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The Household Response to Persistent Natural Disasters: Evidence from Bangladesh

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SUMMARY

Recent literatures examine the short-run effects of natural disasters on household welfare and health outcomes. 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. 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. In this paper, we ask: "what are the impacts on household income, expenditure, asset, and labor market outcomes of recurrent flooding in Bangladesh?" We examine the short-run economic impacts of recurrent flooding on Bangladeshi households surveyed in year 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 treatment (affected) groups using two measures of disaster risk exposure; the self-reported flood hazard data, and historical rainfall data-based flood risk index. The paper directly compares the impacts of climatic disaster (i.e., recurrent flooding) on economic development. We further examine these impacts by pooling the data for the years' 2000, 2005, and 2010 and compare the results with our benchmark estimations. Overall, we find robust evidence of negative impacts on agricultural income and expenditure. Intriguingly, the self-reported treatment group experienced significant positive impacts on crop income.

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.[1] 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 (Beg et al., 2002; McGuigan, Reynolds, & Wiedmer, 2002; OECD, 2003). Recent literatures examine the short-run effects of natural disasters on household welfare and health outcomes (Arouri, Nguyen, & Youssef, 2015; Lohmann & Lechtenfeld, 2015; Lopez-Calva & Ortiz-Juarez, 2009; Rodriguez-Oreggia, de la Fuente, de la Torre, Moreno, & Rodriguez, 2013; Silbert & del Pilar Useche, 2012). 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.[2] In this paper, we ask: "what are the impacts on household income, expenditure, asset, and labor market outcomes of recurrent flooding in Bangladesh?"

We examine the short-run economic impacts of recurrent flooding on Bangladeshi households surveyed in year 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. 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, literatures have identified shortcomings in self-reporting and various determinants of flood risk perception.[3] Therefore, this paper contributes the following in the "disaster-development" literature: first, it identifies treatment (affected) groups using two measures of disaster risk exposure – the self-reported flood hazard data and historical rainfall

[1] See Bandyopadhyay and Skoufias (2015).

[2] 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 spillover effects.

[3] Limitations of self-reported data have been detailed in Section 3(a).

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data-based flood risk index; second, it directly compares the impacts of climate disaster (i.e., recurrent flooding) on four development dimensions i.e., income, expenditure, asset, and on labor market outcomes. Our novelty in this paper is the identification of flood treatment households using self-reported flood hazard data and historical rainfall-based flood risk index. 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. In this paper, 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.

The paper is designed as follows: Section 2 describes the theoretical framework between social vulnerability and community resilience. Section 3 reviews the empirical evidences highlighting recent insights to explore the nexus between climatic disasters and economic development in both developed and developing countries. Section 4 portrays our identification strategy while Section 5 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 6, we present and analyze the estimation results comparing with previous literatures along with robustness checks in Section 7. Finally, in Section 8 we conclude with relevant policy implications and also some insight for further advancements.

2. Social vulnerability and community resilience: theoretical framework

Figure 1 displays the conventional way to consider disaster risk as a function of the following factors:

$$\text{Risk/Disaster Risk} = f(\text{Hazard, Exposure, Vulnerability})$$

where a country's pre-determined geo-physical and climatic characteristics are part of its hazard profile compared to exposure which is largely driven by poverty forcing people to live in more exposed and unsafe conditions (e.g., living in flood plains).[4] Poverty is both a driver and consequence of disaster risk particularly in countries with weak risk governance (Wisner, Blaikie, Cannon, & Davis, 2004). Vulnerability in the above functional form depicts disaster risk not only depends on the severity of hazards or exposure of urban living and human assets but also on the exposed population's capacities to withstand and reduce the socio-economic impacts of hazards.[5] Therefore, disaster risk can be viewed as the intersection of hazard, exposure, and vulnerability. Since resilience has often been defined as the flip-side of vulnerability[6], there seems to be a clear connection between disaster risk reduction efforts and enhancement of community resilience as occurrence and severity of natural hazards is uncontrollable. However, vulnerability is multi-dimensional and dynamic; hence it demands inter-disciplinary approaches to understand both the physical and socio-economic aspects. Literatures have attempted to put forth conceptual frameworks in various contexts and identify global and community-level indicators to quantify vulnerability. Among them; the Hazard-of-Place Model of Vulnerability (Cutter, Boruff, & Shirley, 2003), the Pressure and Release Model (Blaikie, Cannon, Davis, & Wisner, 1994:23), the Social Vulnerability Model (Dwyer, Zoppou, Nielsen, Day, & Roberts, 2004:5) and the framework to approach social vulnerability (Parker & Tapsell, 2009; Tapsell, McCarthy, Faulkner, & Alexander, 2010) could be particularly mentioned. In a study on community resilience to coastal hazards in the Lower Mississippi River Basin (LMRB) region in South-eastern Louisiana, the Resilience Inference Measurement (RIM) Model has been applied to assess the resilience of higher and lower resilient communities (Cai, Lam, Zou, Qiang, & Li, 2016). Interestingly, the authors identified the location of the lower resilient communities to be along the coastline and in lower elevation area (in the context of developed country here) that has also been argued in the context of developing countries (e.g., Karim & Noy, 2016a). Our aim in this paper is to understand this relationship among hazard, vulnerability, and exposure and look at the impacts of climate-induced disaster risks (e.g., flood hazards) on various socio-economic dimensions (i.e., income, consumption, asset, and labor market outcomes).

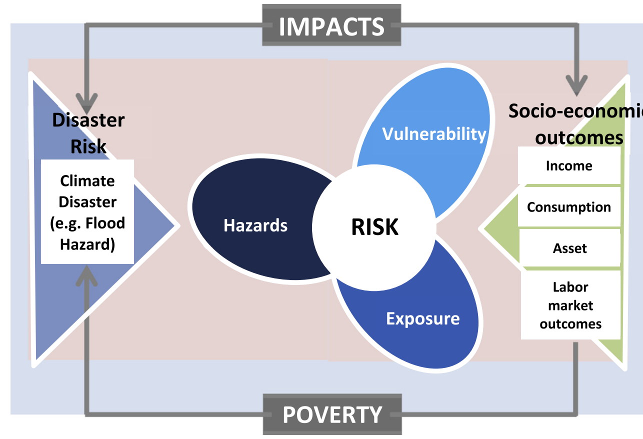

Figure 1. Author's elaboration of the theoretical framework based on Wisner et al. (2004) and IPCC (2014).

3. Climate disasters and development: empirical evidences

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 (Acevedo, 2014; Felbermayr & Gröschl, 2014). Vulnerable economies for example, the Pacific islands could expect a growth drop by 0.7 percentage points for damages equivalent to 1% of GDP in the year of the disaster (Cabezon, Hunter, Tumbarello, Washimi, & Wu, 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 (2013)[7] 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 impacted poverty.[8] Recent studies on rural Vietnam looked at the impacts

[4] See Karim and Noy (2016a).
[5] See Noy and duPont IV (2016).
[6] See Crichton (1999) and Wilson (2012). However, Cutter, Ash, and Emrich (2014) found evidences that inherent resilience is not the opposite of social vulnerability using the Baseline Resilience Indicators for Communities (BRIC) metric.
[7] These studies focus on the short-run effects of natural disasters.
[8] Karim and Noy (2016a) provide a qualitative survey of the empirical literature on poverty and natural disasters.

on climate disasters such as floods, storms, and droughts on household resilience, welfare, and health outcomes (Arouri et al., 2015; Bui, Dungey, Nguyen, & Pham, 2014; Lohmann & 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 & 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. Agricultural specialization-based occupational choices are also found to be negatively affected with high variations in rainfall in the Indian context (Skoufias, Bandyopadhyay, & Olivieri, 2017). 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 temperatures than a threshold of 34.31 °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 literature also explored vulnerability to natural disasters in the context of developed countries; for example, the case of hurricane Katrina in the US city of New Orleans. Evidences suggest that the pre-existing socio-economic conditions and racial inequality in New Orleans played a crucial role in exacerbating damages due to Hurricane Katrina in addition to the failure of flood protection infrastructure and disaster anticipation combined with poor responses management (Cutter et al., 2006; Levitt & Whitaker, 2009; Masozera, Bailey, & Kerchner, 2007). A recent study by Martin (2015) used a grounded theory approach to develop the Social Determinants of Vulnerability Framework and applied on the US city of Boston. The author found that those living with low-to-no income are at the highest risk for negative post-incident outcomes. Bergstrand, Mayer, Brumback, and Zhang (2015) adds to this social vulnerability-community resilience to hazards literature by measuring these indices in counties across the United States and find a correlation between high levels of vulnerability and low levels of resilience (indicating that the most vulnerable counties also tend to be the least resilient). The authors further identified that the Northern parts of the United States, particularly the Midwest and northeast, were more resilient and less vulnerable than the South and West. This finding has also been confirmed by Cutter et al. (2014) using an alternative resilience metric.

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 spillover effects of the 2011 Thailand flood identifying self-reported affected (treatment) group in a difference-in-difference modeling 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.[9]

(a) Limitations of self-reported data

Recent studies have identified various limitations of reported flood risk and showed that perceived flood exposure could be different from actual risk. In a study conducted in Bray, Dublin city; O'Neill, Brereton, Shahumyan, and Clinch (2016) find that distance to the perceived flood zone (perceived flood exposure) is a crucial factor in determining both cognitive and affective components of flood-risk perception. Another recent study by Trumbo et al. (2016) develops an interesting measure of risk perception (in the context of hurricanes) to understand how people make decisions when facing an evacuation order. This literature found to validate previous works and justifies its approach to other contexts within natural hazards, and elsewhere. Self-reporting in terms of being affected could be subjective and might bring biased results due to sorting or selective reporting.[10] Self-reported data could not only be a subject of recall error, but also to other forms of cognitive bias like reference dependence (Guiteras et al., 2015).

4. Identification strategy

Our objective in this paper is to analyze the short-run impacts of recurrent flooding on household income, expenditure, asset, and labor 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.[11] Our estimation strategy identifies affected households using two different measures of disaster risk exposure (i.e., flood hazard) and directly compares the impacts on various socio-economic outcomes. Our primary focus is the year 2010 as shock module was introduced in the 2010 Household Income and Expenditure Survey (HIES) with questionnaire related to natural disasters and no new survey has been published at the national level since then.[12] 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 was not possible. However, Bangladesh as a disaster-prone country, disasters particularly flood are a repeated phenomenon every year. Here, we took flood as persistent natural disaster due to its repeated occurrence every year mostly during the monsoon period (May–October). Due to limitations of the self-reported data (as evident in literatures), we identify two "treatment" groups – treatment group A and treatment group B to compare the impacts using two different measures of disaster risk exposure.

