ more precisely when compared to index-based identifications based on geographical exposure. However, questions’ based on ‘yes/no’ responses (i.e. close-ended) might not be sufficient to identify the true development impacts. The selection of the respondents (sample) in this particular set of questionnaire (shock questions on natural disasters) is also questionable depending on criteria.[73] There is an obvious need to employ both qualitative and quantitative techniques to understand the degrees of experience in impact analysis.[74]

We do not rule out the fact that the dissimilarities in our results in two benchmark treatment cases might also be due to absence of shock modules in self-reported treatment group (treatment group B) in years 2000 and 2005 in the household data that we use. One possible solution is of course, more respondents in addition to incorporating degrees of actual hazard awareness, experience and preparedness questions' to identify the real affected group in repeated natural shocks. However, the evidences and the novel approach that we adopt in this paper could justify future research in estimating welfare adaptation costs of climate-induced persistent natural events in developing countries.

[73] See Hawkes and Rowe (2008).
[74] See Bird (2009).

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FIGURE 1: PRE-TREATMENT TRENDS OF PER CAPITA TOTAL INCOME (TREATMENT GROUP A)

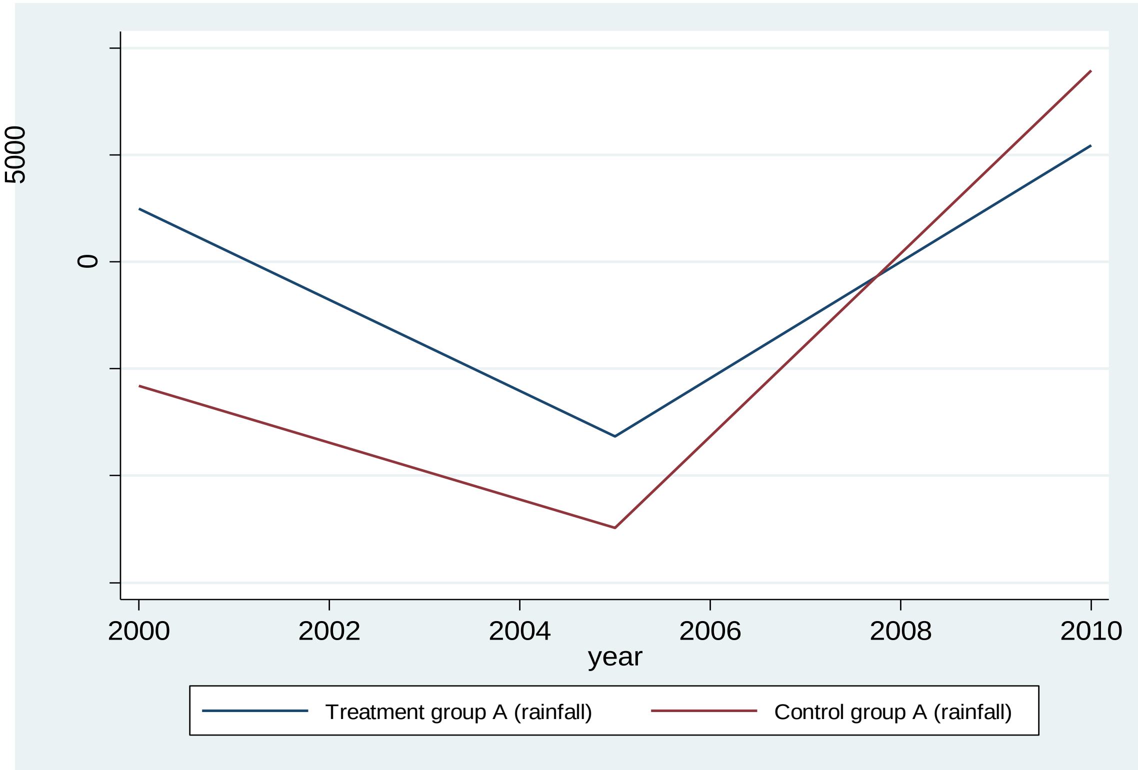

FIGURE 2: PRE-TREATMENT TRENDS OF PER CAPITA TOTAL INCOME (TREATMENT GROUP B)

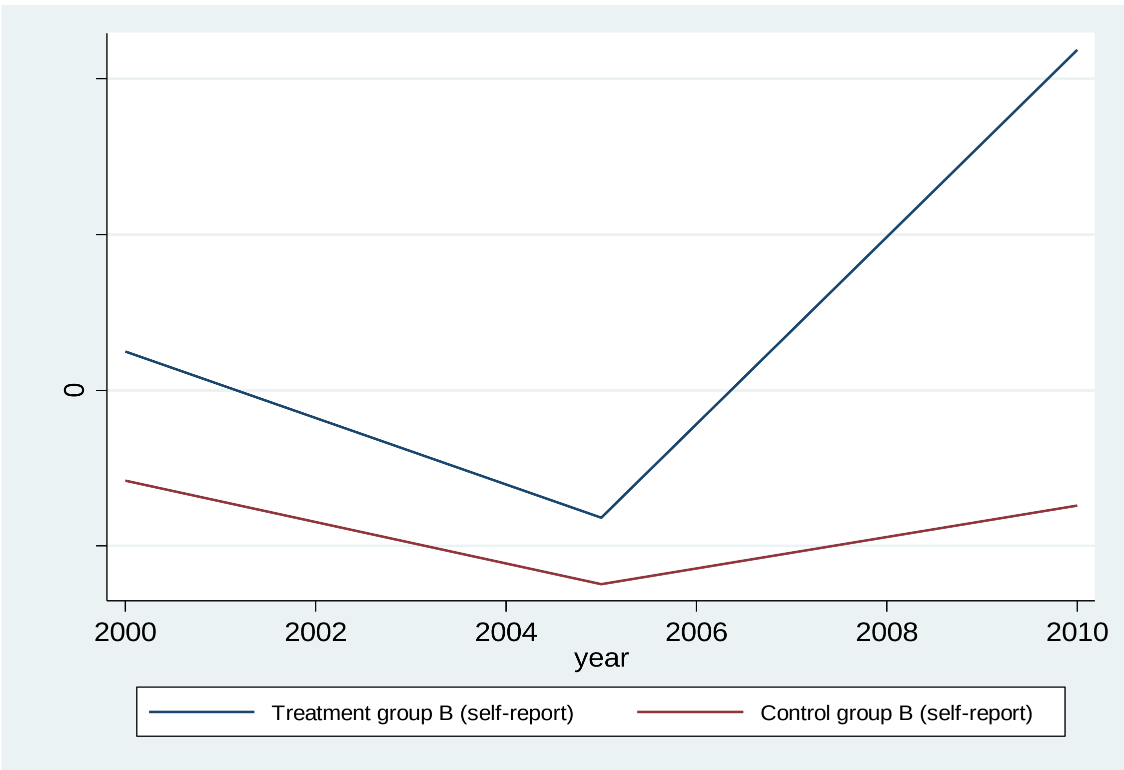

FIGURE 3: PRE-TREATMENT TRENDS OF PER CAPITA TOTAL EXPENDITURE (TREATMENT GROUP A)

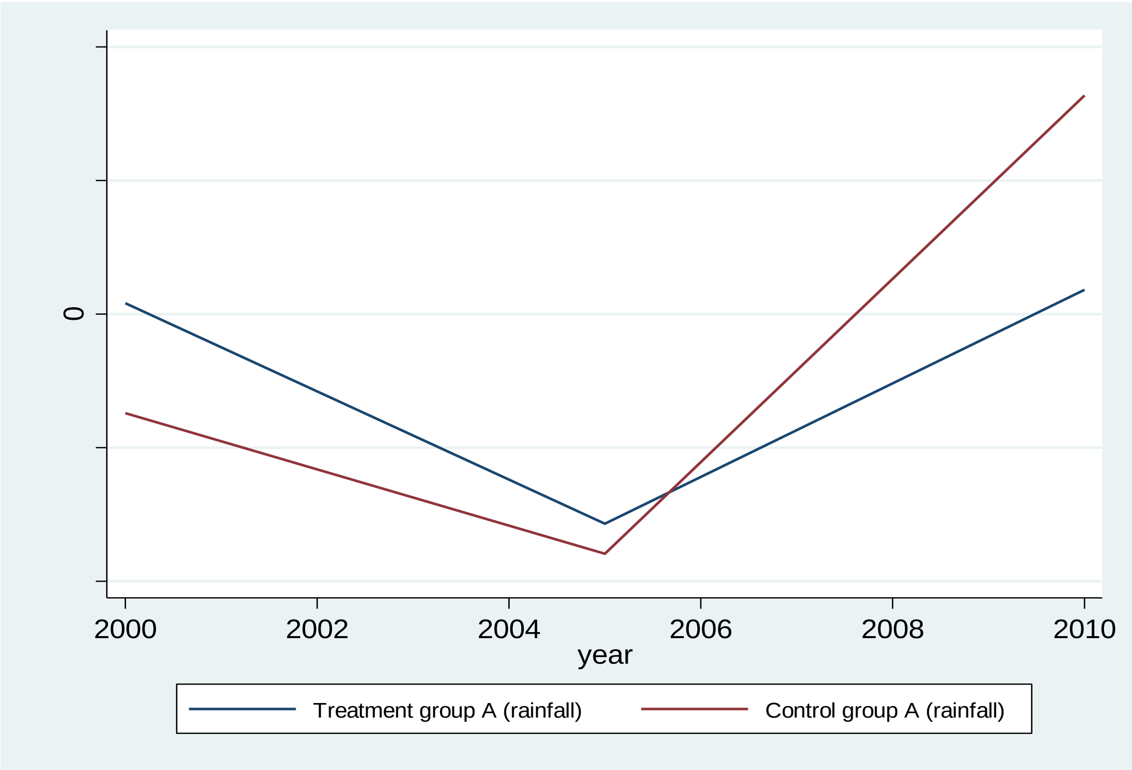

FIGURE 4: PRE-TREATMENT TRENDS OF PER CAPITA TOTAL EXPENDITURE (TREATMENT GROUP B)

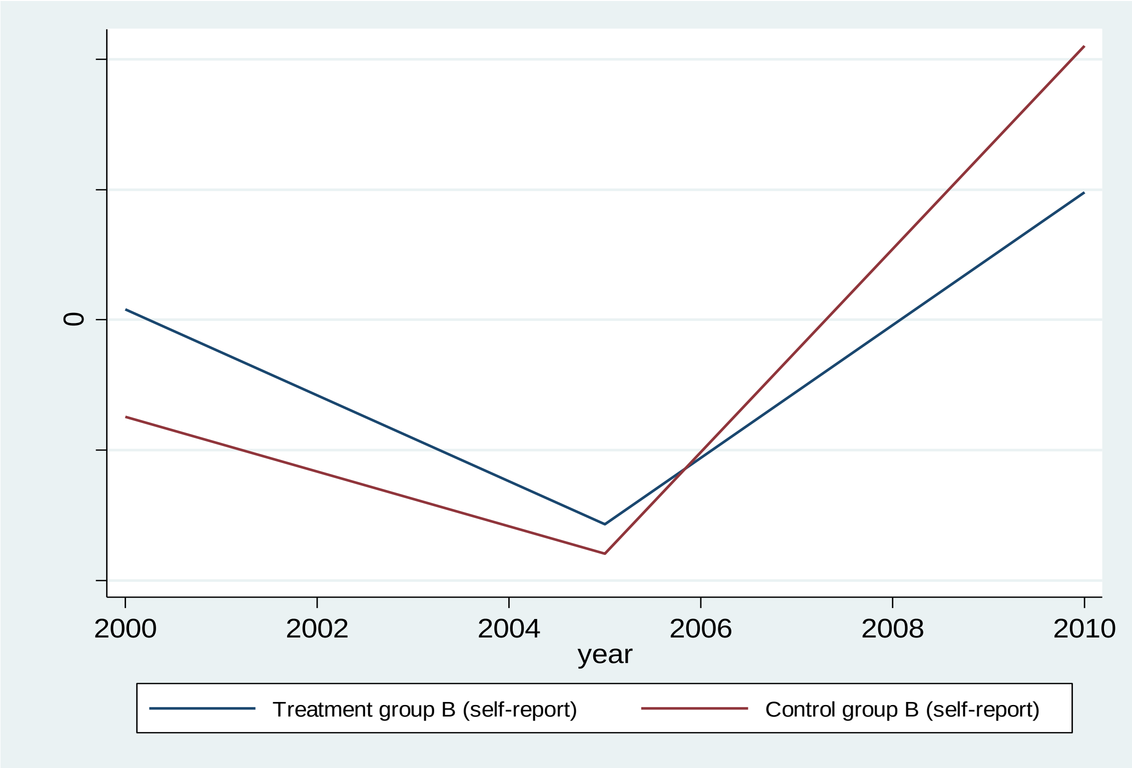

TABLE 1: IMPACT ON HOUSEHOLD INCOME PER CAPITA (TREATMENT GROUP A: RAINFALL-BASED FLOOD AFFECTED GROUP)

	(1)	(2)	(3)	(4)	(5)
VARIABLES	TOTAL INCOME	CROP INCOME	NON-CROP INCOME	BUSINESS INCOME	OTHER INCOME
POST (YEAR 2010)	173,513.18***	49,542.34***	60,365.63***	61,746.82***	-8,946.92***
	(11,755.80)	(3,754.90)	(5,937.03)	(8,236.91)	(3,243.78)
TREATMENT GROUP A	11,237.98**	3,334.38***	708.17	1,650.77**	5,431.69
	(4,902.10)	(508.65)	(1,565.30)	(791.68)	(4,618.95)
POST * TREATMENT GROUP A	-17,806.84	-7,427.99***	-11,700.08	4,882.17	-2,494.28
	(18,374.86)	(2,615.96)	(15,711.15)	(8,503.48)	(4,706.93)
RURAL	-1,630.66	2,627.40*	5,300.90	-7,793.94**	-3,571.06***
	(7,084.05)	(1,446.14)	(7,041.19)	(3,954.21)	(828.62)
MALE HOUSEHOLD HEAD	108,945.46***	5,148.74***	157,383.63***	1,519.88	-16,245.62***
	(16,197.13)	(582.16)	(20,503.23)	(2,706.72)	(2,505.51)
AVERAGE AGE	2,315.59***	283.44***	1,556.93***	824.99***	336.68**
	(180.45)	(26.78)	(119.46)	(63.94)	(147.27)
DEPENDENT	7,864.25***	1,256.42***	2,049.30***	4,570.11***	-10.29
	(122.40)	(39.53)	(55.94)	(89.85)	(17.64)
PROPORTION_FORMAL EDUCATION	20,985.31***	6,013.26***	-6,028.35	15,674.08***	13,960.31***
	(5,623.03)	(1,064.36)	(4,323.55)	(3,171.69)	(3,118.61)
ACCESS TO SANITATION	27,257.80***	3,278.84***	9,958.72*	5,823.20*	11,177.45***
	(6,113.44)	(1,145.45)	(5,794.88)	(3,353.51)	(525.85)
ACCESS TO DRINKING WATER	10,073.11	-2,377.53	3,013.07	11,685.06	1,266.68
	(14,602.87)	(3,066.21)	(14,685.96)	(7,606.62)	(1,013.41)
ACCESS TO ELECTRICITY	13,288.81**	2,802.05**	-3,369.29	4,512.12	10,477.40***
	(6,679.32)	(1,202.26)	(6,473.20)	(3,521.21)	(503.88)
HOUSE OWNERSHIP	9,691.26	1,710.23	7,507.14	-2,791.68	3,013.80
	(8,678.10)	(1,961.60)	(9,530.13)	(5,167.52)	(2,422.80)
LAND OWNERSHIP	67.66*	54.50***	-17.08	12.62	18.75***
	(37.87)	(8.81)	(30.92)	(19.14)	(3.39)

YEAR_2005	-869.04	822.97	3,848.34	8,108.52***	-3,604.57***
	(2,906.62)	(713.53)	(2,423.27)	(2,558.31)	(979.61)
YEAR2005 * TREATMENT GROUP A	-6,838.77	-2,268.54**	-530.05	-953.83	-4,519.26
	(5,382.66)	(884.05)	(2,106.37)	(3,073.81)	(4,774.07)
CONSTANT	-194,510.80***	-16,803.71***	-204,620.98***	-37,911.90***	5,233.63
	(24,052.42)	(3,899.24)	(27,747.18)	(9,572.22)	(4,233.48)
OBSERVATIONS	26,158	19,866	23,452	21,285	26,145
R-SQUARED	0.55	0.59	0.10	0.58	0.03

Source: Author's calculations.
Note: Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.

TABLE 2: IMPACT ON HOUSEHOLD INCOME PER CAPITA (TREATMENT GROUP B: SELF-REPORTED FLOOD AFFECTED GROUP)

	(1)	(2)	(3)	(4)	(5)
VARIABLES	**TOTAL INCOME**	**CROP INCOME**	**NON-CROP INCOME**	**BUSINESS INCOME**	**OTHER INCOME**
POST (YEAR 2010)	174,941.92***	48,880.68***	75,981.24***	49,576.85***	-9,530.30***
	(14,587.51)	(3,940.08)	(10,370.98)	(9,007.10)	(3,233.50)
TREATMENT GROUP B	11,227.45**	3,330.21***	666.64	1,683.56**	5,436.30
	(4,901.54)	(508.68)	(1,566.91)	(790.73)	(4,619.02)
POST * TREATMENT GROUP B	-14,430.78	-2,868.78*	-26,643.73**	18,588.52***	-4,091.70
	(12,744.96)	(1,738.30)	(10,800.95)	(4,875.60)	(4,737.34)
RURAL	-1,637.52	2,627.25*	5,157.57	-7,679.24*	-3,568.37***
	(7,082.60)	(1,446.77)	(7,034.98)	(3,951.35)	(829.35)
MALE HOUSEHOLD HEAD	109,047.11***	5,143.77***	158,160.77***	419.32	-16,289.08***
	(16,154.64)	(585.46)	(20,533.96)	(2,729.62)	(2,501.01)
AVERAGE AGE	2,316.81***	283.24***	1,567.22***	813.35***	336.16**
	(181.05)	(26.66)	(121.47)	(63.97)	(147.27)

DEPENDENT	7,861.43***	1,256.68***	2,023.99***	4,587.87***	-9.11
	(121.31)	(39.67)	(52.23)	(91.23)	(17.70)
PROPORTION_FORMAL EDUCATION	20,858.85***	5,932.07***	-6,276.88	15,849.03***	14,016.76***
	(5,608.17)	(1,063.73)	(4,299.89)	(3,169.94)	(3,120.47)
ACCESS TO SANITATION	27,358.48***	3,377.36***	10,005.34*	5,830.28*	11,131.83***
	(6,130.09)	(1,144.19)	(5,815.42)	(3,348.83)	(528.54)
ACCESS TO DRINKING WATER	10,479.83	-2,094.55	4,119.71	10,856.93	1,085.87
	(14,556.44)	(3,061.19)	(14,611.56)	(7,609.95)	(1,013.53)
ACCESS TO ELECTRICITY	13,363.78**	2,859.13**	-3,202.78	4,406.94	10,443.99***
	(6,650.47)	(1,201.57)	(6,431.59)	(3,520.37)	(505.49)
HOUSE OWNERSHIP	9,680.57	1,697.73	7,340.82	-2,688.16	3,018.32
	(8,676.43)	(1,963.13)	(9,521.82)	(5,159.27)	(2,422.85)
LAND OWNERSHIP	66.78*	54.02***	-18.89	13.75	19.14***
	(37.80)	(8.79)	(30.85)	(19.13)	(3.38)
YEAR_2005	-906.35	799.36	3,819.09	8,160.95***	-3,587.77***
	(2,901.95)	(713.60)	(2,421.78)	(2,557.57)	(979.19)
YEAR2005 * TREATMENT GROUP B	-6,832.13	-2,262.79**	-523.09	-972.75	-4,522.29
	(5,382.82)	(884.17)	(2,111.24)	(3,073.43)	(4,774.18)
CONSTANT	-195,001.90***	-17,061.08***	-206,287.26***	-36,064.98***	5,450.69
	(24,029.19)	(3,884.59)	(27,789.04)	(9,590.04)	(4,229.92)
OBSERVATIONS	26,158	19,866	23,452	21,285	26,145
R-SQUARED	0.55	0.59	0.10	0.58	0.03

Source: Author's calculations.

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

TABLE 3: IMPACT ON HOUSEHOLD EXPENDITURE PER CAPITA (TREATMENT GROUP A: RAINFALL-BASED FLOOD AFFECTED GROUP)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	**TOTAL EXPENDITURE**	**FOOD EXPENDITURE**	**NON-FOOD EXPENDITURE**	**CROP EXPENDITURE**	**NON-CROP EXPENDITURE**	**AGRICULTURAL INPUT EXPENDITURE**	**EDUCATIONAL EXPENDITURE**	**HEALTH EXPENDITURE**
POST (YEAR 2010)	274,945.97***	13,723.54***	168,901.32***	8,831.07***	10,815.29***	38,703.29***	25,347.28***	2,010.88***
	(9,827.20)	(389.92)	(5,865.01)	(1,071.72)	(2,079.96)	(3,135.96)	(1,517.75)	(345.59)
TREATMENT GROUP A	6,165.10***	94.14**	1,803.31***	635.98***	291.67*	3,106.56***	105.73	-159.04***
	(1,207.62)	(42.83)	(677.01)	(211.81)	(172.12)	(693.20)	(157.85)	(40.28)
POST * TREATMENT GROUP A	-22,007.22**	-289.68	-8,490.77	-1,752.97	178.26	-10,526.75***	-665.00	310.01
	(9,094.54)	(316.69)	(5,635.41)	(1,227.00)	(1,373.07)	(3,398.52)	(1,522.67)	(411.21)
RURAL	-1,949.62	-198.61*	-4,002.73*	361.98	881.22*	1,601.51	-1,914.44***	276.28*
	(3,352.70)	(120.52)	(2,065.28)	(611.84)	(497.52)	(1,620.47)	(680.42)	(167.74)
MALE HOUSEHOLD HEAD	26,166.63***	499.81***	2,138.11***	7,083.41***	3,800.63***	38,681.53***	-660.34	278.42***
	(3,539.30)	(94.50)	(827.96)	(833.64)	(452.37)	(4,681.05)	(540.65)	(53.27)
AVERAGE AGE	1,845.25***	89.95***	893.38***	266.95***	176.28***	724.06***	305.86***	5.02***
	(52.56)	(2.08)	(29.28)	(11.23)	(7.53)	(33.91)	(21.01)	(1.87)
DEPENDENT	12,688.46***	796.89***	6,274.01***	1,016.79***	871.56***	2,648.68***	988.69***	100.23***
	(107.84)	(4.05)	(64.62)	(11.81)	(22.19)	(34.97)	(15.47)	(3.05)
PROPORTION_FORMAL EDUCATION	16,871.00***	457.77***	7,190.63***	2,306.37***	1,315.42***	3,955.60***	3,912.70***	455.79***
	(2,335.68)	(80.35)	(1,405.65)	(367.19)	(329.55)	(1,234.88)	(522.10)	(117.78)
ACCESS TO SANITATION	8,224.81***	-47.67	3,611.59*	547.09	1,006.50**	4,259.28***	377.89	-212.31
	(3,122.89)	(110.91)	(1,930.99)	(498.22)	(459.51)	(1,371.73)	(616.26)	(155.74)
ACCESS TO DRINKING WATER	5,722.34	214.29	2,291.20	1,717.08	846.83	1,289.88	251.93	182.42
	(7,594.16)	(254.14)	(4,612.08)	(1,236.52)	(1,325.04)	(3,519.14)	(1,709.64)	(362.02)
ACCESS TO ELECTRICITY	11,716.31***	560.80***	8,965.72***	834.00	560.64	-68.49	1,186.30*	271.41
	(3,235.46)	(113.91)	(1,991.60)	(509.83)	(472.92)	(1,456.61)	(640.86)	(169.44)