The first treatment group i.e., treatment group A is identified through the self-reported information using the shock module in year 2010. From 2010 survey, the treatment group are the respondents who have said "Yes" as being affected by flood hazard only. In 2010, the comparison groups are those households who have

[9] See Guiteras, Jina, and Mobarak (2015) and Heltberg, Oviedo, and Talukdar (2015).

[10] See Heltberg et al. (2015) for a discussion on how survey modules fall short of expectations in several ways.

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

[12] The HIES 2015 survey is currently underway according to the information provided by the current Project Director.

responded "No" to being affected by flood hazard only. To identify our second treatment group i.e., treatment group B, we use a rainfall-based flood risk probability index using historical rainfall dataset[13] from the Bangladesh Meteorological Department (BMD) to identify upazilas/thanas[14] (in particular, the survey areas) which are affected by more than average rainfall over a long period (1948–2012).[15] The rule of thumb is the survey areas (i.e., upazilas/thanas) which have experienced more than average rainfall compared to the benchmark of average rainfall of 64 years in the corresponding weather station in year 2010 only, the surveyed households in those upazilas fall under treatment group B. The comparison (not affected) group here 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 year 2010 only. The advantages of using different flood risk measure in comparable contexts are twofold. First, it justifies homogeneous circumstances among affected households in terms of a common natural shock i.e., flood. Second, we can directly compare the development impacts on two different treatment groups and the differences could refer to discrepancies in capturing the true impacts using shock module. Also, it fits well with the distinction between covariate and idiosyncratic shocks. Households located in the areas with rainfall shocks may not report that they are affected by floods or droughts e.g., if they are not engaged in agriculture. Richer or more educated households may be able to smooth consumption and in this case might not report being affected by rainfall shocks.[16] It is also possible that individuals with higher level of education over-report their preparedness behavior in order to present themselves in a positive way following socially accepted standards (Hoffmann & Muttarak, 2017).

Figure 2 represents the map showing the upazilas/thanas (i.e., sub-districts) in which the two treatment groups had been located. The red symbol exhibits the self-reported treatment areas (i.e., treatment group A) whereas the blue symbol locates the rainfall-based treatment areas (i.e., treatment group B). There are some upazilas which are found similar in terms of treatment (for both groups – A and B) and have been identified using the box structure in Fig. 2.

5. Data and methodology

(a) Data description

We use the 2010 Household Income and Expenditure Survey (HIES) of the Bangladesh economy in our main analysis. 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 labor 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 the large sample size covering a broad range of households. However, limitations are there in capturing the impacts over time. We further utilize HIES data spanning over a time period of 10 years consisting of years 2000, 2005, and 2010 to check robustness of our main results. The number of households in year 2000 is 7,440 with 10,080 and 12,240 in year 2005 and in 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.

(b) Methodological framework

Our main aim here is to examine the short-run economic impacts of recurrent flooding on households socio-economic outcomes i.e., income, consumption, asset, and on labor market outcomes. We start by examining the most parsimonious specification:

$$y_{ij} = \alpha + \beta_1 \mathrm{A}_{ij} + \beta_2 \mathrm{B}_{ij} + \beta_3 \mathrm{C}_{ij} + \gamma(X_{ij}) + u_{ij} \tag{1}$$

where y_{ij} is the outcome variable for household (i) in sub-district (j) (i.e., income, expenditure, asset and labor market outcomes), β_1 represents the coefficient for treatment group A (self-reported flood impacts only), β_2 represents the coefficient for treatment group B (flood-risk index based shocks only), β_3 represents the coefficient for both self-reported disaster (flood) impact and index-based identifications (C), X_{ij} denotes the control variables indicating households socio-economic characteristics and infrastructural features, and u_{ij} indicate the error term. We use robust standard errors for our hypothesis tests. The distinction between treatment group A (self-reported) and treatment group B (flood-risk index based) will allow us to directly compare the differences in terms of impacts using these two different measures of disaster risk exposure on household welfare. The constant term, α in our benchmark model will define the impacts on the comparison groups i.e., households who are not affected by repeated flood hazards. The number of households in treatment group A, B, and C is 271, 2,031, and 46 consecutively with 9,938 households being in the control group.

To further investigate whether household-level characteristics (e.g., rural, landownership, and more education) has impacts on disaster-risk identifications, we further estimate the following equation:

$$\begin{aligned} y_{ij} = {} & \alpha + \beta_1 \mathrm{A}_{ij} + \beta_2 \mathrm{B}_{ij} + \beta_3 \mathrm{C}_{ij} + \gamma^1(X^1_{ij}) + \gamma^2(X^2_{ij}) + \delta^1(\mathrm{A}_{ij}.X^2_{ij}) \\ & + \delta^2(\mathrm{B}_{ij}.X^2_{ij}) + \delta^3(\mathrm{C}_{ij}.X^2_{ij}) + u_{ij} \end{aligned} \tag{2}$$

The coefficients of the interaction among the treatment groups – A, B, C and the household-level characteristics i.e., rural, landownership, and formal education (δ^1, δ^2 and δ^3) will define the effect of these characteristics on the magnitude of the impacts on the outcome variables.

(c) Outcome variables and choice of the control variables

Table 7 shows the lists of key outcome and the control variables (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 labor market outcomes. Income and expenditure are divided into various sub-groups with statistics shown in per capita household measures. Asset and labor market outcomes are also sub-divided into various categories (also described in Table 7). The continuous (monetary) variables in each category are inflation-adjusted using consumer price index (CPI)

[13] Guiteras et al. (2015) use satellite data for rainfall, but find that these data are poorly correlated with actual flooding.

[14] Sub-districts are named as "Upazilas/Thanas" in Bangladesh.

[15] A breakdown of the index construction has been provided in the Appendix. See Karim and Noy (2015) for more details.

[16] We thank an anonymous reviewer for pointing out this interesting insight in our analysis.

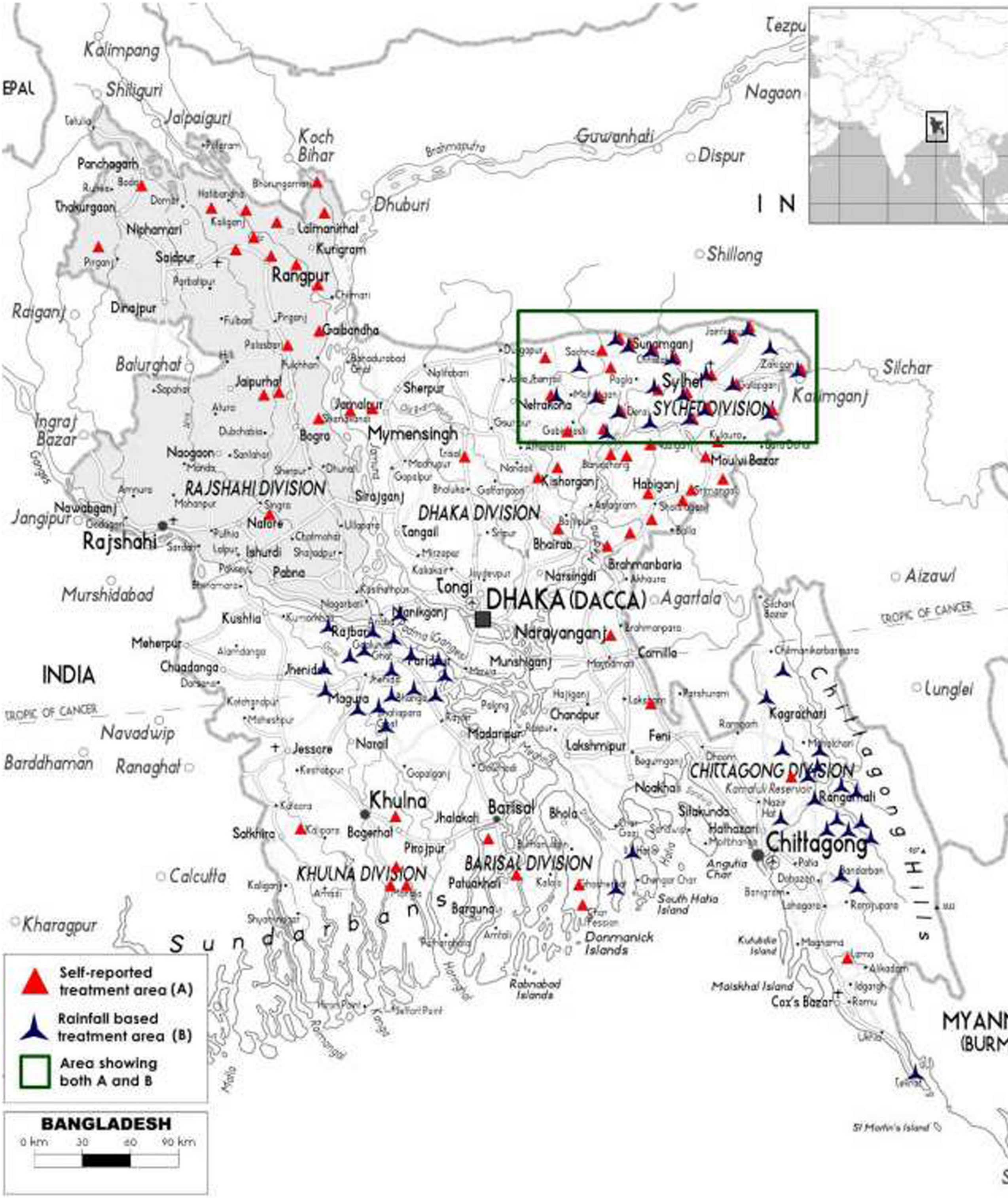

Figure 2. Map showing the treatment areas (sub-districts) in the study.

data from the Bangladesh Bank[17] 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 (Fadeeva, 2014; Ferdousi & Dehai, 2014; Japan Bank for International Cooperation, 2007). 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

[17] Bangladesh Bank is the Central Bank of Bangladesh.