HOUSE OWNERSHIP	2,671.88	-177.80	319.42	1,435.57	1,082.48	1,441.48	-1,649.23*	204.32
	(4,251.99)	(152.74)	(2,620.99)	(890.82)	(729.28)	(2,231.17)	(913.79)	(190.37)
LAND OWNERSHIP	127.82***	1.71**	27.22**	20.42***	12.02***	59.18***	8.14**	-0.41
	(22.30)	(0.70)	(12.58)	(3.40)	(2.86)	(9.81)	(3.65)	(0.70)
YEAR_2005	-9,626.51***	104.27**	-5,853.02***	-319.65	-1,174.67***	319.81	-258.10	85.16
	(1,355.62)	(50.62)	(774.13)	(239.07)	(197.42)	(694.19)	(269.39)	(70.70)
YEAR2005 * TREATMENT GROUP A	-3,380.24**	-5.19	-1,037.81	200.92	124.81	-1,844.22**	180.94	121.66**
	(1,411.98)	(50.63)	(785.47)	(291.83)	(198.90)	(940.37)	(259.55)	(57.30)
CONSTANT	-99,469.00***	-4,260.60***	-35,948.64***	-16,407.09***	-11,178.54***	-64,072.25***	-7,028.34***	-1,069.70***
	(9,386.58)	(311.19)	(5,257.11)	(1,731.98)	(1,532.03)	(6,379.58)	(2,025.19)	(378.96)
OBSERVATIONS	26,162	26,162	26,148	19,866	23,452	20,757	21,226	20,041
R-SQUARED	0.93	0.97	0.90	0.74	0.71	0.74	0.70	0.26

Source: Author's calculations.
Note: Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.

TABLE 4: IMPACT ON HOUSEHOLD EXPENDITURE PER CAPITA (TREATMENT GROUP B: SELF-REPORTED FLOOD AFFECTED GROUP)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	**TOTAL EXPENDITURE**	**FOOD EXPENDITURE**	**NON-FOOD EXPENDITURE**	**CROP EXPENDITURE**	**NON-CROP EXPENDITURE**	**AGRICULTURAL INPUT EXPENDITURE**	**EDUCATIONAL EXPENDITURE**	**HEALTH EXPENDITURE**
POST (YEAR 2010)	265,149.75***	12,637.44***	162,053.02***	10,003.20***	10,786.41***	36,939.44***	23,847.92***	2,559.69***
	(10,287.16)	(417.44)	(6,296.24)	(1,088.48)	(2,351.64)	(3,175.90)	(1,549.01)	(476.22)
TREATMENT GROUP B	6,162.48***	95.77**	1,806.87***	632.16***	292.28*	3,101.46***	108.78	-159.86***
	(1,207.95)	(42.82)	(677.07)	(212.11)	(172.09)	(693.26)	(157.63)	(40.29)
POST * TREATMENT GROUP B	7,067.58	1,594.94***	8,071.29**	-2,613.12***	-182.37	-1,391.21	2,188.68**	-688.81***
	(5,639.15)	(201.67)	(3,465.59)	(747.09)	(810.32)	(2,153.44)	(923.48)	(250.67)

RURAL	-1,870.25	-190.64	-3,949.59*	346.87	881.98*	1,612.92	-1,900.75***	271.18
	(3,351.87)	(120.17)	(2,064.57)	(611.54)	(497.68)	(1,620.78)	(680.22)	(167.43)
MALE HOUSEHOLD HEAD	25,931.90***	462.00***	1,940.77**	7,203.63***	3,795.67***	38,651.50***	-740.45	313.26***
	(3,498.89)	(90.09)	(813.89)	(846.47)	(450.76)	(4,660.32)	(538.91)	(55.56)
AVERAGE AGE	1,841.81***	89.44***	890.61***	268.15***	176.22***	723.23***	303.71***	5.52***
	(52.47)	(2.07)	(29.27)	(11.31)	(7.46)	(33.84)	(20.84)	(1.81)
DEPENDENT	12,700.11***	798.38***	6,282.70***	1,014.71***	871.69***	2,650.21***	990.70***	99.49***
	(108.19)	(4.06)	(65.07)	(11.69)	(22.52)	(34.67)	(15.47)	(3.20)
PROPORTION_FORMAL EDUCATION	16,597.94***	456.73***	7,081.84***	2,280.32***	1,324.83***	3,805.64***	3,916.31***	457.03***
	(2,334.34)	(80.10)	(1,404.56)	(367.27)	(328.89)	(1,233.69)	(521.59)	(117.23)
ACCESS TO SANITATION	8,598.21***	-33.53	3,796.13**	557.36	997.88**	4,441.13***	407.43	-222.41
	(3,120.44)	(110.69)	(1,929.82)	(498.05)	(459.72)	(1,368.23)	(617.60)	(156.36)
ACCESS TO DRINKING WATER	6,400.27	200.67	2,516.40	1,834.14	816.03	1,776.98	249.89	187.42
	(7,612.35)	(254.92)	(4,618.95)	(1,229.70)	(1,318.13)	(3,515.07)	(1,704.85)	(358.61)
ACCESS TO ELECTRICITY	11,874.90***	561.13***	9,028.13***	853.13*	554.82	28.58	1,190.76*	270.61
	(3,235.28)	(113.54)	(1,990.29)	(509.07)	(473.13)	(1,458.04)	(639.65)	(168.84)
HOUSE OWNERSHIP	2,713.47	-172.36	350.82	1,418.25	1,084.03	1,427.99	-1,639.97*	200.78
	(4,249.44)	(151.95)	(2,618.89)	(890.65)	(729.03)	(2,232.07)	(913.25)	(190.11)
LAND OWNERSHIP	126.08***	1.72**	26.57**	20.25***	12.08***	58.31***	8.11**	-0.41
	(22.25)	(0.70)	(12.55)	(3.38)	(2.86)	(9.78)	(3.63)	(0.71)
YEAR_2005	-9,733.49***	101.69**	-5,901.85***	-325.81	-1,172.06***	281.37	-265.81	87.59
	(1,355.64)	(50.48)	(774.08)	(239.50)	(197.35)	(694.14)	(269.26)	(70.70)
YEAR2005 * TREATMENT GROUP B	-3,359.16**	-4.54	-1,027.83	203.14	123.96	-1,832.19*	183.14	121.27**
	(1,412.45)	(50.58)	(785.56)	(292.32)	(198.89)	(940.46)	(259.36)	(57.34)
CONSTANT	-99,987.94***	-4,218.69***	-36,032.43***	-16,625.41***	-11,145.19***	-64,508.80***	-6,938.28***	-1,107.85***
	(9,382.26)	(310.27)	(5,257.48)	(1,735.95)	(1,528.49)	(6,360.11)	(2,021.18)	(380.21)
OBSERVATIONS	26,162	26,162	26,148	19,866	23,452	20,757	21,226	20,041
R-SQUARED	0.93	0.97	0.90	0.74	0.71	0.74	0.70	0.26

Source: Author's calculations.
Note: Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.

TABLE 5: IMPACT ON TOTAL ASSET OUTCOMES (TREATMENT GROUP A: RAINFALL-BASED FLOOD AFFECTED GROUP)

	(1)	(2)	(3)
VARIABLES	**TOTAL CHANGE IN AGRICULTURAL AND OTHER BUSINESS ASSET**	**TOTAL AGRICULTURAL INPUT ASSET VALUE**	**TOTAL CONSUMER DURABLE ASSET VALUE**
POST (YEAR 2010)	-24,575.16**	-21,782.69***	699,645.49***
	(11,627.68)	(5,580.80)	(30,193.69)
TREATMENT GROUP A	2,215.49	2,906.11**	28,004.98***
	(1,418.26)	(1,305.49)	(3,783.79)
POST * TREATMENT GROUP A	-6,144.23	-9,866.73	-29,369.54
	(14,637.09)	(6,665.00)	(37,593.50)
RURAL	-15,002.08**	-6.50	-41,995.48***
	(6,998.56)	(3,678.55)	(14,171.84)
MALE HOUSEHOLD HEAD	3,328.83***	10,817.53***	33,480.03***
	(1,098.97)	(1,057.23)	(5,701.04)
AVERAGE AGE	628.46***	234.00***	3,330.81***
	(128.51)	(58.88)	(166.11)
DEPENDENT	2,278.04***	2,734.02***	25,258.75***
	(136.91)	(64.66)	(332.34)
PROPORTION_FORMAL EDUCATION	4,585.75	13,888.43***	34,540.15***
	(4,537.68)	(2,927.93)	(9,267.88)
ACCESS TO SANITATION	3,762.83	1,756.99	36,735.69***
	(5,968.49)	(3,250.93)	(12,854.83)
ACCESS TO DRINKING WATER	-23,795.35	2,442.58	-58,753.10
	(17,890.77)	(7,733.67)	(36,325.16)
ACCESS TO ELECTRICITY	-4,866.77	2,751.39	23,898.82*
	(6,187.89)	(3,362.34)	(13,536.43)
HOUSE OWNERSHIP	8,119.07	11,029.83**	-10,849.16

	(9,297.59)	(4,703.64)	(18,309.79)
LAND OWNERSHIP	42.35	43.48**	141.18
	(45.96)	(20.11)	(106.11)
YEAR_2005	-898.89	3,254.94*	-23,834.66***
	(2,155.10)	(1,884.39)	(5,031.14)
YEAR2005 * TREATMENT GROUP A	1,842.43	-3,476.79	-20,159.09***
	(2,718.88)	(2,389.55)	(4,336.77)
CONSTANT	3,360.49	-35,550.45***	-76,309.11*
	(19,755.20)	(9,047.27)	(40,505.33)
OBSERVATIONS	21,285	19,455	26,077
R-SQUARED	0.06	0.29	0.76

Source: Author's calculations.
Note: Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.

TABLE 6: IMPACT ON TOTAL ASSET OUTCOMES (TREATMENT GROUP B: SELF-REPORTED FLOOD AFFECTED GROUP)

	(1)	(2)	(3)
VARIABLES	TOTAL CHANGE IN AGRICULTURAL AND OTHER BUSINESS ASSET	TOTAL AGRICULTURAL INPUT ASSET VALUE	TOTAL CONSUMER DURABLE ASSET VALUE
POST (YEAR 2010)	39,014.03***	-33,118.44***	787,048.50***
	(12,312.88)	(6,703.46)	(34,962.38)
TREATMENT GROUP B	2,081.67	2,921.69**	27,852.68***
	(1,417.51)	(1,305.09)	(3,782.49)
POST * TREATMENT GROUP B	-103,610.87***	14,088.17***	-166,368.01***
	(9,714.95)	(4,442.57)	(24,776.12)
RURAL	-15,610.62**	111.53	-42,629.63***

	(6,967.65)	(3,677.45)	(14,154.10)
MALE HOUSEHOLD HEAD	8,650.43***	9,773.22***	36,666.23***
	(1,219.68)	(1,045.37)	(6,043.68)
AVERAGE AGE	686.10***	222.15***	3,373.24***
	(129.49)	(58.88)	(168.01)
DEPENDENT	2,188.95***	2,748.97***	25,136.90***
	(132.69)	(66.11)	(331.52)
PROPORTION_FORMAL EDUCATION	4,307.66	13,763.97***	34,304.66***
	(4,502.87)	(2,925.55)	(9,251.67)
ACCESS TO SANITATION	3,078.17	2,066.00	35,895.94***
	(5,925.03)	(3,248.69)	(12,832.96)
ACCESS TO DRINKING WATER	-21,705.88	2,644.13	-56,673.77
	(17,853.99)	(7,720.74)	(36,201.54)
ACCESS TO ELECTRICITY	-4,711.43	2,830.98	24,060.10*
	(6,148.60)	(3,359.83)	(13,502.97)
HOUSE OWNERSHIP	7,645.44	11,098.94**	-11,298.19
	(9,234.67)	(4,704.59)	(18,277.88)
LAND OWNERSHIP	40.21	42.91**	138.46
	(45.35)	(20.09)	(105.46)
YEAR_2005	-914.85	3,203.97*	-23,729.38***
	(2,141.20)	(1,883.95)	(5,025.26)
YEAR2005 * TREATMENT GROUP B	1,837.03	-3,445.14	-20,191.93***
	(2,717.59)	(2,389.22)	(4,336.69)
CONSTANT	-3,683.68	-34,717.65***	-80,797.96**
	(19,741.35)	(9,031.38)	(40,441.53)
OBSERVATIONS	21,285	19,455	26,077
R-SQUARED	0.07	0.29	0.76

Source: Author's calculations.
Note: Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.

TABLE 7: IMPACT ON LABOUR MARKET OUTCOMES (TREATMENT GROUP A: RAINFALL-BASED FLOOD AFFECTED GROUP)

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	TOTAL MONTH PER YEAR	TOTAL DAYS PER MONTH	TOTAL HOURS PER DAY	DAILY WAGE	SALARIED WAGE	YEARLY BENEFITS
POST (YEAR 2010)	70.51***	156.70***	58.07***	392.73***	1,290.62	-15,437.51***
	(3.01)	(6.83)	(2.30)	(25.95)	(1,095.69)	(2,004.09)
TREATMENT GROUP A	3.05***	4.92***	0.72*	6.36	-19.79	-243.70
	(0.53)	(1.22)	(0.41)	(5.22)	(216.62)	(462.62)
POST * TREATMENT GROUP A	-2.55	0.52	-0.75	10.58	-202.77	-2,360.76
	(2.99)	(7.05)	(2.30)	(29.80)	(1,191.00)	(2,416.49)
RURAL	0.17	1.29	0.52	5.92	-722.84	-1,789.51
	(1.13)	(2.62)	(0.85)	(13.16)	(542.63)	(1,107.53)
MALE HOUSEHOLD HEAD	9.47***	25.85***	9.82***	-92.65***	4,641.64***	11,768.02***
	(1.34)	(3.54)	(1.27)	(17.11)	(652.69)	(1,569.76)
AVERAGE AGE	0.96***	2.14***	0.68***	4.23***	259.70***	416.91***
	(0.02)	(0.06)	(0.02)	(0.27)	(10.72)	(23.64)
DEPENDENT	8.04***	17.91***	6.16***	39.57***	1,100.74***	1,561.88***
	(0.03)	(0.08)	(0.03)	(0.29)	(13.03)	(22.50)
PROPORTION_FORMAL EDUCATION	6.47***	13.54***	3.16***	-62.23***	5,274.34***	8,855.72***
	(0.79)	(1.85)	(0.61)	(9.57)	(410.27)	(1,034.96)
ACCESS TO SANITATION	-3.51***	-6.20***	-2.10***	-35.81***	-45.96	-1,902.14*
	(1.03)	(2.40)	(0.78)	(12.19)	(502.32)	(1,021.62)
ACCESS TO DRINKING WATER	-0.33	3.37	-0.01	-19.56	2,298.36*	2,528.27
	(2.47)	(5.76)	(1.91)	(29.27)	(1,181.80)	(2,439.49)
ACCESS TO ELECTRICITY	3.07***	6.62***	1.81**	15.04	2,393.12***	4,787.14***
	(1.07)	(2.49)	(0.81)	(12.89)	(533.11)	(1,080.23)
HOUSE OWNERSHIP	-3.20**	-8.67***	-2.96***	3.29	-2,399.71***	-3,239.89**

	(1.39)	(3.24)	(1.05)	(15.27)	(642.38)	(1,315.69)
LAND OWNERSHIP	0.01*	0.03	0.01	-0.20***	2.12	1.69
	(0.01)	(0.02)	(0.01)	(0.07)	(2.66)	(5.33)
YEAR_2005	-1.18**	-6.03***	-2.16***	18.30***	231.32	308.97
	(0.55)	(1.26)	(0.43)	(5.87)	(234.58)	(473.71)
YEAR2005 * TREATMENT GROUP A	-1.70***	0.18	1.26***	-9.21	-459.43*	255.78
	(0.62)	(1.42)	(0.48)	(6.33)	(275.44)	(625.41)
CONSTANT	-32.24***	-76.49***	-24.10***	36.96	-13,198.95***	-24,023.06***
	(3.15)	(7.57)	(2.55)	(36.80)	(1,485.32)	(3,146.37)
OBSERVATIONS	25,506	25,506	25,506	20,738	20,738	20,738
R-SQUARED	0.97	0.97	0.97	0.88	0.76	0.56

Source: Author's calculations.
Note: Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.

TABLE 8: IMPACT ON LABOUR MARKET OUTCOMES (TREATMENT GROUP B: SELF-REPORTED FLOOD AFFECTED GROUP)

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	TOTAL MONTH PER YEAR	TOTAL DAYS PER MONTH	TOTAL HOURS PER DAY	DAILY WAGE	SALARIED WAGE	YEARLY BENEFITS
POST (YEAR 2010)	53.46***	120.79***	46.35***	326.20***	-1,180.90	-20,950.37***
	(3.12)	(7.10)	(2.34)	(27.18)	(1,192.58)	(2,283.23)
TREATMENT GROUP B	3.08***	4.99***	0.74*	6.57	-13.67	-234.27
	(0.53)	(1.22)	(0.41)	(5.22)	(216.03)	(461.40)
POST * TREATMENT GROUP B	23.98***	52.64***	17.81***	101.13***	3,894.18***	8,591.28***
	(1.81)	(4.22)	(1.38)	(17.90)	(751.68)	(1,531.00)
RURAL	0.30	1.57	0.61	6.56	-698.51	-1,734.03

	(1.11)	(2.60)	(0.85)	(13.14)	(542.03)	(1,105.34)
MALE HOUSEHOLD HEAD	8.59***	23.94***	9.22***	-97.71***	4,464.26***	11,398.44***
	(1.25)	(3.33)	(1.20)	(17.59)	(633.19)	(1,526.12)
AVERAGE AGE	0.95***	2.12***	0.67***	4.15***	256.92***	411.11***
	(0.02)	(0.06)	(0.02)	(0.27)	(10.67)	(23.34)
DEPENDENT	8.06***	17.96***	6.17***	39.66***	1,104.15***	1,569.22***
	(0.03)	(0.08)	(0.03)	(0.29)	(13.10)	(22.68)
PROPORTION_FORMAL EDUCATION	6.54***	13.77***	3.20***	-61.36***	5,285.01***	8,826.31***
	(0.79)	(1.84)	(0.60)	(9.55)	(409.22)	(1,032.20)
ACCESS TO SANITATION	-3.34***	-5.92**	-1.98**	-35.36***	-10.41	-1,776.53*
	(1.03)	(2.38)	(0.77)	(12.17)	(501.07)	(1,018.73)
ACCESS TO DRINKING WATER	-0.75	2.22	-0.28	-22.73	2,243.35*	2,559.98
	(2.45)	(5.73)	(1.90)	(29.26)	(1,179.10)	(2,430.87)
ACCESS TO ELECTRICITY	3.05***	6.51***	1.80**	14.72	2,392.89***	4,815.43***
	(1.06)	(2.47)	(0.80)	(12.87)	(532.37)	(1,078.38)
HOUSE OWNERSHIP	-3.11**	-8.47***	-2.89***	3.74	-2,383.17***	-3,203.86**
	(1.37)	(3.21)	(1.04)	(15.25)	(640.81)	(1,312.54)
LAND OWNERSHIP	0.01**	0.03*	0.01	-0.19***	2.15	1.51
	(0.01)	(0.02)	(0.01)	(0.07)	(2.64)	(5.28)
YEAR_2005	-1.19**	-6.03***	-2.17***	18.29***	224.58	278.09
	(0.55)	(1.25)	(0.43)	(5.88)	(233.82)	(471.71)
YEAR2005 * TREATMENT GROUP B	-1.68***	0.20	1.27***	-9.22	-457.70*	265.41
	(0.62)	(1.41)	(0.48)	(6.34)	(274.69)	(623.88)
CONSTANT	-31.06***	-73.70***	-23.31***	45.22	-12,965.60***	-23,684.80***
	(3.08)	(7.41)	(2.50)	(37.04)	(1,473.13)	(3,116.12)
OBSERVATIONS	25,506	25,506	25,506	20,738	20,738	20,738
R-SQUARED	0.97	0.97	0.97	0.88	0.76	0.56

Source: Author's calculations.

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

TABLE 9: IMPACT ON VARIOUS INCOME AND EXPENDITURE BRACKETS PER CAPITA (TREATMENT GROUP A: RAINFALL-BASED FLOOD AFFECTED GROUP)

VARIABLES	I 15TH	II 25TH	III 50TH	IV 75TH	V 85TH
INCOME					
TOTAL INCOME	152,021.83***	-572.46	-7,895.24***	-15,835.66*	-40,390.71***
	(2,043.65)	(1,311.80)	(2,131.86)	(9,262.68)	(4,060.23)
CROP INCOME	-3,198.41***	-3,795.53***	-3,308.52***	-6,388.10***	-5,593.55***
	(383.72)	(360.21)	(619.48)	(1,167.21)	(1,935.75)
NON-CROP INCOME	445,555.98***	200.23	-2,709.12***	-7,398.63***	-9,205.69***
	(370.68)	(227.58)	(264.23)	(473.76)	(821.47)
BUSINESS INCOME	-555.30	4,047.79***	635.15	-2,855.96	-3.86
	(805.42)	(833.85)	(1,134.40)	(1,898.68)	(3,298.74)
OTHER INCOME	-33.74***	133.20*	1,542.76***	2,857.56***	3,360.76***
	(0.66)	(78.39)	(224.47)	(660.63)	(1,175.64)
EXPENDITURE					
TOTAL EXPENDITURE	-19,911.78***	-40,648.91***	-49,033.41***	-25,161.09***	-40,409.66***
	(2,297.79)	(2,125.93)	(1,905.56)	(2,127.35)	(2,638.77)
FOOD EXPENDITURE	-473.48***	-225.12*	-382.37***	-590.81***	-205.07***
	(151.18)	(117.37)	(92.81)	(89.38)	(74.68)
NON-FOOD EXPENDITURE	-1,220.43	-4,921.23***	-6,813.76***	-3,414.29***	-8,147.88***
	(995.42)	(940.39)	(964.61)	(929.63)	(1,257.81)
CROP EXPENDITURE	-870.66***	-1,594.03***	-2,603.85***	-2,163.09***	-671.60
	(331.19)	(329.33)	(468.92)	(556.44)	(795.72)
NON-CROP EXPENDITURE	-940.27***	-1,118.04***	-603.65***	-324.51	-2,049.00***
	(178.68)	(161.28)	(195.40)	(296.19)	(496.29)
AGRICULTURAL INPUT	-6,964.92***	-7,551.65***	-9,123.63***	-6,533.64***	-8,872.74***

EXPENDITURE					
	(578.74)	(604.57)	(606.67)	(1,021.10)	(1,345.61)
EDUCATIONAL EXPENDITURE	-185.82	-596.55**	249.69	-1,100.02***	-2,981.39***
	(222.97)	(264.17)	(287.57)	(375.79)	(438.90)
HEALTH EXPENDITURE	9.08	-22.91	-14.16	-111.10**	132.58
	(23.49)	(25.78)	(25.06)	(54.97)	(88.96)

Source: Author's calculations.

Notes: [a] This table only presents the coefficient estimates for the Post*Treatment Group A 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 upon request.