(Aritomi, Olgiati, & Beatriz Orlando, 2008; Buvinic & Gupta, 1997; Mallick & Rafi, 2010). Female-headed households are particularly vulnerable to climate variability as well (Flatø, Muttarak, & Pelser, 2017). 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 are critical to analyze poverty status and one might expect larger number of dependents leads to greater poverty (Haughton & Khandker, 2009; Kotikula, Narayan, & Zaman, 2010; Lanjouw & Ravallion, 1995). Education is also related with lower poverty (Kotikula et al., 2010). Community-level characteristics such as access to sanitation and access to safe drinking water are clearly associated with better health outcomes improving poverty status (Duflo, Galiani, & Mobarak, 2012; World Bank, 2014) 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., Gerstter, Kaphengst, Knoblauch, & Timeus, 2011; Khatun, 2015; Meinzen-Dick, 2009; Rayhan, 2010; Tasneem & Shindaini, 2013). A description of these variables including summary statistics is also provided in Table 7.

(d) Descriptive statistics

We provide descriptive statistics for two different treatment and comparison groups (treatment group A and treatment group B) in Table 7. We present mean and standard deviation for various outcome categories and control variables for both rainfall-based and self-reported treatment (affected) and comparison (not affected) groups. Most of the income categories seem to be higher for the comparison group compared to treatment for treatment group A (self-reported) with exception in the "crop income" category. The crop income per capita for treatment group A is on average, almost 11% higher compared to the comparison group. The other treatment group i.e., treatment group B (rainfall-based flood treatment households) also do not show too much variation in terms of mean income by categories. However, mean of the "other income" turns out to be almost 10% lower for the comparison group compared to treatment in treatment group B. The comparison group also have around 1.2% less business income compared to treatment in contrary to most income categories in the non-self-reported case. The expenditure categories also reveal interesting patterns in agricultural expenditure (i.e., crop and non-crop), in particular. Non-crop expenditure in treatment group A is about 4.5% higher with having a lesser variation in crop expenditure (around 1.5% higher) compared to the comparison group. Agricultural input also reveals a higher expenditure amount (i.e., approximately 2.5%) in treatment compared to comparison group A. Interestingly, most of the expenditure categories in comparison group B seems to be higher than treatment with exceptions in "non-crop" expenditures (around 0.4% lower). Interesting contrast could also be portrayed in educational and health expenditure categories for both treatment groups. Educational and health expenditures are found to be less in comparison group B with exceptions in comparison group A (in health expenditures) compared to their respective treatment groups – B and A. However, on average, the educational and health expenditure are found to be higher in self-reported treatment group (A) compared to the non-self-reported one (B). It is here to note that, the proportion of household members getting access to formal education exhibits almost a similar pattern in both treatment and comparison groups - A and B. Parallel trends could also be observed in terms of total change in agricultural and other business asset categories between both treatment and comparison groups with marginal variation (approximately 2.2% higher) observed in treatment in rainfall-based identifications. Observable differences could also be seen in labor market outcomes between both treatment and comparison groups. Daily wages are found to be somewhat higher (almost 0.7%) in treatment group B whereas households identified in treatment group A seem to earn more salaried wages (around 2% higher) compared to their respective comparison groups – B and A. Intriguingly, the rainfall-based treatment households (B) are found to earn more daily wages compared to more salaried wages earned by the self-reported treatment (A) cases. There are interesting parallel trends in the mean results of the control variables (independent variables) between the two treatment groups. More self-reported households are found to reside in the rural areas showing their dependency in rain-fed agriculture.[18] The rainfall-based flood treatment households (treatment group B) have more working adults i.e., fewer dependents (around 0.3%) compared to the self-reported identifications. However, the self-reported flood treatment group owns more land (around 11%) and houses (almost 6% higher) compared to the non-self-reported ones. Community characteristics such as access to sanitation, safe drinking water, and electricity also show parallel trends in their mean outcomes in both treatment groups – A and B.

6. Estimation results

We start by estimating our benchmark model (as specified in Eqn. (1)) with treatment groups identified using two measures of disaster risk exposure: self-reported data (treatment group A) and historical rainfall-based flood risk index (treatment group B). We estimate our model on development dimensions such as income, expenditure, assets, and labor market outcomes. We therefore, compare our results for each category (in terms of aggregate and disaggregated outcome measures) with previous literatures and extend our analysis by estimating our model specified in Eqn. (2).

(a) Income

Table 1 reports the impacts of recurrent-flooding on different income categories i.e., crop, non-crop, business, and other income for self-reported treatment group (A) and rainfall-based flood affected treatment group (B). We find both treatment (affected) households experience negative impacts on total income being consistent with previous disaster literatures (e.g., Asiimwe & Mpuga, 2007; De la Fuente, 2010; Thomas, Christiaensen, Do, & Trung, 2010). Our results indicate that total income reduces by almost 1.1% more (estimated to be approximately BDT 11,665) for treatment group B compared to the mean.[19] A decline in crop income is significantly higher for treatment group B (by around BDT 3,456) whereas both treatment group (C) observe comparatively greater reduction in non-crop income (by approx. BDT 23,601) being consistent with evidences that show decline in agricultural income due to rainfall shocks (e.g., Baez & Mason, 2008; Skoufias, Katayama, & Essama-Nssah, 2012; 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).

The rainfall-based affected group (treatment group B) experienced a fall in both crop and non-crop income (although coefficient of crop income is significant). Although the self-reported affected

[18] See Haile (2005).

[19] 1 US Dollar = 77.88 Bangladeshi Taka (BDT).

Table 1
Impact on household income per capita

Variables	(1) Total income	(2) Crop income	(3) Non-crop income	(4) Business income	(5) Other income
Treatment group A (Self-report)	−1,566.17 (37,329.74)	21,884.21*** (8,328.57)	−4,933.50 (33,804.55)	−16,937.20 (15,403.25)	−1,329.77 (2,070.46)
Treatment group B (Rainfall-based)	−11,665.43 (12,850.91)	−3,455.71* (2,094.36)	−17,499.10 (10,849.45)	6,634.50 (6,593.46)	1,780.13 (1,564.46)
Both treatment group C	70,484.30 (70,701.24)	−3,764.62 (12,313.16)	−23,600.94 (32,642.82)	97,687.97 (59,432.73)	294.26 (4,747.52)
Constant	−3898785.83*** (151,241.77)	−18,342.35 (18,239.77)	−3925239.35*** (134,173.44)	898.32 (47,079.97)	−52,667.38 (39,908.79)
Observations	12,242	12,222	12,232	12,242	12,242
R-squared	0.19	0.12	0.12	0.21	0.05
Treatment group A (Self-report)	332,832.82** (130,063.55)	142,294.50** (66,072.70)	109,491.86 (93,443.48)	78,193.44 (59,470.25)	6,665.53 (7,903.15)
Treatment group B (Rainfall-based)	−32,407.34 (40,347.94)	−13,883.61* (7,825.42)	−41,104.20* (23,314.76)	2,247.68 (23,700.09)	1,127.58 (4,797.41)
Both treatment group C	250,726.57 (250,456.37)	−34,353.69 (31,556.09)	71,339.47 (108,105.23)	212,991.08 (289,247.54)	4,037.39 (9,569.99)
Constant	−3909442.31*** (151,012.71)	−21,563.08 (18,140.35)	−3924719.01*** (134,578.19)	−3,824.37 (47,057.14)	−53,964.73 (40,194.24)
Observations	12,242	12,222	12,232	12,242	12,242
R-squared	0.20	0.13	0.12	0.21	0.05

Source: Author's calculations.
Notes: [a]Robust standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
[b]The upper part of the Table (above the middle line) shows estimation results using Eqn. (1) i.e., regression without interaction terms. The bottom part of the Table (below the middle line) shows estimation results using Eqn. (2) i.e., regression with the interaction terms. All control variables are included in the models, but not displayed.

group (A) observed a fall in total income, there has been a significant increase in crop income. However, crop income decreases by almost BDT 3,765 for both treatment groups (C). The interesting thing to note here is that persistent flooding seems to impact non-crop income in higher magnitude. Our results show that treatment group B (rainfall-based) experienced a drop of almost BDT 12,566 more in non-crop income compared to the treatment group A (self-reported). The other two categories of income we analyze are business and other incomes which are more indirectly affected by flood hazards. Business and other income are found to decrease (not significant) for the self-reported affected households. However, in both of these categories, we observe positive coefficients for affected households who had been identified through rainfall-based identifications.

We extend our analysis on households agricultural income (as assumed to have direct impact through repeated flooding) by further investigating their relationship with rural (defining reliance on agriculture), formal education and ownership of land.[20] Agricultural incomes (crop and non-crop) are found to drop significantly for rainfall-based affected households (B). Crop income is also found to decrease in higher magnitude in both self and non-self-reported cases (but not significant). The interesting thing to note here is that, crop income had increased quite significantly (around 5.6% more) compared to the mean for treatment group A impacting on total income as well.

(b) 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 Table 2. Our results show a significant decline of around 1% compared to the mean in total expenditure per capita (i.e., drop by approx. BDT 14,742) for treatment group B (non-self-reported) being consistent with previous literatures (e.g., Asiimwe & Mpuga, 2007; Auffret, 2003; Dercon, 2004; Foltz, Gars, Özdogan, Simane, & Zaitchik, 2013; Jha, 2006; Shoji, 2010). Our focal categories i.e., crop and agricultural input expenditures (as we assume these categories are directly related to rainfall shocks and flood) show negative impacts for rainfall-based affected households. This evidence, however demonstrates a significant decrease in agricultural input expenditure in particular. Food and non-food expenditures are found to decrease in treatment groups – A and B. However, although both categories show sign consistencies, non-food expenditures are found to be statistically significant for treatment group B. This observation is found to aggravate in further investigations associated with the interactions. This decrease in non-food spending is particularly of concern as it implies the possibility that disasters prevent longer term investments and therefore trap households in cycles of poorer education and health outcomes and persistent poverty (Karim & Noy, 2016b). These evidences turn out to be interesting when we extend our analysis by further investigating the relationship with rural, formal education, and landownership of households.[20] Interestingly, we find that crop expenditure increases significantly for self-reported treatment group (A) (estimated BDT 21,798) whereas non-crop expenditure per capita significantly increases (estimated approx. BDT 37,026) for both rainfall-based and self-reported treatment group (C).

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 longer term impacts. The treatment households (A only and B only) experienced significant contrast in terms of the direct impacts (food and non-food in estimated model with interactions).[21] Positive estimates have been observed in education and health spending for treatment groups A and B as well. However,

[20] Full tables are shown in the appendix and also in an online appendix.

[21] Estimated using Eqn. (2).