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

TABLE 10: IMPACT ON VARIOUS INCOME AND EXPENDITURE BRACKETS PER CAPITA (TREATMENT GROUP B: SELF-REPORTED FLOOD AFFECTED GROUP)

VARIABLES	I 15TH	II 25TH	III 50TH	IV 75TH	V 85TH
INCOME					
TOTAL INCOME	-10,148.74***	-13,463.04***	15,987.59***	47,715.77***	89,658.70***
	(1,180.19)	(1,135.27)	(1,751.44)	(2,402.18)	(3,301.30)
CROP INCOME	3,259.10***	4,919.58***	-4,849.77***	-14,434.85***	-21,142.78***
	(261.13)	(288.23)	(546.27)	(923.53)	(1,589.63)
NON-CROP INCOME	10,858.02***	3,373.86***	2,681.22***	-75,458.03***	62,379.60***
	(178.22)	(192.40)	(219.15)	(693.16)	(705.25)
BUSINESS INCOME	-319,521.66***	-30,000.50***	-26,655.15***	-50.36	30,561.53***
	(77,899.91)	(741.29)	(957.84)	(1,557.96)	(2,487.58)
OTHER INCOME	-28.61***	-150.94***	-351.81*	-87.66	-1,098.86
	(0.44)	(54.19)	(213.86)	(521.90)	(1,020.38)
EXPENDITURE					

TOTAL EXPENDITURE	65,126.04***	-301,631.73***	326,400.32***	-44,274.31***	-47,967.13***
	(1,685.49)	(1,939.23)	(1,657.72)	(1,673.07)	(2,174.96)
FOOD EXPENDITURE	2,352.46***	2,162.76***	815.03***	754.29***	1,974.11***
	(105.58)	(101.78)	(82.08)	(70.99)	(67.29)
NON-FOOD EXPENDITURE	28,503.82***	17,501.96***	-34,523.00***	5,224.30***	-27,610.97***
	(861.22)	(803.72)	(857.43)	(755.39)	(962.25)
CROP EXPENDITURE	-3,521.57***	-182.49	478.49	118.26	-3,564.41***
	(266.82)	(271.01)	(411.19)	(499.72)	(653.23)
NON-CROP EXPENDITURE	-4,133.14***	-3,969.57***	2,655.39***	3,909.25***	9,722.32***
	(142.20)	(132.51)	(165.48)	(243.52)	(407.32)
AGRICULTURAL INPUT EXPENDITURE	13,327.75***	8,584.68***	2,249.37***	-9,722.74***	-45,470.77***
	(447.95)	(519.94)	(537.37)	(871.71)	(1,127.26)
EDUCATIONAL EXPENDITURE	3,521.72***	-214.33	-2,261.07***	2,731.51***	7,693.01***
	(195.74)	(227.59)	(234.07)	(329.83)	(384.41)
HEALTH EXPENDITURE	372.00***	358.85***	126.77***	318.98***	1,843.89***
	(15.82)	(19.33)	(22.56)	(42.09)	(78.80)

Source: Author's calculations.

Notes: [a] This table only presents the coefficient estimates for the Post*Treatment Group B 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 upon request.

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

APPENDIX TABLE 1: KEY VARIABLES WITH DESCRIPTIVE STATISTICS (TREATMENT AND CONTROL GROUP A: RAINFALL-BASED IDENTIFICATIONS)

VARIABLES	TYPE	MEAN		STANDARD DEVIATION		DESCRIPTION OF VARIABLES
OUTCOME VARIABLES		TREATMENT	CONTROL	TREATMENT	CONTROL	
PER CAPITA TOTAL INCOME	Continuous	122609.3	585579.1	350281.8	670960.9	Sum of per capita crop, non-crop, business and other incomes.
PER CAPITA CROP INCOME	Continuous	42914.52	134535.2	80916.75	109717	Per capita income earned through selling of crops.
PER CAPITA NON-CROP INCOME	Continuous	39591.31	175023.1	217985.1	470222.2	Per capita income earned through selling of livestock and poultry, livestock products, fish farming and fish capture and farm forestry.
PER CAPITA BUSINESS INCOME	Continuous	95109.46	362796.5	225754.1	329750.4	Per capita net revenues earned from non-agricultural enterprises and rental income from agricultural assets.
PER CAPITA OTHER INCOME	Continuous	15599.26	15401.97	84804.43	45366.48	Per capita income earned from other assets (e.g. stocks, bonds, jewellery etc.), rent, insurance, charity, gift, remittances, bank interest and social safety net.
PER CAPITA TOTAL EXPENDITURE	Continuous	163587.6	902204.4	451583.2	772266.5	Sum of per capita food, non-food, crop, non-crop, agricultural input, education and health expenditures.
PER CAPITA FOOD EXPENDITURE	Continuous	9428.717	53264.84	26657.94	44630.27	Per capita daily and weekly food consumption.
PER CAPITA NON-FOOD EXPENDITURE	Continuous	84195.85	464748.6	235125.7	404613.2	Per capita monthly and annual non-food consumption.
PER CAPITA CROP EXPENDITURE	Continuous	27164.83	82950.47	47425.52	59216.15	Per capita crop consumption by household.
PER CAPITA NON-CROP EXPENDITURE	Continuous	16060.38	64966.32	38283.58	56794.33	Per capita consumption of livestock and poultry, livestock products, fish farming and fish capture and farm forestry products by household.
PER CAPITA AGRICULTURAL INPUT EXPENDITURE	Continuous	59887.13	216886.8	123287.5	165543.5	Per capita expenses on agricultural inputs.
PER CAPITA EDUCATIONAL EXPENDITURE	Continuous	20565.26	85667.89	47419.52	70960.43	Per capita expenditure for educational services.
PER CAPITA HEALTH EXPENDITURE	Continuous	2226.591	8581.544	7182.878	11793.97	Per capita expenditure for health services.
TOTAL CHANGE IN AGRICULTURAL AND OTHER BUSINESS ASSET (IN REAL TERMS)	Continuous	34085.83	137203.9	223634.9	435505.3	Sum of agricultural assets households bought in the last 12 months and expenditure in capital goods (in non-agricultural enterprises) in the last 12 months.

TOTAL AGRICULTURAL INPUT ASSET VALUE (IN REAL TERMS)	Continuous	58562.68	188197.2	147132	241979.5	Value of owned equipment and asset used in agriculture.
TOTAL CONSUMER DURABLE ASSET VALUE (IN REAL TERMS)	Continuous	351885.9	1888812	1016351	1830325	Total asset value of consumer durable goods.
TOTAL MONTH PER YEAR WORKED	Continuous	103.9289	517.5979	255.4481	417.7093	Total number of months per year worked.
TOTAL DAYS PER MONTH WORKED	Continuous	233.9744	1155.402	571.3488	932.6239	Total number of days per month worked.
TOTAL HOURS PER DAY WORKED	Continuous	80.24236	398.9724	196.6285	321.3238	Total number of hours per day worked.
DAILY WAGE (IN REAL TERMS)	Continuous	696.1671	2873.078	1489.233	2067.039	Daily wage in cash (if paid daily).
SALARIED WAGE (IN REAL TERMS)	Continuous	18725.12	77322.4	41691.76	61527.92	Total net take-home monthly remuneration after all deduction at source.
YEARLY BENEFITS (IN REAL TERMS)	Continuous	24275.35	98172.85	59626.65	95530.79	Total value of yearly in-kind or other benefits (tips, bonuses or transport) from employment.
COVARIATES						
RURAL	Binary	0.6362126	0.655756	0.4811085	0.475134	Whether living in a rural area = 1, otherwise 0.
HEAD OF HOUSEHOLD IS MALE	Binary	0.9127907	0.965463	0.2833284	0.196886	Whether head of the household is male = 1, otherwise 0.
AVERAGE AGE	Continuous	26.50556	26.54462	10.01851	6.61305	Average age of household members.
DEPENDENT	Continuous	11.15075	57.09819	28.11758	46.92759	Age of the household member is <15 and >=65.
PROPORTION OF FORMAL EDUCATION	Continuous	0.4785376	0.777077	0.3603159	0.34971	Proportion of household members attended school, college, university or madrasa.
ACCESS TO SANITATION	Binary	0.4536468	0.510949	0.4978674	0.499894	Whether the household use sanitary or pacca latrines (water seal and pit) = 1, otherwise 0.
ACCESS TO SAFE DRINKING WATER	Binary	0.9683555	0.965628	0.1750591	0.182188	Whether the household has access to supply water or tube well water = 1, otherwise 0.
ACCESS TO ELECTRICITY	Binary	0.4669435	0.505446	0.4989268	0.499984	Whether the household has got electricity connection = 1, otherwise 0.
HOUSE OWNERSHIP	Binary	0.8113631	0.833399	0.3912362	0.37263	Whether the household own a house = 1, otherwise 0.
LAND OWNERSHIP (IN REAL TERMS)	Continuous	12.07561	40.88366	67.71542	104.1996	Amount of total operating land (in acres).

Source: Author’s elaborations.

APPENDIX TABLE 2: KEY VARIABLES WITH DESCRIPTIVE STATISTICS (TREATMENT AND CONTROL GROUP B: SELF-REPORTED IDENTIFICATIONS)

VARIABLES	TYPE	MEAN		STANDARD DEVIATION		DESCRIPTION OF VARIABLES
OUTCOME VARIABLES		TREATMENT	CONTROL	TREATMENT	CONTROL	
PER CAPITA TOTAL INCOME	Continuous	373423.5	434201.8	536564	696302	Sum of per capita crop, non-crop, business and other incomes.
PER CAPITA CROP INCOME	Continuous	106895.8	110779.8	108175.3	113151.7	Per capita income earned through selling of crops.
PER CAPITA NON-CROP INCOME	Continuous	119383.3	142421.5	234059.7	561244.2	Per capita income earned through selling of livestock and poultry, livestock products, fish farming and fish capture and farm forestry.
PER CAPITA BUSINESS INCOME	Continuous	262397.1	285835.9	343133.1	295508.2	Per capita net revenues earned from non-agricultural enterprises and rental income from agricultural assets.
PER CAPITA OTHER INCOME	Continuous	16123.11	14555.04	78380.95	35069.85	Per capita income earned from other assets (e.g. stocks, bonds, jewellery etc.), rent, insurance, charity, gift, remittances, bank interest and social safety net.
PER CAPITA TOTAL EXPENDITURE	Continuous	565384	658288.1	743532.6	766395.6	Sum of per capita food, non-food, crop, non-crop, agricultural input, education and health expenditures.
PER CAPITA FOOD EXPENDITURE	Continuous	33397.13	38612.06	43509.96	44531.1	Per capita daily and weekly food consumption.
PER CAPITA NON-FOOD EXPENDITURE	Continuous	291933.9	338133.9	388660.5	398508.1	Per capita monthly and annual non-food consumption.
PER CAPITA CROP EXPENDITURE	Continuous	65298.17	69545.04	60440.5	62756.02	Per capita crop consumption by household.
PER CAPITA NON-CROP EXPENDITURE	Continuous	46754.38	50691.94	54652.11	58273.61	Per capita consumption of livestock and poultry, livestock products, fish farming and fish capture and farm forestry products by household.
PER CAPITA AGRICULTURAL INPUT EXPENDITURE	Continuous	164668.1	175283.9	167023.6	173735.7	Per capita expenses on agricultural inputs.
PER CAPITA EDUCATIONAL EXPENDITURE	Continuous	60773.71	66948.93	71753.8	69686.33	Per capita expenditure for educational services.
PER CAPITA HEALTH EXPENDITURE	Continuous	5945.219	7229.639	7618.373	14244.29	Per capita expenditure for health services.
TOTAL CHANGE IN AGRICULTURAL AND OTHER BUSINESS ASSET (IN REAL TERMS)	Continuous	73565	142607.6	214724	529612.6	Sum of agricultural assets households bought in the last 12 months and expenditure in capital goods (in non-agricultural enterprises) in the last 12 months.