Table 2
Impact on household expenditure per capita

Variables	(1) Total exp	(2) Food exp	(3) Non-food exp	(4) Crop exp	(5) Non-crop exp	(6) Agri input exp	(7) Edu exp	(8) Health exp
Treatment group A	19,801.55	−66.47	−2,326.36	2,171.13	5,506.69	9,650.88	2,922.63	2,067.18
(Self-report)	(18,141.33)	(489.80)	(10,839.23)	(2,263.55)	(3,974.32)	(7,286.28)	(3,523.85)	(1,430.33)
Treatment group B	−14,742.40**	−89.76	−6,897.35*	−773.76	624.42	−6,963.83***	−752.76	164.74
(Rainfall-based)	(6,432.06)	(153.68)	(4,145.87)	(930.07)	(1,063.60)	(2,598.86)	(1,160.53)	(323.03)
Both treatment group C	10,980.94	−1,262.74	−14,489.95	181.87	1,460.01	20,035.51	1,641.43	3,364.20
	(45,247.27)	(886.03)	(24,036.11)	(6,207.58)	(4,511.67)	(21,969.91)	(6,914.43)	(3,867.18)
Constant	−1114279.73***	−22,677.58***	−257,176.61***	−102,041.95***	−151,561.73***	−640,434.52***	42,389.94***	5,984.99***
	(54,989.83)	(1,386.18)	(31,418.65)	(8,324.48)	(8,163.02)	(23,707.98)	(8,298.83)	(1,786.27)
Observations	12,242	12,242	12,242	12,222	12,232	12,242	12,242	12,242
R-squared	0.63	0.92	0.52	0.36	0.25	0.31	0.27	0.04
Treatment group A	109,304.40	−893.17	24,065.29	21,798.01***	23,606.10	29,781.65	8,633.44	3,046.33
(Self-report)	(66,457.58)	(1,842.23)	(38,785.57)	(7,093.41)	(32,813.66)	(26,748.11)	(11,254.61)	(3,285.08)
Treatment group B	−30,077.56	−471.48	−28,168.21**	−3,412.53	9,460.94	−3,632.92	−3,452.94	204.28
(Rainfall-based)	(24,804.11)	(585.81)	(14,352.09)	(2,967.95)	(8,839.87)	(9,704.29)	(3,460.80)	(856.08)
Both treatment group C	110,647.41	−975.08	8,624.64	−11,033.88	37,025.74*	82,551.46	−17,473.19	12,004.26
	(190,050.55)	(3,115.48)	(90,739.61)	(12,885.29)	(21,240.47)	(81,685.85)	(20,801.70)	(13,917.93)
Constant	−1117883.19***	−22,543.11***	−257,255.92***	−102,577.12***	−153,919.47***	−641,350.11***	42,321.43***	5,901.83***
	(55,285.22)	(1,394.69)	(31,353.61)	(8,307.50)	(8,140.76)	(23,813.61)	(8,316.00)	(1,793.13)
Observations	12,242	12,242	12,242	12,222	12,232	12,242	12,242	12,242
R-squared	0.63	0.92	0.52	0.36	0.25	0.31	0.27	0.04

Source: Author's calculations.
Notes: [a]Robust standard errors in parentheses $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. [b]The upper part of the Table (above the middle line) shows estimation results using Eqn. (1) i.e., regression without interaction terms. The bottom part of the Table (below the middle line) shows estimation results using Eqn. (2) i.e., regression with the interaction terms. All control variables are included in the models, but not displayed.

Table 3
Impact on total asset outcomes

Variables	(1) Total change in agricultural and other business asset	(2) Total agricultural input asset value	(3) Total consumer durable asset value
Treatment group A (Self-report)	−1,990.73 (33,184.36)	−15,691.41 (14,723.87)	−17,421.92 (88,561.35)
Treatment group B (Rainfall-based)	4,475.63 (12,235.93)	−6,620.57 (5,435.37)	25,310.38 (30,435.15)
Both treatment group C	11,009.94 (69,402.10)	−16,831.74 (21,241.71)	−154,958.27 (122,824.84)
Constant	−633,711.13*** (103,531.85)	−184,938.08*** (36,826.19)	−1197123.52*** (234,716.60)
Observations	12,242	12,242	12,242
R-squared	0.02	0.07	0.23
Treatment group A (Self-report)	111,132.59 (75,127.02)	90,455.01* (47,600.49)	−256,836.22 (220,139.63)
Treatment group B (Rainfall-based)	−28,898.86 (30,787.83)	3,374.68 (15,521.03)	−7,225.67 (91,144.36)
Both treatment group C	−178,097.20* (101,758.84)	−82,060.72 (57,755.00)	−291,623.55 (469,256.70)
Constant	−637,696.80*** (103,626.07)	−191,216.45*** (36,935.21)	−1195841.23*** (235,092.39)
Observations	12,242	12,242	12,242
R-squared	0.02	0.07	0.24

Source: Author's calculations.
Notes: [a]Robust standard errors in parentheses $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. [b]The upper part of the Table (above the middle line) shows estimation results using Eqn. (1) i.e., regression without interaction terms. The bottom part of the Table (below the middle line) shows estimation results using Eqn. (2) i.e., regression with the interaction terms. All control variables are included in the models, but not displayed.

the rainfall-based affected households experienced a decrease in educational expenditure (approximately by BDT 3,453) compared to a sharp decrease by both flood treatment households (C) (estimated approx. by BDT 17,473). Intriguingly, the total expenditure in the self-reported treatment group (A) increases (although not significant) compared to a significant decline for the non-self-reported group in our benchmark estimation.

(c) Asset

Table 3 demonstrates 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. Both treatment group (C) experienced significant negative impacts (estimated by BDT 178,097) on change in agricultural and other business asset quite consistent with previous evidences on asset categories (e.g., Anttila-Hughes & Solomon, 2013; Mogues, 2011). Intriguingly, the self-reported flood affected group (treatment group A) observe significant positive impacts (estimated by BDT 90,455) in the category representing agricultural input asset value. These evidences are particularly valid when we incorporate interaction terms in our estimated model.[20] Nevertheless, the self-reported flood treatment households (A) experienced a decline on change in agricultural and other business assets when the estimated model do not account for the interaction terms.

(d) Labor market

We present impacts on labor market for both treatment groups – A and B in Table 4 and our results reveal contrasts in households experiences. Daily wages are not found to be severely affected (positive impact) with statistical significance for rainfall-based flood treatment households (estimated by BDT 146).[22] This somewhat has been justified in some previous empirical researches (e.g., Banerjee, 2007; Shah & Steinberg, 2012).[23] However, real wages are found to decrease for flood-affected (self-reported) households in both estimations 1 and 2 (but in this case without statistical significance). Interestingly, salaried wage seems 2.7% higher compared to the mean (estimated approx. BDT 2,969) in treatment group A with 0.3% drop (compared to the mean) for treatment group B but without statistical significance as well.[24] This result is also partially found consistent with the findings of Mueller and Quisumbing (2011). The other labor market outcomes are found to significantly improve for flood-affected (rainfall-based) households when the estimated model (Eqn. (2)) interacted with rural, formal education and land ownership status.[20] We also observe a contrast in estimates of yearly benefits for treatment groups – A and B.

(e) Control variables

We present the coefficients of the control variables for the main variables of interest in Table 5.[20] The coefficients of the control variables do not vary substantially in terms of sign and significance for treatment groups – A, B, and C. Among the controls; male-headed households, average age, and formal education seem to have a stronger positive association (highly significant) with total income and total expenditure per capita in addition to community characteristic such as access to sanitation. Ownership of land demonstrates a stronger positive impact (highly significant) on per capita total expenditure. It is more likely that the household heads possess control over ownership of land and house.[25] However, the number of dependents displays a stronger negative association with total expenditure as evident in the literatures as well. We also anticipate similar reasoning as of previous literatures for

[22] Estimated using Eqn. (2).

[23] 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.

[24] Estimated using Eqn. (1).

[25] See Zaman (1999).

Table 4
Impact on labor market outcomes

Variables	(1) Total month per year	(2) Total days per month	(3) Total hours per day	(4) Daily wage	(5) Salaried wage	(6) Yearly benefits
Treatment group A	−1.03	−5.56	−1.60	−69.98	2,969.25	5,611.90
(Self-report)	(5.50)	(12.53)	(4.02)	(61.39)	(2,771.30)	(5,455.67)
Treatment group B	2.92	9.61**	1.74	26.60	−356.90	−2,381.25
(Rainfall-based)	(1.94)	(4.53)	(1.52)	(22.82)	(936.56)	(1,954.30)
Both treatment group C	−15.43	−16.51	−10.98	−77.83	−243.26	7,051.62
	(9.39)	(24.12)	(7.63)	(125.25)	(6,422.49)	(12,622.45)
Constant	−339.91***	−829.15***	−246.68***	773.85***	−121,717.37***	−287,370.86***
	(19.96)	(44.49)	(13.77)	(183.22)	(7,021.86)	(14,980.65)
Observations	12,242	12,242	12,242	12,242	12,242	12,242
R-squared	0.87	0.87	0.87	0.54	0.35	0.21
Treatment group A	1.85	−3.30	−6.16	−256.80	2,432.84	24,475.78
(Self-report)	(19.25)	(42.47)	(13.81)	(190.89)	(9,676.01)	(17,064.58)
Treatment group B	16.67**	26.18*	10.35**	146.17*	−1,858.83	−6,788.29
(Rainfall-based)	(6.91)	(15.46)	(5.07)	(76.18)	(3,296.66)	(6,395.29)
Both treatment group C	−25.53	−23.47	7.65	−594.95	−374.09	9,007.80
	(31.79)	(79.09)	(29.26)	(416.49)	(22,900.16)	(42,232.08)
Constant	−341.74***	−831.20***	−247.55***	775.72***	−121,591.01***	−287,205.30***
	(20.36)	(45.04)	(13.93)	(186.37)	(7,032.51)	(14,982.38)
Observations	12,242	12,242	12,242	12,242	12,242	12,242
R-squared	0.87	0.87	0.87	0.54	0.35	0.21

Source: Author's calculations.
Notes: [a]Robust standard errors in parentheses $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. [b]The upper part of the Table (above the middle line) shows estimation results using Eqn. (1) i.e., regression without interaction terms. The bottom part of the Table (below the middle line) shows estimation results using Eqn. (2) i.e., regression with the interaction terms. All control variables are included in the models, but not displayed.

Table 5
Effects of controls on outcome variables

Variables	(1) Total income	(2) Total exp	(3) Asset stock	(4) Daily wage	(5) Total income	(6) Total exp	(7) Asset stock	(8) Daily wage
Rural	3,246.72	−2,452.84	−19,365.10*	21.61	10,588.13	−1,802.73	−14,252.62	10.61
	(13,260.48)	(5,785.10)	(10,920.89)	(20.06)	(14,485.90)	(6,285.55)	(11,702.90)	(21.82)
Male-headed HH	2,370,129.94***	392,158.61***	−5,389.58	−1,546.64***	2,368,798.65***	391,391.05***	−8,218.23	−1,541.51***
	(71,988.86)	(18,834.92)	(22,300.52)	(70.46)	(71,878.91)	(18,671.89)	(22,034.97)	(71.77)
Average age	57,433.59***	29,019.50***	25,045.10***	30.07***	57,682.42***	29,159.82***	25,416.28***	29.37***
	(5,128.94)	(2,439.89)	(4,168.51)	(7.92)	(5,132.86)	(2,415.98)	(4,157.71)	(8.00)
Dependent	−96.50	−2,413.53***	5,188.91***	10.99***	−90.86	−2,399.32***	5,228.63***	10.94***
	(728.14)	(342.55)	(791.12)	(1.33)	(727.59)	(341.96)	(790.41)	(1.34)
Formal education	11,329.07***	20,519.20***	−3,548.28***	38.48***	11,341.01***	20,513.60***	−3,649.11***	38.76***
	(866.99)	(421.58)	(944.08)	(1.65)	(872.70)	(420.18)	(945.78)	(1.66)
Access to sanitation	42,722.54***	17,254.61***	4,356.36	−42.37**	43,113.45***	17,293.25***	4,299.30	−42.27**
	(11,057.01)	(5,193.54)	(9,517.48)	(17.95)	(11,035.25)	(5,193.54)	(9,519.76)	(17.96)
Access to safe drinking water	17,101.60	8,929.27	−37,269.07	−35.25	17,789.45	9,517.59	−38,126.05	−36.23
	(28,182.97)	(13,160.49)	(28,588.08)	(45.52)	(28,262.85)	(13,168.53)	(28,610.75)	(45.58)
Access to electricity	3,600.44	8,376.70	−8,381.50	15.66	3,523.53	8,420.74	−8,129.74	15.70
	(12,373.04)	(5,550.28)	(10,063.28)	(19.20)	(12,379.56)	(5,550.62)	(10,016.54)	(19.21)
House ownership	6,480.10	919.13	9,091.28	3.63	6,097.00	994.99	9,210.96	3.80
	(14,178.52)	(6,574.19)	(12,448.63)	(22.71)	(14,170.55)	(6,575.79)	(12,464.21)	(22.73)
Land ownership	56.47	126.65***	36.87	−0.20***	35.75	105.74***	11.72	−0.16**
	(37.49)	(20.49)	(46.59)	(0.06)	(41.86)	(22.18)	(43.81)	(0.07)
Constant	−3898785.83***	−1114279.73***	−633,711.13***	773.85***	−3909442.31***	−1117883.19***	−637,696.80***	775.72***
	(151,241.77)	(54,989.83)	(103,531.85)	(183.22)	(151,012.71)	(55,285.22)	(103,626.07)	(186.37)
Observations	12,242	12,242	12,242	12,242	12,242	12,242	12,242	12,242
R-squared	0.19	0.63	0.02	0.54	0.20	0.63	0.02	0.54

Source: Author's calculations.
Notes: [a]Robust standard errors in parentheses $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. [b]Each column shows the effects of the control variables in the estimated regression results. The first four columns (i.e., columns 1–4) show the estimation results using Eqn. (1) i.e., regression without interaction terms for the main variables of interest. The last four columns (i.e., columns 5–8) show the estimation results using Eqn. (2) i.e., regression with the interaction terms. The variable "Asset Stock" represents total change in agricultural and other business asset in both columns 3 and 7. All other variables are included in the models, but not displayed.

observing the control variables to be in expected directions for asset categories and labor market outcomes. The directions of the control variables are also found quite similar when the model has been estimated by incorporating the interaction terms (Eqn. (2)).

(f) Interaction terms

To further investigate whether household characteristics e.g., rural, formal education and landownership status have impacted declines in the development dimensions; we estimate our model

Table 6
Coefficients of the interaction terms of main outcome variables of interest

Variables	(1) Total income	(2) Total exp	(3) Asset stock	(4) Daily wage
Treatment group A*Education	−3,426.55***	−1,586.93*	−1,959.09**	2.71
	(1,277.09)	(843.68)	(942.53)	(2.46)
Treatment group B*Education	377.46	147.16	559.43	−1.84*
	(474.31)	(318.76)	(402.79)	(0.97)
Treatment group A*Landownership	−1.33	111.22	−339.02*	−0.34
	(142.78)	(155.19)	(192.74)	(0.56)
Treatment group B*Landownership	153.40*	131.33***	228.12	−0.25
	(88.02)	(48.84)	(196.41)	(0.18)
Treatment group A*Rural	−105,290.92	36,706.85	90,296.50	4.07
	(103,140.17)	(42,104.29)	(65,845.48)	(138.43)
Treatment group B*Rural	−28,266.56	−6,592.90	−37,888.60	60.27
	(26,892.41)	(13,508.65)	(27,284.49)	(48.49)
Both treatment C*Education	13.84	−307.93	4,540.33	2.14
	(3,046.68)	(2,278.24)	(3,247.31)	(5.70)
Both treatment C*Landownership	216.98	177.94	−187.55	−0.42
	(475.39)	(205.67)	(197.76)	(0.52)
Both treatment C*Rural	−285,759.28*	−124,226.08	−254,137.66	540.58*
	(154,600.41)	(95,121.54)	(222,356.04)	(290.29)
Constant	−3909442.31***	−1117883.19***	−637,696.80***	775.72***
	(151,012.71)	(55,285.22)	(103,626.07)	(186.37)
Observations	12,242	12,242	12,242	12,242
R-squared	0.20	0.63	0.02	0.54

Source: Author's calculations.
Notes: [a]Robust standard errors in parentheses ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. [b]Each column shows the coefficients of the interaction terms in the estimated regression results of main outcome variables of interest (i.e., estimated using Eqn. (2)). The variable "Asset Stock" represents total change in agricultural and other business asset in column 3. All other variables are included in the models, but not displayed.

(Eqn. (2)) by incorporating the interaction terms. Table 6 present only the results of the interplay among the identified treatment groups – A, B, and C with rural, formal education, and landownership status.[20] Interestingly, when the interaction terms are included in the model, they seem to increase both the main effects of the treatment groups and the respective control variables. When interacted with rural, treatment group C experienced lower total income but higher daily wage with the latter indicating coping and/or adaptation strategy e.g., diversifying livelihoods and income source. The interaction terms between self-reported flood treatment households and education in total income and total expenditure per capita are found to be negative and statistically significant. Alternatively, education has a positive influence on disaster preparedness only for those who have not yet experienced a disaster in the past (Hoffmann & Muttarak, 2017). Landownership seems to play a crucial role for the rainfall-based flood treatment households. The coefficients of the interaction terms for per capita total income and expenditure between treatment group B and landownership are found to be positive and statistically significant (not in higher magnitude) and are also consistent with previous literatures (e.g., Kurosaki, 2015) (see Tables 8–13).

7. Robustness checks

As robustness checks, we further examine these impacts by pooling the data for the years 2000, 2005, and 2010 and compare the results with our benchmark estimations. As self-reported data were unavailable for years' 2000 and 2005; we therefore, estimate Eqns. (1) and (2) through identifications of flood treatment households using rainfall-based disaster risk measure only to check robustness of our main results.[26] We also add year fixed effects in our estimated models.[27]

In the income category, we observe significantly negative impacts on non-crop income (drop by approx. BDT 8,497)[28] due to persistent flood hazard. The interesting aspect to note here is that agricultural income (in particular, non-crop income) is found to decline more (additional drop by around BDT 9,402) in our focal year 2010 for flood-treatment households that are rainfall-based only. However, business income is found to increase significantly when the estimated model interacted with rural, formal education, and landownership status (Eqn. (2)). Our findings also reveal a significant positive increase in other income category with no interactions being consistent with our prior estimations.

We find consistency in the robust coefficients in total expenditure category compared to our baseline model specifications. Flood treatment households experienced a significant decline in total expenditure, in particular non-food and agricultural input expenditure (Eqn. (1)). These impact evidences are found to exacerbate when food expenditures are also observed to decrease significantly.[29] The noticeable aspect here is that findings reveal an additional decline in agricultural input expenditure (estimated around BDT 4,606) significantly contributing to an excess decline in total expenditure (by approx. BDT 10,225) for flood treatment households (rainfall-based). Non-food expenditures also seems to contribute to this overall expenditure decline (an additional drop by approx. BDT 4,238) and are found consistent with the benchmark estimation results. Educational and health expenditures are also found to be consistent with our prior estimations.

The impacts on agricultural input asset value display negative impacts on treatment households (rainfall-based flood risk measure) that are found consistent with the benchmark results. Interestingly, the impacts on changes in agricultural and other business asset category exhibit positive coefficient (not significant) compared to a decline in prior estimation results.[30] The category on consumer durable asset value also illustrates consistency in the esti-

[26] The full tables of the robustness check estimation results are shown in the appendix and also in an online appendix.
[27] We estimate the following equation and extend by adding the interaction terms (as of Eqn. (2)) to check robustness of our main results: $y_{ijt} = \alpha_t + \beta_2\ \beta_{ijt} + \gamma\ (X_{ijt}) + u_{ijt}$.
[28] Estimated using Eqn. (1) i.e., without interaction terms.
[29] This is evident when the estimated model interacted with landownership, rural and formal education of households.
[30] Estimated using Eqn. (2).

mated coefficients for flood treatment households. The various outcomes of the labor market do not seem to significantly vary with prior estimations as well.