Total agricultural input asset value (in real terms)	Continuous	151046.5	151352	246957.3	197233.6	Value of owned equipment and asset used in agriculture.
Total consumer durable asset value (in real terms)	Continuous	1163556	1420042	1565000	1927552	Total asset value of consumer durable goods.
Total month per year worked	Continuous	334.5448	379.3605	414.1053	414.2008	Total number of months per year worked.
Total days per month worked	Continuous	747.2892	848.02	923.1851	926.0869	Total number of days per month worked.
Total hours per day worked	Continuous	257.5589	292.9975	318.1137	319.5673	Total number of hours per day worked.
Daily wage (in real terms)	Continuous	2019.562	2256.998	2177.093	2109.863	Daily wage in cash (if paid daily).
Salaried wage (in real terms)	Continuous	54633.38	60337.16	61341.99	62946.09	Total net take-home monthly remuneration after all deduction at source.
Yearly benefits (in real terms)	Continuous	70386.54	75589.07	91639.38	91995.92	Total value of yearly in-kind or other benefits (tips, bonuses or transport) from employment.
COVARIATES						
Rural	Binary	0.6320787	0.670638	0.4822535	0.470001	Whether living in a rural area = 1, otherwise 0.
Head of household is male	Binary	0.9431431	0.945613	0.2440097	0.226789	Whether head of the household is male = 1, otherwise 0.
Average age	Continuous	26.58561	26.44676	8.317239	7.935949	Average age of household members.
Dependent	Continuous	35.85337	42.34686	45.34921	47.27546	Age of the household member is <15 and >=65.
Proportion of formal education	Continuous	0.6430289	0.675469	0.3841798	0.380877	Proportion of household members attended school, college, university or madrasa.
Access to sanitation	Binary	0.4828272	0.494906	0.4997192	0.499995	Whether the household use sanitary or pacca latrines (water seal and pit) = 1, otherwise 0.
Access to safe drinking water	Binary	0.9708324	0.960805	0.1682809	0.194066	Whether the household has access to supply water or tube well water = 1, otherwise 0.
Access to electricity	Binary	0.5085285	0.462904	0.4999415	0.498642	Whether the household has got electricity connection = 1, otherwise 0.
House ownership	Binary	0.8086086	0.847424	0.3934076	0.359593	Whether the household own a house = 1, otherwise 0.
Land ownership (in real terms)	Continuous	28.40776	32.68995	91.94583	95.34276	Amount of total operating land (in acres).

Source: Author's elaborations.

Appendix Table 3: Impact on log of household income per capita (Treatment Group A: Rainfall-based flood affected group)

VARIABLES	(1) Log of Total income	(2) Log of Crop income	(3) Log of Non-crop income	(4) Log of Business income	(5) Log of Other income
Post (year 2010)	1.569***	1.822***	2.402***	1.890***	-1.002***
	(0.0519)	(0.0756)	(0.0881)	(0.0699)	(0.0859)
Treatment group A	0.254***	0.491***	0.135*	-0.0955	-0.0650
	(0.0422)	(0.0583)	(0.0784)	(0.0780)	(0.0587)
Post * treatment group A	-0.229***	-0.527***	-0.166**	0.137*	0.325***
	(0.0455)	(0.0619)	(0.0825)	(0.0796)	(0.0787)
rural	-0.0706***	-0.0388**	-0.0132	-0.0465***	-0.234***
	(0.0170)	(0.0190)	(0.0236)	(0.0143)	(0.0276)
male household head	-0.353***	0.289***	0.359***	0.206***	-0.915***
	(0.0440)	(0.0809)	(0.0784)	(0.0794)	(0.0508)
average age	0.0161***	0.0145***	0.0248***	0.00596***	0.0187***
	(0.00109)	(0.00207)	(0.00199)	(0.00200)	(0.00126)
dependent	0.0147***	0.0143***	0.0195***	0.0139***	-0.000778
	(0.000367)	(0.000510)	(0.000525)	(0.000291)	(0.000755)
proportion_formal education	1.316***	0.982***	0.344***	0.825***	0.768***
	(0.0381)	(0.0630)	(0.0685)	(0.0596)	(0.0447)
access to sanitation	0.185***	-0.00214	-0.00889	0.0928***	0.697***
	(0.0143)	(0.0157)	(0.0205)	(0.0124)	(0.0248)
access to drinking water	0.0140	-0.0249	-0.121**	0.0671*	-0.108*
	(0.0330)	(0.0395)	(0.0526)	(0.0389)	(0.0549)
access to electricity	0.257***	0.0702***	-0.0253	0.0932***	0.785***
	(0.0151)	(0.0168)	(0.0221)	(0.0134)	(0.0260)
house ownership	0.0633***	-0.0506**	-0.0155	-0.0291*	0.211***
	(0.0234)	(0.0222)	(0.0289)	(0.0169)	(0.0369)
log of land ownership	0.116***	0.136***	0.0905***	-0.0321***	0.152***
	(0.00425)	(0.00515)	(0.00574)	(0.00369)	(0.00693)
year_2005	-0.0680*	0.136**	-0.258***	0.108	-0.0230

	(0.0398)	(0.0603)	(0.0690)	(0.0679)	(0.0505)
YEAR2005 * TREATMENT GROUP A	-0.304***	-0.306***	-0.228**	0.191**	-0.121*
	(0.0508)	(0.0785)	(0.0929)	(0.0910)	(0.0659)
CONSTANT	8.696***	6.794***	6.301***	8.570***	8.260***
	(0.0759)	(0.115)	(0.128)	(0.116)	(0.104)
OBSERVATIONS	23,749	16,823	18,601	15,186	19,359
R-SQUARED	0.816	0.785	0.780	0.807	0.228

Source: Author's calculations.
Note: Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.

APPENDIX TABLE 4: IMPACT ON LOG OF HOUSEHOLD INCOME PER CAPITA (TREATMENT GROUP B: SELF-REPORTED FLOOD AFFECTED GROUP)

	(1)	(2)	(3)	(4)	(5)
VARIABLES	**LOG OF TOTAL INCOME**	**LOG OF CROP INCOME**	**LOG OF NON-CROP INCOME**	**LOG OF BUSINESS INCOME**	**LOG OF OTHER INCOME**
POST (YEAR 2010)	1.547***	1.815***	2.312***	1.902***	-0.967***
	(0.0533)	(0.0767)	(0.0884)	(0.0704)	(0.0878)
TREATMENT GROUP B	0.254***	0.491***	0.135*	-0.0956	-0.0648
	(0.0422)	(0.0583)	(0.0784)	(0.0780)	(0.0587)
POST * TREATMENT GROUP B	-0.216***	-0.487***	-0.000951	0.0821	0.0573
	(0.0435)	(0.0595)	(0.0801)	(0.0786)	(0.0685)
RURAL	-0.0702***	-0.0391**	-0.0123	-0.0464***	-0.234***
	(0.0170)	(0.0190)	(0.0236)	(0.0143)	(0.0276)
MALE HOUSEHOLD HEAD	-0.354***	0.288***	0.353***	0.207***	-0.917***
	(0.0440)	(0.0810)	(0.0780)	(0.0795)	(0.0508)
AVERAGE AGE	0.0161***	0.0145***	0.0247***	0.00597***	0.0187***
	(0.00109)	(0.00207)	(0.00199)	(0.00200)	(0.00126)
DEPENDENT	0.0148***	0.0143***	0.0196***	0.0139***	-0.000791

	(0.000369)	(0.000511)	(0.000523)	(0.000292)	(0.000755)
PROPORTION_FORMAL EDUCATION	1.316***	0.981***	0.343***	0.826***	0.775***
	(0.0380)	(0.0630)	(0.0685)	(0.0596)	(0.0447)
ACCESS TO SANITATION	0.185***	-0.00140	-0.00701	0.0917***	0.691***
	(0.0143)	(0.0156)	(0.0204)	(0.0124)	(0.0248)
ACCESS TO DRINKING WATER	0.0115	-0.0212	-0.121**	0.0625	-0.128**
	(0.0330)	(0.0393)	(0.0524)	(0.0388)	(0.0549)
ACCESS TO ELECTRICITY	0.257***	0.0709***	-0.0245	0.0924***	0.779***
	(0.0151)	(0.0168)	(0.0221)	(0.0134)	(0.0260)
HOUSE OWNERSHIP	0.0635***	-0.0507**	-0.0144	-0.0292*	0.211***
	(0.0234)	(0.0222)	(0.0288)	(0.0169)	(0.0369)
LOG OF LAND OWNERSHIP	0.116***	0.136***	0.0905***	-0.0320***	0.152***
	(0.00425)	(0.00516)	(0.00574)	(0.00369)	(0.00694)
YEAR_2005	-0.0679*	0.136**	-0.259***	0.109	-0.0194
	(0.0398)	(0.0604)	(0.0690)	(0.0679)	(0.0505)
YEAR2005 * TREATMENT GROUP B	-0.304***	-0.306***	-0.228**	0.191**	-0.121*
	(0.0508)	(0.0786)	(0.0929)	(0.0910)	(0.0659)
CONSTANT	8.699***	6.791***	6.306***	8.573***	8.282***
	(0.0759)	(0.115)	(0.128)	(0.116)	(0.104)
OBSERVATIONS	23,749	16,823	18,601	15,186	19,359
R-SQUARED	0.816	0.785	0.780	0.807	0.227

Source: Author's calculations.

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

APPENDIX TABLE 5: IMPACT ON LOG OF HOUSEHOLD EXPENDITURE PER CAPITA (TREATMENT GROUP A: RAINFALL-BASED FLOOD AFFECTED GROUP)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	LOG OF TOTAL EXPENDITURE	LOG OF FOOD EXPENDITURE	LOG OF NON-FOOD EXPENDITURE	LOG OF CROP EXPENDITURE	LOG OF NON-CROP EXPENDITURE	LOG OF AGRICULTURAL INPUT EXPENDITURE	LOG OF EDUCATIONAL EXPENDITURE	LOG OF HEALTH EXPENDITURE
POST (YEAR 2010)	1.997***	3.329***	2.734***	1.246***	1.895***	1.873***	2.241***	2.617***
	(0.0347)	(0.0245)	(0.0358)	(0.0548)	(0.0678)	(0.0684)	(0.0563)	(0.0712)
TREATMENT GROUP A	0.137***	0.0602***	0.0936***	0.107***	0.276***	0.286***	-0.0935	-0.260***
	(0.0218)	(0.0128)	(0.0241)	(0.0393)	(0.0612)	(0.0420)	(0.0570)	(0.0658)
POST * TREATMENT GROUP A	-0.144***	-0.0546***	-0.0750***	-0.127***	-0.268***	-0.315***	0.126**	0.273***
	(0.0256)	(0.0152)	(0.0269)	(0.0426)	(0.0633)	(0.0463)	(0.0588)	(0.0681)
RURAL	-0.0305***	-0.00729	-0.0510***	-0.0124	0.0326*	0.00573	-0.0804***	0.0571***
	(0.0101)	(0.00518)	(0.0109)	(0.0160)	(0.0170)	(0.0199)	(0.0151)	(0.0178)
MALE HOUSEHOLD HEAD	0.122***	0.0383***	-0.0696**	0.258***	0.237***	0.484***	-0.370***	-0.0190
	(0.0249)	(0.0138)	(0.0279)	(0.0629)	(0.0496)	(0.0773)	(0.0504)	(0.0605)
AVERAGE AGE	0.00562***	0.00597***	0.00632***	0.0113***	0.0168***	0.0199***	0.0258***	0.0113***
	(0.000736)	(0.000393)	(0.000763)	(0.00146)	(0.00141)	(0.00173)	(0.00214)	(0.00171)
DEPENDENT	0.0138***	0.0141***	0.0132***	0.0163***	0.0173***	0.0175***	0.0143***	0.0164***
	(0.000294)	(0.000230)	(0.000285)	(0.000380)	(0.000429)	(0.000527)	(0.000344)	(0.000387)
PROPORTION_FORMAL EDUCATION	1.055***	0.407***	1.084***	0.501***	0.650***	0.656***	2.776***	0.558***
	(0.0223)	(0.0110)	(0.0247)	(0.0460)	(0.0480)	(0.0558)	(0.0465)	(0.0569)
ACCESS TO SANITATION	0.0530***	0.0567***	0.111***	-0.0246*	-0.0155	-0.00304	0.155***	0.0755***
	(0.00853)	(0.00437)	(0.00897)	(0.0130)	(0.0149)	(0.0158)	(0.0135)	(0.0154)
ACCESS TO DRINKING WATER	0.146***	-0.00973	0.161***	-0.0231	0.0259	0.162***	0.0495	-0.0774*
	(0.0215)	(0.0101)	(0.0210)	(0.0310)	(0.0385)	(0.0394)	(0.0332)	(0.0396)
ACCESS TO ELECTRICITY	0.132***	0.0914***	0.171***	0.0520***	0.0304*	0.0747***	0.145***	0.0829***
	(0.00903)	(0.00472)	(0.00956)	(0.0135)	(0.0158)	(0.0170)	(0.0146)	(0.0166)
HOUSE OWNERSHIP	-0.0341**	-0.0459***	-0.0570***	-0.114***	-0.00544	-0.134***	-0.118***	-0.0352
	(0.0135)	(0.00720)	(0.0145)	(0.0195)	(0.0207)	(0.0227)	(0.0199)	(0.0234)
LOG OF LAND OWNERSHIP	0.157***	0.0194***	0.0323***	0.177***	0.111***	0.201***	0.0135***	-0.00416