8. Conclusion

Our objective in this paper is to estimate the impacts of recurrent flooding on income, expenditure, asset, and labor market outcomes. We start with identification of the treatment (affected) groups adopting two measures of disaster risk exposure i.e., using self-reported flood hazard data and non-self-reported (historical rainfall-based flood risk index) information in year 2010. We examine a parsimonious model to directly compare the short-run impacts of climatic disaster (i.e., repeated flood hazard) on households socio-economic outcomes. Our results suggest a decline in agricultural income (crop and non-crop) for both treatment groups – A (self-reported) and B (rainfall-based). 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 especially in agriculture-based economy like Bangladesh. As per expenditure in concerned, we also observe a negative response to crop and agricultural input expenditure in our focal categories (as we assume these categories are directly related to rainfall shocks and flood) and are found consistent with our theoretical prior for rainfall-based flood treatment households. In particular, this evidence demonstrates a significant decrease in agricultural input expenditure for treatment group B. A sharp decline in non-food spending for these treatment households is also of policy concern as this suggests decreased spending in health and education impacting longer term investment.[31]

We extend our analysis by further interacting treatment groups with household characteristics such as rural, formal education, and ownership of land status. The interaction terms seem to increase both the main effects of the treatment groups and the respective control variables. Agricultural incomes (crop and non-crop) are found to drop significantly for rainfall-based affected households (B). Interestingly, we find that crop expenditure increases significantly for self-reported flood treatment households whereas non-crop expenditure per capita significantly increases for households who have both self-reported and identified through geographical exposure (C). We further strengthen our results pooling data from the earlier years i.e., 2000, 2005, and 2010 as robustness checks and observe consistencies in most cases with our benchmark estimation results. We however, only use the rainfall-based index measure in our robustness check due to unavailability of self-reported data in years 2000 and 2005.

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, literatures have identified shortcomings in self-reporting and various determinants of flood risk perception. The dissimilarities in the results in terms of the development impacts on flood treatment households using different measures of disaster risk exposure might be due to the various shortcomings identified in the literatures. Moreover, 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.[32] There is an obvious need to employ both qualitative and quantitative techniques to understand the degrees of experience in impact analysis.[33] One possible solution is, of course, more respondents and data availability in addition to incorporating degrees of actual hazard awareness, experience, and preparedness questions to identify the real affected group in repeated natural shocks. There is a need to thoroughly analyze the inconsistencies in the robust research findings based on the shortcomings identified in the literature. However, the evidence and the novel approach that we adopt in this paper could justify future research in estimating welfare impacts of climate-induced persistent natural events in developing countries.

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Appendix A

Construction of rainfall-based flood risk index

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).[34] 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 station. We next calculated the mean and standard deviation for each month for each sub-district by matching weather stations with sub-districts.[35] 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% 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.[36] We calculate the average number of months with extreme rainfall to obtain the

[31] See Karim & Noy, 2016b for a detailed analysis on this issue.

[32] See Hawkes and Rowe (2008).

[33] See Bird (2009).

[34] The available data were for the years 1948–2012.

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

[36] 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.

Table 7
Key variables with descriptive statistics (treatment and control group a, treatment and control group b)

Variables	Type	Mean standard deviation				Description of variables
Outcome variables		Treatment A	Control A	Treatment B	Control B	
Per capita total income	Continuous	911940.4 606662.3	926187.1 641924.1	910175.2 581756.4	928971.5 652139.9	Sum of per capita crop, non-crop, business and other incomes
Per capita crop income	Continuous	194200.9 120641.9	172257.1 94183.72	169420 91191.19	173286.1 95445.03	Per capita income earned through selling of crops
Per capita non-crop income	Continuous	233546.5 537408.4	248931.6 543124.3	230389.3 456983.5	252173 558031.4	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	468905.9 255953.5	488696 296302.3	493480 303387.3	487336.6 294090.6	Per capita net revenues earned from non-agricultural enterprises and rental income from agricultural assets
Per capita other income	Continuous	15287.03 31811.08	16796.23 51837.51	18149.76 66344.03	16501.34 48152.93	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	1454900 431931.9	1441364 434467.7	1426657 431057.4	1444506 435013.9	Sum of per capita food, non-food, crop, non-crop, agricultural input, education and health expenditures
Per capita food expenditure	Continuous	85007.71 23346.4	85364.12 22095.96	85224.26 22023.35	85383.35 22137.98	Per capita daily and weekly food consumption
Per capita non-food expenditure	Continuous	737893.7 236691.1	742763.1 242337.5	736179.2 243034.8	743929.7 242061.4	Per capita monthly and annual non-food consumption
Per capita crop expenditure	Continuous	107859.9 41673.97	106216.5 46624.14	105621.7 47004.28	106367.3 46447.4	Per capita crop consumption by household
Per capita non-crop expenditure	Continuous	96695 62587.95	92351.51 46292.79	92745.11 48930.08	92370.86 46192.2	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	292600.7 132586.7	285233.4 129633	278433.5 126025.8	286710.1 130345.6	Per capita expenses on agricultural inputs
PER CAPITA EDUCATIONAL EXPENDITURE	Continuous	121299.4 60326.1	118282.5 56320.71	117582.6 55490.5	118484 56570.64	Per capita expenditure for educational services
Per capita health expenditure	Continuous	13543.29 21518.79	11406.69 12382.97	11530.68 13545.26	11429.57 12424.67	Per capita expenditure for health services
Total change in agricultural and other business asset (in real terms)	Continuous	174977.2 491300.3	185579.5 497618.8	188845 504566.3	184715.4 496126.6	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	222404.2 221172.2	237534.1 248540	232030.2 225549.4	238266.7 252185	Value of owned equipment and asset used in agriculture
Total consumer durable asset value (in real terms)	Continuous	2976063 1500622	3019571 1413280	3037415 1413003	3015165 1415285	Total asset value of consumer durable goods
Total month per year worked	Continuous	801.2356 227.3714	806.6025 217.8752	808.5736 214.9811	806.1035 218.6407	Total number of months per year worked
Total days per month worked	Continuous	1784.529 512.2758	1800.281 489.88	1807.041 487.7013	1798.628 490.7934	Total number of days per month worked.
Total hours per day worked	Continuous	617.1022 174.0195	621.6139 166.3709	622.7273 165.55	621.2996 166.7001	Total number of hours per day worked
Daily wage (in real terms)	Continuous	3852.178 1414.781	3941.571 1354.073	3965.141 1331.947	3935.052 1359.669	Daily wage in cash (if paid daily)
Salaried wage (in real terms)	Continuous	108128.6 50919.97	105938.3 47547.04	105521 47314.31	106067.1 47668.63	Total net take-home monthly remuneration after all deduction at source
Yearly benefits (in real terms)	Continuous	138585.8 90501.7	134053.7 88512.07	131762.1 88682.74	134596.3 88518.13	Total value of yearly in-kind or other benefits (tips, bonuses or transport) from employment.
Covariates						
Rural	Binary	0.675556 0.469211	0.63976 0.48009	0.626008 0.483984	0.643205 0.479077	Whether living in a rural area = 1, otherwise 0
Head of household is male	Binary	1.004444 0.066667	1.003994 0.066918	1.00252 0.067322	1.004289 0.066831	Whether head of the household is male = 1, otherwise 0
Average age	Continuous	26.4378 1.347331	26.67 1.386957	26.63367 1.643582	26.67193 1.331109	Average age of household members
Dependent	Continuous	90.41333 24.58355	90.62736 24.16744	90.70716 24.26731	90.60723 24.15725	Age of the household member is <15 and ≥65
Proportion of formal education	Continuous	76.81407 19.83074	76.97305 19.25972	76.95353 19.29904	76.97334 19.26478	Proportion of household members attended school, college, university or madrasa
Access to sanitation	Binary	0.488889 0.500991	0.528168 0.499227	0.524194 0.49954	0.528076 0.499236	Whether the household use sanitary or pacca latrines (water seal and pit) = 1, otherwise 0
Access to safe drinking water	Binary	0.991111 0.09407	0.963968 0.186378	0.970262 0.169906	0.963346 0.187921	Whether the household has access to supply water or tube well water = 1, otherwise 0
Access to electricity	Binary	0.608889 0.489087	0.575934 0.494221	0.571573 0.494976	0.577501 0.493981	Whether the household has got electricity connection = 1, otherwise 0
House ownership	Binary	0.857778 0.350057	0.809603 0.392631	0.806452 0.395179	0.811269 0.391314	Whether the household own a house = 1, otherwise 0
Land ownership (in real terms)	Continuous	69.48 128.0451	62.74894 128.9109	61.85938 121.0524	63.06863 130.3597	Amount of total operating land (in acres)

Source: Author's calculations and elaborations.

Table 8
Impact on household income per capita

Variables	(1) Total income	(2) Crop income	(3) Non-crop income	(4) Business income	(5) Other income
Treatment group A	332,832.82**	142,294.50**	109,491.86	78,193.44	6,665.53
(Self-report)	(130,063.55)	(66,072.70)	(93,443.48)	(59,470.25)	(7,903.15)
Treatment group B	−32,407.34	−13,883.61*	−41,104.20*	2,247.68	1,127.58
(Rainfall-based)	(40,347.94)	(7,825.42)	(23,314.76)	(23,700.09)	(4,797.41)
Both treatment group C	250,726.57	−34,353.69	71,339.47	212,991.08	4,037.39
	(250,456.37)	(31,556.09)	(108,105.23)	(289,247.54)	(9,569.99)
Rural	10,588.13	2,848.28	11,912.35	−2,120.64	−3,122.61**
	(14,485.90)	(2,177.35)	(12,997.85)	(6,267.27)	(1,264.07)
Male headed HH	2,368,798.65***	11,914.41***	2,490,203.56***	−78,471.56***	36,387.45
	(71,878.91)	(1,669.76)	(10,589.02)	(4,771.17)	(36,918.57)
Avg age	57,682.42***	1,698.52***	54,323.07***	1,159.21	522.45*
	(5,132.86)	(604.68)	(5,414.47)	(1,798.51)	(301.25)
Dependent	−90.86	101.30	4,633.54***	−4,768.54***	−7.79
	(727.59)	(97.28)	(557.06)	(516.23)	(52.47)
Proportion_formal education	11,341.01***	1,581.53***	−2,684.13***	12,438.64***	−9.55
	(872.70)	(122.12)	(646.46)	(646.73)	(63.21)
Access_sanitation	43,113.45***	5,138.40***	17,808.24*	6,257.87	13,642.42***
	(11,035.25)	(1,749.42)	(9,757.08)	(5,074.56)	(808.18)
Access_drinking water	17,789.45	−4,721.25	2,483.01	16,305.28	3,296.77**
	(28,262.85)	(4,847.53)	(25,741.41)	(11,427.32)	(1,373.56)
Access_electricity	3,523.53	2,720.74	−7,322.33	−4,293.78	11,884.05***
	(12,379.56)	(1,878.93)	(11,128.56)	(5,419.89)	(827.41)
House ownership	6,097.00	1,485.33	1,106.72	−2,103.23	6,006.25***
	(14,170.55)	(2,212.30)	(12,431.79)	(6,588.55)	(1,335.07)
Land ownership	35.75	51.92***	−38.66	2.29	21.41***
	(41.86)	(10.05)	(35.27)	(19.71)	(3.54)
Interaction_edu*self	−3,426.55***	−1,541.98*	−547.17	−1,246.72	−138.35
	(1,277.09)	(797.44)	(528.88)	(769.64)	(102.86)
Interaction_edu*rain	377.46	73.70	277.13	143.83	89.13
	(474.31)	(100.56)	(231.69)	(314.11)	(64.34)
Interaction_land*self	−1.33	−73.89	26.56	74.79	−27.98**
	(142.78)	(51.88)	(117.67)	(85.74)	(11.88)
Interaction_land*rain	153.40*	19.84	65.61	79.40	−11.00*
	(88.02)	(18.30)	(63.88)	(53.63)	(6.47)
Interaction_rural*self	−105,290.92	4,794.74	−109,936.88	−6,766.19	6,706.57
	(103,140.17)	(17,866.76)	(98,365.55)	(36,778.21)	(4,377.83)
Interaction_rural*rain	−28,266.56	5,564.84	−2,883.13	−18,448.15	−8,784.48**
	(26,892.41)	(4,424.02)	(22,237.89)	(14,453.90)	(3,935.12)
Interaction_edu*both	13.84	600.20	−534.65	−112.16	19.12
	(3,046.68)	(523.88)	(1,343.91)	(3,118.24)	(181.29)
Interaction_land*both	216.98	−74.37**	151.12	143.02	−4.19
	(475.39)	(37.38)	(112.73)	(433.10)	(18.90)
Interaction_rural*both	−285,759.28*	−21,735.52	−87,400.23	−168,448.08	−7,538.56
	(154,600.41)	(31,745.12)	(87,197.53)	(113,814.19)	(14,271.53)
Constant	−3909442.31***	−21,563.08	−3924719.01***	−3,824.37	−53,964.73
	(151,012.71)	(18,140.35)	(134,578.19)	(47,057.14)	(40,194.24)
Observations	12,242	12,222	12,232	12,242	12,242
R-squared	0.20	0.13	0.12	0.21	0.05

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

Table 9
Impact on household expenditure per capita

Variables	(1) Total exp	(2) Food exp	(3) Non-food exp	(4) Crop exp	(5) Non-crop exp	(6) Agri input exp	(7) Edu exp	(8) Health exp
Treatment group A	109,304.40	−893.17	24,065.29	21,798.01***	23,606.10	29,781.65	8,633.44	3,046.33
(Self-report)	(66,457.58)	(1,842.23)	(38,785.57)	(7,093.41)	(32,813.66)	(26,748.11)	(11,254.61)	(3,285.08)
Treatment group b	−30,077.56	−471.48	−28,168.21**	−3,412.53	9,460.94	−3,632.92	−3,452.94	204.28
(Rainfall-based)	(24,804.11)	(585.81)	(14,352.09)	(2,967.95)	(8,839.87)	(9,704.29)	(3,460.80)	(856.08)
both treatment group c	110,647.41	−975.08	8,624.64	−11,033.88	37,025.74*	82,551.46	−17,473.19	12,004.26
	(190,050.55)	(3,115.48)	(90,739.61)	(12,885.29)	(21,240.47)	(81,685.85)	(20,801.70)	(13,917.93)
Rural	−1,802.73	−242.36	−3,407.63	373.74	1,560.82*	1,948.22	−2,257.43**	189.02
	(6,285.55)	(150.46)	(3,971.61)	(883.11)	(913.55)	(2,598.06)	(1,143.68)	(267.27)
Male Headed HH	391,391.05***	5,186.41***	3,699.66	34,917.76***	42,366.12***	303,488.83***	−2,049.84*	2,951.47***
	(18,671.89)	(460.12)	(9,928.50)	(757.43)	(709.18)	(8,601.82)	(1,108.28)	(324.14)
Avg age	29,159.82***	671.78***	11,272.68***	2,159.28***	3,988.52***	13,060.39***	−1,233.69***	−305.68***
	(2,415.98)	(61.62)	(1,386.27)	(311.37)	(264.12)	(933.72)	(302.28)	(59.24)
Dependent	−2,399.32***	−166.58***	−2,661.61***	−316.63***	234.31***	1,625.64***	−1,087.52***	2.60
	(341.96)	(10.28)	(180.25)	(99.47)	(44.56)	(134.08)	(53.06)	(11.00)

(*continued on next page*)

Table 9 (*continued*)

Variables	(1) Total exp	(2) Food exp	(3) Non-food exp	(4) Crop exp	(5) Non-crop exp	(6) Agri input exp	(7) Edu exp	(8) Health exp
Proportion_formal education	20,513.60***	1,292.96***	12,034.98***	1,806.85***	928.99***	1,549.82***	2,741.30***	128.32***
	(420.18)	(12.64)	(222.66)	(124.28)	(63.13)	(163.31)	(62.75)	(12.46)
Access_sanitation	17,293.25***	117.35	6,720.77**	1,167.83	1,946.89**	6,901.97***	741.57	−347.54
	(5,193.54)	(125.61)	(3,316.55)	(725.81)	(796.11)	(2,103.76)	(932.48)	(237.55)
Access_drinking water	9,517.59	273.53	3,805.46	2,711.73	1,026.78	1,442.23	124.06	141.81
	(13,168.53)	(316.18)	(8,210.24)	(1,843.18)	(2,367.63)	(5,550.99)	(2,551.95)	(532.75)
Access_electricity	8,420.74	376.49***	8,771.70**	56.34	414.91	−1,847.10	241.60	338.17
	(5,550.62)	(133.52)	(3,524.65)	(763.14)	(837.94)	(2,274.92)	(998.96)	(262.60)
House ownership	994.99	−166.91	806.85	1,243.84	718.72	−662.14	−1,317.05	372.74
	(6,575.79)	(158.83)	(4,179.84)	(950.78)	(960.10)	(2,642.09)	(1,261.40)	(269.49)
Land ownership	105.74***	1.98***	15.31	19.06***	9.50***	53.11***	7.21*	−0.46
	(22.18)	(0.50)	(12.64)	(3.48)	(3.03)	(10.65)	(3.96)	(0.76)
Interaction_edu*self	−1,586.93*	7.00	−587.34	−240.48***	−314.78	−354.30	−69.40	−36.78
	(843.68)	(22.81)	(477.28)	(85.77)	(434.43)	(337.07)	(115.75)	(38.18)
Interaction_edu*rain	147.16	1.96	249.64	34.98	−104.70	−67.41	35.44	−8.49
	(318.76)	(7.56)	(184.61)	(43.20)	(104.74)	(122.33)	(42.05)	(9.42)
Interaction_land*self	111.22	3.04	101.79	18.53	−18.21	42.81	−25.66	−11.37
	(155.19)	(3.91)	(81.16)	(14.57)	(20.41)	(90.36)	(19.28)	(7.65)
Interaction_land*rain	131.33***	−0.78	68.11*	8.54	15.11*	21.03	17.64**	1.50
	(48.84)	(1.30)	(34.78)	(10.04)	(8.14)	(22.58)	(8.04)	(2.26)
Interaction_rural*self	36,706.85	117.90	17,354.04	−3,606.60	10,884.55	6,127.46	2,088.09	3,912.85
	(42,104.29)	(1,053.46)	(24,960.06)	(5,193.34)	(8,662.20)	(15,892.27)	(8,463.01)	(2,734.17)
Interaction_rural*rain	−6,592.90	443.68	−3,455.71	−941.26	−2,704.26	879.13	−1,783.21	827.14
	(13,508.65)	(323.38)	(8,710.50)	(2,028.72)	(2,307.33)	(5,467.69)	(2,477.04)	(635.08)
Interaction_edu*both	−307.93	10.76	255.17	197.26	−425.43	−469.93	261.43	−139.77
	(2,278.24)	(40.58)	(1,209.62)	(179.59)	(267.90)	(964.24)	(272.62)	(177.90)
Interaction_land*both	177.94	−9.56*	295.31**	18.03	14.48	−135.72**	11.18	−15.51
	(205.67)	(4.89)	(127.41)	(25.91)	(16.14)	(61.45)	(62.09)	(21.35)
Interaction_rural*both	−124,226.08	−1,021.28	−86,641.55*	−8,501.37	−2,720.75	−26,390.71	−4,019.46	5,161.58
	(95,121.54)	(1,850.98)	(50,266.06)	(11,330.75)	(10,575.23)	(55,480.81)	(11,952.45)	(8,642.57)
Constant	−1117883.19***	−22,543.11***	−257,255.92***	−102,577.12***	−153,919.47***	−641,350.11***	42,321.43***	5,901.83***
	(55,285.22)	(1,394.69)	(31,353.61)	(8,307.50)	(8,140.76)	(23,813.61)	(8,316.00)	(1,793.13)
Observations	12,242	12,242	12,242	12,222	12,232	12,242	12,242	12,242
R-squared	0.63	0.92	0.52	0.36	0.25	0.31	0.27	0.04

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

Table 10
Impact on total asset outcomes

Variables	(1) Asset stock	(2) Agri input asset value	(3) Durable asset value
Treatment group A	111,132.59	90,455.01*	−256,836.22
(Self-report)	(75,127.02)	(47,600.49)	(220,139.63)
Treatment group N	−28,898.86	3,374.68	−7,225.67
(Rainfall-based)	(30,787.83)	(15,521.03)	(91,144.36)
Both treatment group C	−178,097.20*	−82,060.72	−291,623.55
	(101,758.84)	(57,755.00)	(469,256.70)
Rural	−14,252.62	−71.63	−61,639.28**
	(11,702.90)	(5,656.31)	(29,687.66)
Male headed HH	−8,218.23	40,935.76***	504,722.21***
	(22,034.97)	(3,894.96)	(36,784.03)
Avg age	25,416.28***	4,417.15***	42,026.79***
	(4,157.71)	(1,346.94)	(8,571.44)
Dependent	5,228.63***	2,944.75***	−6,514.56***
	(790.41)	(229.34)	(1,579.32)
Proportion_formal education	−3,649.11***	−183.31	42,871.98***
	(945.78)	(281.99)	(1,981.59)
Access_sanitation	4,299.30	1,113.03	62,287.27***
	(9,519.76)	(4,791.74)	(24,043.79)
Access_drinking water	−38,126.05	3,462.39	−112,338.24
	(28,610.75)	(11,583.60)	(72,140.41)
Access_electricity	−8,129.74	3,359.32	2,443.59
	(10,016.54)	(5,031.24)	(25,963.45)
House ownership	9,210.96	11,980.88**	−22,809.59
	(12,464.21)	(5,625.60)	(31,497.00)
Land ownership	11.72	43.39*	104.46
	(43.81)	(23.22)	(108.47)
Interaction_edu*self	−1,959.09**	−1,482.33**	−53.84
	(942.53)	(597.10)	(2,847.95)