	(0.00283)	(0.00128)	(0.00268)	(0.00511)	(0.00415)	(0.00564)	(0.00382)	(0.00442)
YEAR_2005	-0.525***	0.133***	-0.616***	-0.216***	-0.237***	-0.488***	0.199***	-0.0827
	(0.0212)	(0.0112)	(0.0238)	(0.0423)	(0.0532)	(0.0492)	(0.0467)	(0.0585)
YEAR2005 * TREATMENT GROUP A	-0.121***	-0.105***	-0.173***	0.162***	-0.195***	-0.00682	0.0534	0.228***
	(0.0273)	(0.0150)	(0.0305)	(0.0544)	(0.0697)	(0.0642)	(0.0656)	(0.0778)
CONSTANT	8.903***	6.007***	8.011***	7.285***	6.125***	6.636***	4.842***	4.171***
	(0.0435)	(0.0222)	(0.0471)	(0.0859)	(0.0897)	(0.103)	(0.0865)	(0.0997)
OBSERVATIONS	24,107	24,107	24,093	18,475	19,951	18,594	19,557	18,425
R-SQUARED	0.943	0.984	0.942	0.826	0.834	0.841	0.892	0.833

Source: Author's calculations.

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

APPENDIX TABLE 6: IMPACT ON LOG OF HOUSEHOLD EXPENDITURE PER CAPITA (TREATMENT GROUP B: SELF-REPORTED FLOOD AFFECTED GROUP)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	**LOG OF TOTAL EXPENDITURE**	**LOG OF FOOD EXPENDITURE**	**LOG OF NON-FOOD EXPENDITURE**	**LOG OF CROP EXPENDITURE**	**LOG OF NON-CROP EXPENDITURE**	**LOG OF AGRICULTURAL INPUT EXPENDITURE**	**LOG OF EDUCATIONAL EXPENDITURE**	**LOG OF HEALTH EXPENDITURE**
POST (YEAR 2010)	1.988***	3.311***	2.723***	1.258***	1.897***	1.861***	2.243***	2.601***
	(0.0358)	(0.0257)	(0.0368)	(0.0549)	(0.0684)	(0.0686)	(0.0564)	(0.0723)
TREATMENT GROUP B	0.137***	0.0602***	0.0936***	0.107***	0.276***	0.286***	-0.0934	-0.260***
	(0.0218)	(0.0128)	(0.0241)	(0.0394)	(0.0612)	(0.0420)	(0.0570)	(0.0658)
POST * TREATMENT GROUP B	-0.124***	-0.0300**	-0.0740***	-0.129***	-0.278***	-0.271***	0.0943	0.288***
	(0.0231)	(0.0136)	(0.0250)	(0.0406)	(0.0620)	(0.0436)	(0.0576)	(0.0668)
RURAL	-0.0304***	-0.00708	-0.0508***	-0.0127	0.0326*	0.00564	-0.0802***	0.0574***
	(0.0101)	(0.00518)	(0.0109)	(0.0160)	(0.0171)	(0.0200)	(0.0152)	(0.0178)
MALE HOUSEHOLD HEAD	0.122***	0.0376***	-0.0701**	0.260***	0.237***	0.483***	-0.370***	-0.0203
	(0.0249)	(0.0138)	(0.0279)	(0.0630)	(0.0496)	(0.0773)	(0.0504)	(0.0605)

AVERAGE AGE	0.00561***	0.00596***	0.00632***	0.0113***	0.0168***	0.0199***	0.0258***	0.0113***
	(0.000736)	(0.000393)	(0.000763)	(0.00146)	(0.00141)	(0.00173)	(0.00215)	(0.00171)
DEPENDENT	0.0138***	0.0141***	0.0132***	0.0162***	0.0173***	0.0175***	0.0143***	0.0164***
	(0.000295)	(0.000231)	(0.000286)	(0.000380)	(0.000430)	(0.000527)	(0.000344)	(0.000389)
PROPORTION_FORMAL EDUCATION	1.055***	0.407***	1.084***	0.501***	0.650***	0.655***	2.777***	0.558***
	(0.0223)	(0.0110)	(0.0247)	(0.0460)	(0.0480)	(0.0558)	(0.0465)	(0.0569)
ACCESS TO SANITATION	0.0532***	0.0569***	0.111***	-0.0244*	-0.0156	-0.00239	0.155***	0.0756***
	(0.00854)	(0.00437)	(0.00897)	(0.0130)	(0.0149)	(0.0158)	(0.0135)	(0.0154)
ACCESS TO DRINKING WATER	0.146***	-0.0107	0.159***	-0.0207	0.0251	0.165***	0.0465	-0.0794**
	(0.0215)	(0.0100)	(0.0210)	(0.0309)	(0.0384)	(0.0393)	(0.0331)	(0.0394)
ACCESS TO ELECTRICITY	0.132***	0.0914***	0.170***	0.0523***	0.0303*	0.0752***	0.144***	0.0827***
	(0.00903)	(0.00471)	(0.00955)	(0.0135)	(0.0158)	(0.0170)	(0.0146)	(0.0166)
HOUSE OWNERSHIP	-0.0340**	-0.0457***	-0.0570***	-0.115***	-0.00544	-0.134***	-0.118***	-0.0350
	(0.0135)	(0.00719)	(0.0145)	(0.0195)	(0.0207)	(0.0227)	(0.0199)	(0.0234)
LOG OF LAND OWNERSHIP	0.157***	0.0194***	0.0323***	0.177***	0.111***	0.201***	0.0135***	-0.00414
	(0.00283)	(0.00128)	(0.00268)	(0.00511)	(0.00415)	(0.00564)	(0.00382)	(0.00442)
YEAR_2005	-0.525***	0.133***	-0.616***	-0.216***	-0.237***	-0.488***	0.200***	-0.0826
	(0.0212)	(0.0112)	(0.0238)	(0.0423)	(0.0532)	(0.0492)	(0.0467)	(0.0585)
YEAR2005 * TREATMENT GROUP B	-0.121***	-0.105***	-0.173***	0.162***	-0.195***	-0.00678	0.0534	0.228***
	(0.0273)	(0.0150)	(0.0305)	(0.0544)	(0.0697)	(0.0642)	(0.0656)	(0.0778)
CONSTANT	8.903***	6.009***	8.013***	7.282***	6.126***	6.635***	4.845***	4.174***
	(0.0434)	(0.0221)	(0.0470)	(0.0859)	(0.0896)	(0.103)	(0.0865)	(0.0997)
OBSERVATIONS	24,107	24,107	24,093	18,475	19,951	18,594	19,557	18,425
R-SQUARED	0.943	0.984	0.942	0.826	0.834	0.841	0.892	0.833

Source: Author’s calculations.

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

APPENDIX TABLE 7: IMPACT ON LOG OF TOTAL ASSET OUTCOMES (TREATMENT GROUP A: RAINFALL-BASED FLOOD AFFECTED GROUP)

	(1)	(2)	(3)
VARIABLES	LOG OF TOTAL CHANGE IN AGRICULTURAL AND OTHER BUSINESS ASSET	LOG OF TOTAL AGRICULTURAL INPUT ASSET VALUE	LOG OF TOTAL CONSUMER DURABLE ASSET VALUE
POST (YEAR 2010)	0.384***	1.162***	2.639***
	(0.133)	(0.0862)	(0.0471)
TREATMENT GROUP A	-0.202	0.295***	0.521***
	(0.129)	(0.0732)	(0.0390)
POST * TREATMENT GROUP A	0.212	-0.275***	-0.455***
	(0.137)	(0.0786)	(0.0423)
RURAL	-0.0724**	0.000385	-0.137***
	(0.0349)	(0.0234)	(0.0149)
MALE HOUSEHOLD HEAD	0.706***	0.750***	0.116***
	(0.123)	(0.0946)	(0.0394)
AVERAGE AGE	0.0155***	0.00282	-0.00328***
	(0.00506)	(0.00253)	(0.00101)
DEPENDENT	0.0233***	0.0203***	0.0141***
	(0.000596)	(0.000502)	(0.000327)
PROPORTION_FORMAL EDUCATION	1.292***	1.117***	1.795***
	(0.139)	(0.0795)	(0.0338)
ACCESS TO SANITATION	0.0620**	0.0625***	0.197***
	(0.0296)	(0.0204)	(0.0124)
ACCESS TO DRINKING WATER	-0.0698	-0.0142	0.138***
	(0.0795)	(0.0517)	(0.0355)
ACCESS TO ELECTRICITY	0.0828***	0.0691***	0.447***
	(0.0314)	(0.0214)	(0.0133)
HOUSE OWNERSHIP	-0.00918	-0.0542**	0.0699***
	(0.0437)	(0.0274)	(0.0199)
LOG OF LAND OWNERSHIP	0.00984	0.0973***	0.0691***
	(0.00848)	(0.00591)	(0.00377)

YEAR_2005	-0.460***	-0.582***	-0.442***
	(0.121)	(0.0728)	(0.0357)
YEAR2005 * TREATMENT GROUP A	0.346**	-0.341***	-0.452***
	(0.167)	(0.0968)	(0.0463)
CONSTANT	6.030***	6.714***	8.404***
	(0.212)	(0.139)	(0.0696)
OBSERVATIONS	13,217	15,941	23,807
R-SQUARED	0.436	0.751	0.910

Source: Author's calculations.

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

APPENDIX TABLE 8: IMPACT ON LOG OF TOTAL ASSET OUTCOMES (TREATMENT GROUP B: SELF-REPORTED FLOOD AFFECTED GROUP)

	(1)	(2)	(3)
VARIABLES	**LOG OF TOTAL CHANGE IN AGRICULTURAL AND OTHER BUSINESS ASSET**	**LOG OF TOTAL AGRICULTURAL INPUT ASSET VALUE**	**LOG OF TOTAL CONSUMER DURABLE ASSET VALUE**
POST (YEAR 2010)	0.599***	1.177***	2.636***
	(0.134)	(0.0868)	(0.0482)
TREATMENT GROUP B	-0.202	0.295***	0.521***
	(0.129)	(0.0732)	(0.0390)
POST * TREATMENT GROUP B	-0.139	-0.316***	-0.507***
	(0.132)	(0.0753)	(0.0402)
RURAL	-0.0767**	0.000315	-0.136***
	(0.0347)	(0.0234)	(0.0149)
MALE HOUSEHOLD HEAD	0.776***	0.752***	0.116***
	(0.126)	(0.0946)	(0.0394)
AVERAGE AGE	0.0164***	0.00284	-0.00328***

	(0.00507)	(0.00253)	(0.00101)
DEPENDENT	0.0230***	0.0203***	0.0142***
	(0.000594)	(0.000503)	(0.000328)
PROPORTION_FORMAL EDUCATION	1.290***	1.117***	1.797***
	(0.139)	(0.0795)	(0.0338)
ACCESS TO SANITATION	0.0571*	0.0619***	0.197***
	(0.0294)	(0.0204)	(0.0124)
ACCESS TO DRINKING WATER	-0.0605	-0.0160	0.133***
	(0.0788)	(0.0515)	(0.0355)
ACCESS TO ELECTRICITY	0.0811***	0.0687***	0.446***
	(0.0313)	(0.0214)	(0.0133)
HOUSE OWNERSHIP	-0.0135	-0.0543**	0.0698***
	(0.0433)	(0.0274)	(0.0199)
LOG OF LAND OWNERSHIP	0.00983	0.0974***	0.0692***
	(0.00844)	(0.00591)	(0.00377)
YEAR_2005	-0.459***	-0.581***	-0.442***
	(0.121)	(0.0728)	(0.0357)
YEAR2005 * TREATMENT GROUP B	0.345**	-0.341***	-0.452***
	(0.167)	(0.0968)	(0.0463)
CONSTANT	5.944***	6.714***	8.410***
	(0.214)	(0.139)	(0.0696)
OBSERVATIONS	13,217	15,941	23,807
R-SQUARED	0.442	0.751	0.910

Source: Author's calculations.
Note: Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.

APPENDIX TABLE 9: IMPACT ON VARIOUS INCOME AND EXPENDITURE BRACKETS PER CAPITA (TREAT GROUP A: RAINFALL-BASED FLOOD AFFECTED GROUP)

VARIABLES	I 15TH	II 25TH	III 50TH	IV 75TH	V 85TH
INCOME					
TOTAL INCOME	-8,684.68***	8,446.09***	436.31	-22,268.13***	-13,699.11***
	(456.81)	(780.54)	(1,704.79)	(3,094.70)	(5,224.42)
CROP INCOME	-3,849.69***	-4,090.00***	1,418.15***	-3,181.12*	-6,615.66***
	(430.00)	(4.41)	(449.69)	(1,643.33)	(1,197.43)
NON-CROP INCOME	-146.66	1,946.66	-3,359.52***	-635.47*	-51,378.16***
	(131.02)	(2,223.99)	(116.93)	(353.80)	(1,043.89)
BUSINESS INCOME	0.00	7,433.31***	8,643.20***	-14,115.48***	-9,749.66**
	(677.82)	(493.02)	(68.78)	(2,174.70)	(4,201.40)
OTHER INCOME	0.00	43.78***	2,070.04***	510.03	-1,762.24
	(2.01)	(6.56)	(361.38)	(1,290.58)	(2,626.63)
EXPENDITURE					
TOTAL EXPENDITURE	-808.53***	-24,087.06***	-5,357.88***	-8,871.79***	-31,949.62***
	(273.02)	(355.66)	(802.60)	(1,639.79)	(2,694.14)
FOOD EXPENDITURE	770.49***	-125.71***	-98.26***	1,022.91***	110.73***
	(14.31)	(13.12)	(16.39)	(28.35)	(37.05)
NON-FOOD EXPENDITURE	-2,222.90***	-10,549.13***	-2,176.59***	-21,474.10***	-13,547.52***
	(88.14)	(110.43)	(236.76)	(624.43)	(964.09)
CROP EXPENDITURE	1,208.29***	-71.07	-2,361.67***	-601.92	-435.27
	(230.31)	(281.77)	(445.68)	(707.91)	(731.81)
NON-CROP EXPENDITURE	708.00***	-1,222.90***	-136.89	-3,964.10***	-1,195.00***
	(65.13)	(62.82)	(141.31)	(342.22)	(448.64)
AGRICULTURAL INPUT	582.67***	-2,991.49***	-9,122.85***	-7,339.18***	-17,790.28***

EXPENDITURE					
	(2.26)	(105.19)	(422.66)	(999.41)	(1,730.57)
EDUCATIONAL EXPENDITURE	9.34	-233.82***	-397.61**	-1,738.33***	-1,230.27**
	(20.71)	(43.86)	(158.94)	(358.27)	(568.46)
HEALTH EXPENDITURE	-101.97***	-2.90	-113.02***	-54.37	127.51**
	(2.85)	(5.15)	(13.33)	(38.36)	(62.78)

Source: Author's calculations.

Notes: [a] This table only presents the coefficient estimates for the Post*Treat Group A variable, our main estimated parameter. All other controls were not included in these regressions.

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

APPENDIX TABLE 10: IMPACT ON VARIOUS INCOME AND EXPENDITURE BRACKETS PER CAPITA (TREAT GROUP B: SELF-REPORTED FLOOD AFFECTED GROUP)

VARIABLES	I 15TH	II 25TH	III 50TH	IV 75TH	V 85TH
INCOME					
TOTAL INCOME	-38,371.00***	-77,008.91***	16,693.69***	43,108.87***	148,187.89***
	(368.88)	(581.29)	(1,421.33)	(2,476.48)	(3,862.80)
CROP INCOME	-9,327.00***	-9,201.70***	-4,635.45***	-112.83	-6,862.55***
	(555.90)	(3.16)	(353.17)	(1,046.94)	(670.10)
NON-CROP INCOME	12,419.98***	20,550.00***	6,377.88***	32,379.83***	73,085.09***
	(1,094.04)	(613.00)	(81.40)	(322.69)	(725.28)
BUSINESS INCOME	-32,866.70***	-23,281.31***	-47,990.18***	-29,561.85***	79,527.03***
	(1,243.73)	(854.74)	(53.53)	(1,224.90)	(2,706.31)
OTHER INCOME	0.00	-289.55***	-513.30	-1,491.63	-2,095.57
	(1.54)	(4.49)	(330.61)	(968.46)	(2,149.39)
EXPENDITURE					

Total expenditure	-56,713.22***	18,016.19***	-13,414.00***	-39,815.17***	-113,040.00***
	(180.36)	(250.64)	(503.54)	(1,002.04)	(1,653.98)
Food expenditure	-6,099.71***	-1,940.31***	4,235.44***	-1,780.30***	1,348.30***
	(9.17)	(8.76)	(10.07)	(19.47)	(21.62)
Non-Food expenditure	-10,082.90***	32,942.18***	-15,039.21***	-29,247.10***	-35,751.58***
	(56.34)	(73.07)	(158.56)	(398.29)	(820.01)
Crop expenditure	-6,414.05***	-2,305.74***	-1,614.01***	-6,052.92***	4,804.73***
	(149.49)	(240.00)	(214.63)	(472.92)	(533.45)
Non-Crop expenditure	-8,169.34***	-2,509.57***	1,306.45***	-4,544.11***	1,679.67***
	(55.10)	(47.52)	(79.69)	(218.83)	(293.02)
Agricultural input expenditure	8,044.00***	21,020.51***	7,650.48***	9,418.78***	-44,504.28***
	(1.51)	(62.09)	(295.02)	(463.42)	(922.90)
Educational expenditure	-6,125.34***	-5,854.16***	3,361.73***	-6,333.33***	-3,001.75***
	(13.17)	(29.73)	(107.00)	(247.74)	(341.57)
Health expenditure	-101.97***	-312.23***	276.65***	284.30***	52.51
	(1.81)	(3.75)	(8.94)	(26.09)	(42.43)

Source: Author's calculations.

Notes: [a] This table only presents the coefficient estimates for the Post*Treat Group B variable, our main estimated parameter. All other controls were not included in these regressions.

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

CONCLUSION OF THE THESIS:

In Chapter One, we survey the literature that examines the direct and indirect impact of natural disaster events specifically on the poor and their impact on various income groups. We argue that it is perhaps even more important to determine the long-term effects of catastrophic disasters on various income groups, rather than only their direct and indirect short-term impacts. One issue that may turn out to be the most important in determining post-disaster outcomes is not the degree and level of destruction, or the degree of preparedness, but the adjustment in expectations with regard to future events that catastrophes often prompt. Kobe, for example, was not perceived to be a high-risk area for earthquakes before 1995, an assessment which unsurprisingly changed in the disaster's aftermath. This may be especially important as these changes in the subjective probabilities assigned to plausible hazards may well matter differently for people from different socio-economic backgrounds, given the additional exposure of the poor to risk and given the possibility of decreased investment leading into poverty traps. However, this is still an open empirical question.

Natural disasters affect households adversely, and they do so especially for people with lower incomes and wealth that are less able to smooth their consumption. In Chapter Two, we conducted a meta-regression analysis of the existing literature on the impacts of disasters on households, focusing especially on the poor and on poverty measures. We find much heterogeneity in these impacts which is most likely the most important insight gleaned from our analysis. Nevertheless, several general patterns that are observed in individual case studies also emerge. Incomes are clearly impacted adversely, with the impact observed specifically in per-capita measures. Consumption is also reduced, but to a lesser extent than incomes. Importantly, poor households appear to smooth their food consumption by reducing the consumption of non-food items; the most significant items in this category are spending on health and education. This suggests potentially long-term adverse consequences as consumption of health and education services is often better viewed as long-term investment. However, there are limits to what we can conclude using our methodology covering a fairly large and diverse literature and they are quite obvious as we note that we observe no robust insight on the impact of disasters in the longer term.

It is well understood that any government's public spending decision-making processes are affected by other considerations rather than need, but the balance between these competing pressures is not obviously clear. Our objective in Chapter Three is to identify the determinants' of publicly allocated and realized DRR spending at the local government (sub-district) level in Bangladesh. We employ the Heckman two-stage selection model to empirically estimate the covariates where we assume public spending is a function of the probability of flood risks, population size, poverty rate, socio-economic development, political connections, ethnic composition, and details about the geo-location of the sub-district. We find little evidence (and some counter-evidence) of any rationale in the regional funding allocation decisions of the Bangladesh government. The DRR regional allocations do not seem to be determined by risk and exposure, and only weakly by vulnerability. Even obvious and transparent political economy motivations do not seem to explain much of the variation in inter-regional funding. We do not rule out the possibility that our results are biased because of the absence of long-term data, a possible omitted variable bias and reverse causality. All these justify future research in this area. Whether our conclusions apply to other types of central government funding in Bangladesh, or whether this is indeed typical of regional allocations in lower-income countries, are also all still open questions that require more evidence-based answers.

The last few years have seen a new wave of empirical research on the consequences of changes in precipitation patterns, temperature and other climatic variables on economic development and household welfare. Our objective in Chapter Four is to estimate the impacts of recurrent-flooding on income, expenditure, asset and labour market outcomes. We start with identification of the treatment (affected) groups with setting two benchmarks i.e. using self- and non-self-reported information. We employ a difference-in-difference estimation model to understand the impacts of disaster on households surveyed in 2000, 2005 and 2010. Our results suggest a sharp decline in agricultural income (crop and non-crop) for both treatment group – A (rainfall-based) and B (self-reported). This significant decline in agricultural income, being consistent with previous literatures reveals a clear message on timely adoption of insurance in the context of increased climatic threat to achieve sustainable poverty goals for the extreme poor especially in agriculture-based economy like Bangladesh. As per expenditure in concerned, we also observe a negative response to crop and agricultural input expenditure consistent with our theoretical prior in both treatment cases. We extend our analysis for income and expenditure categories for households of various socio-economic backgrounds. We find a contrast in terms of impact for the ultra (bottom 15 percent) poor in total income and expenditure between treatment groups – A and B. The 'disaster-development' literature has made considerably less progress on the use of shock modules in survey data to empirically estimate the impacts of natural disasters on development outcomes. The recent addition of shock questionnaires in nationally representative household income and expenditure surveys provides an ample scope to identify the self-reported affected groups in repeated natural disasters. This self-identification in the questionnaire could be advantageous to capture the disaster impacts on households' more precisely when compared to index-based identifications based on geographical exposure. However, questions' based on 'yes/no' responses (i.e. close-ended) might not be sufficient to identify the true development impacts. One possible solution is of course, more respondents in addition to incorporating degrees of actual hazard awareness, experience and preparedness questions' to identify the real affected group in repeated natural shocks. However, the evidences and the novel approach that we adopt in this paper could justify future research in estimating welfare adaptation costs of climate-induced persistent natural events in developing countries.