Table 10 (*continued*)

Variables	(1) Asset stock	(2) Agri input asset value	(3) Durable asset value
Interaction_edu*rain	559.43	−69.95	239.14
	(402.79)	(212.63)	(1,135.26)
Interaction_land*self	-339.02^{*}	−1.56	−78.07
	(192.74)	(121.02)	(664.81)
Interaction_land*rain	228.12	−11.03	319.24
	(196.41)	(43.53)	(357.72)
Interaction_rural*self	90,296.50	11,563.94	$369{,}207.02^{**}$
	(65,845.48)	(29,702.03)	(162,794.83)
Interaction_rural*rain	−37,888.60	−6,252.62	−9,190.84
	(27,284.49)	(11,606.95)	(66,058.85)
Interaction_edu*both	4,540.33	476.40	3,673.89
	(3,247.31)	(801.11)	(5,963.49)
Interaction_land*both	−187.55	93.08	$1{,}698.96^{***}$
	(197.76)	(135.75)	(405.34)
Interaction_rural*both	−254,137.66	32,259.61	−364,719.94
	(222,356.04)	(37,424.74)	(267,690.81)
Constant	$-637{,}696.80^{***}$	$-191{,}216.45^{***}$	-1195841.23^{***}
	(103,626.07)	(36,935.21)	(235,092.39)
Observations	12,242	12,242	12,242
R-squared	0.02	0.07	0.24

Source: Author's calculations.
Notes: [a]Robust standard errors in parentheses $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. [b]The variable "Asset Stock" represents total change in agricultural and other business asset in column 1.

Table 11
Impact on labor market outcomes

Variables	(1) Month per year_total	(2) Days per month_total	(3) Hours per day_total	(4) Daily wage	(5) Salaried wage	(6) Yearly benefits
Treatment group A	1.85	−3.30	−6.16	−256.80	2,432.84	24,475.78
(Self-report)	(19.25)	(42.47)	(13.81)	(190.89)	(9,676.01)	(17,064.58)
Treatment group B	16.67^{**}	26.18^{*}	10.35^{**}	146.17^{*}	−1,858.83	−6,788.29
(Rainfall-based)	(6.91)	(15.46)	(5.07)	(76.18)	(3,296.66)	(6,395.29)
Both treatment group C	−25.53	−23.47	7.65	−594.95	−374.09	9,007.80
	(31.79)	(79.09)	(29.26)	(416.49)	(22,900.16)	(42,232.08)
Rural	2.44	7.19^{*}	2.72^{*}	10.61	−746.98	−1,602.13
	(1.87)	(4.28)	(1.42)	(21.82)	(915.78)	(1,865.95)
Male headed HH	80.25^{***}	235.55^{***}	93.15^{***}	$-1{,}541.51^{***}$	$40{,}308.60^{***}$	$108{,}647.86^{***}$
	(6.85)	(14.89)	(4.21)	(71.77)	(1,825.63)	(4,795.39)
Avg age	9.75^{***}	21.68^{***}	5.92^{***}	29.37^{***}	$2{,}804.36^{***}$	$5{,}869.62^{***}$
	(0.89)	(1.89)	(0.55)	(8.00)	(271.08)	(542.37)
Dependent	1.95^{***}	3.40^{***}	1.59^{***}	10.94^{***}	363.76^{***}	881.66^{***}
	(0.21)	(0.48)	(0.16)	(1.34)	(50.29)	(87.44)
Proportion_formal education	8.27^{***}	19.65^{***}	6.18^{***}	38.76^{***}	$1{,}013.08^{***}$	977.55^{***}
	(0.26)	(0.60)	(0.19)	(1.66)	(61.96)	(109.81)
Access_sanitation	-3.91^{**}	−5.70	−1.61	-42.27^{**}	−642.50	$-3{,}830.55^{**}$
	(1.54)	(3.51)	(1.16)	(17.96)	(749.87)	(1,542.10)
Access_drinking water	−4.00	−0.98	−1.44	−36.23	$3{,}331.43^{*}$	4,005.18
	(4.02)	(9.27)	(3.19)	(45.58)	(1,819.89)	(3,773.47)
Access_electricity	1.86	3.36	1.17	15.70	$2{,}218.86^{***}$	$5{,}551.05^{***}$
	(1.64)	(3.74)	(1.24)	(19.21)	(807.38)	(1,658.07)
House ownership	-4.60^{**}	-12.83^{***}	-4.33^{***}	3.80	$-2{,}863.53^{***}$	$-3{,}400.65^{*}$
	(1.94)	(4.47)	(1.48)	(22.73)	(969.74)	(1,966.14)
Land ownership	0.02^{**}	0.03^{*}	0.01^{*}	-0.16^{**}	0.43	−6.40
	(0.01)	(0.02)	(0.01)	(0.07)	(2.82)	(5.51)
Interaction_edu*self	−0.08	−0.05	0.04	2.71	−5.69	−150.66
	(0.25)	(0.56)	(0.18)	(2.46)	(123.02)	(223.76)
Interaction_edu*rain	−0.15	−0.17	−0.10	-1.84^{*}	17.09	16.48
	(0.09)	(0.21)	(0.07)	(0.97)	(43.89)	(83.51)
Interaction_land*self	0.03	0.09	0.01	−0.34	33.03	109.46^{*}
	(0.04)	(0.09)	(0.02)	(0.56)	(21.64)	(58.92)
Interaction_land*rain	−0.02	−0.02	−0.01	−0.25	8.52	36.01^{**}
	(0.02)	(0.04)	(0.01)	(0.18)	(7.21)	(17.08)
Interaction_rural*self	1.96	−7.12	0.17	4.07	−1,947.38	$-22{,}003.46^{*}$
	(11.68)	(26.72)	(8.60)	(138.43)	(6,181.85)	(12,776.98)
Interaction_rural*rain	−1.58	−2.77	0.17	60.27	−545.85	1,437.62
	(4.25)	(9.94)	(3.32)	(48.49)	(1,995.69)	(4,105.48)

(*continued on next page*)

Table 11 (*continued*)

Variables	(1) Month per year_total	(2) Days per month_total	(3) Hours per day_total	(4) Daily wage	(5) Salaried wage	(6) Yearly benefits
Interaction_edu*both	0.08	−0.11	−0.34	2.14	−5.49	−211.64
	(0.39)	(1.03)	(0.37)	(5.70)	(332.72)	(573.90)
Interaction_land*both	0.09**	0.06	0.03	−0.42	17.67	63.62
	(0.04)	(0.10)	(0.03)	(0.52)	(34.77)	(97.04)
Interaction_rural*both	−1.31	19.23	10.85	540.58*	−447.52	17,898.27
	(23.68)	(54.57)	(17.32)	(290.29)	(14,984.88)	(25,735.38)
Constant	−341.74***	−831.20***	−247.55***	775.72***	−121,591.01***	−287,205.30***
	(20.36)	(45.04)	(13.93)	(186.37)	(7,032.51)	(14,982.38)
Observations	12,242	12,242	12,242	12,242	12,242	12,242
R-squared	0.87	0.87	0.87	0.54	0.35	0.21

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

Table 12
Impact on household income per capita (robustness checks)

Variables	(1) Total income	(2) Crop income	(3) Non-crop income	(4) Business income	(5) Other income
Rainfall-based treatment group	10,225.32	−1,670.12	2,504.74	8,684.94*	4,942.52
	(7,873.66)	(2,287.10)	(8,157.23)	(5,218.46)	(3,241.37)
Rural	3,826.76	1,843.09	6,906.42	−2,742.50	−2,366.68**
	(9,563.84)	(1,771.04)	(9,458.35)	(4,844.04)	(962.72)
Male headed HH	106,190.04***	4,279.77***	156,315.88***	−5,036.55*	−15,297.99***
	(15,454.73)	(498.48)	(20,270.46)	(2,910.89)	(2,542.05)
Avg age	1,229.06***	123.71***	1,341.71***	−303.98***	352.41**
	(184.92)	(25.66)	(122.21)	(75.12)	(153.94)
Dependent	−4,684.33***	−13.21	44.39	−4,684.31***	−89.25*
	(527.99)	(88.52)	(306.13)	(464.95)	(52.48)
Proportion_formal education	16,788.64***	1,699.21***	2,730.44***	12,318.84***	105.94*
	(638.38)	(116.66)	(370.16)	(577.17)	(61.70)
Access_sanitation	28,361.03***	3,757.93***	9,622.42*	6,950.32**	12,395.65***
	(5,839.73)	(1,116.63)	(5,636.50)	(3,141.17)	(661.46)
Access_drinking water	9,251.90	−2,119.32	3,675.13	9,253.10	1,255.88
	(14,324.94)	(3,048.48)	(14,606.39)	(7,150.69)	(1,009.04)
Access_electricity	8,490.24	2,503.22**	−4,780.99	883.74	11,592.06***
	(6,403.19)	(1,181.74)	(6,285.21)	(3,342.68)	(554.27)
House ownership	11,404.29	1,779.07	7,090.97	−2,421.60	3,523.03
	(8,474.06)	(1,955.37)	(9,531.14)	(4,900.32)	(2,249.82)
Land ownership	48.88	52.14***	−28.24	4.27	21.87***
	(41.01)	(9.84)	(34.77)	(19.19)	(3.49)
Interaction_edu*rain	−309.70*	−59.93*	−320.86**	54.45	14.54
	(183.39)	(32.74)	(150.39)	(100.45)	(29.87)
Interaction_land*rain	122.67	16.54	64.23	66.93	−19.69***
	(87.21)	(17.75)	(64.00)	(51.85)	(7.59)
Interaction_rural*rain	−9,898.18	3,256.91	−3,842.42	−11,769.63*	−4,200.86
	(10,316.34)	(2,531.01)	(10,339.58)	(6,190.84)	(2,863.08)
Year_2005	−20,867.16*	−35,071.41***	−25,279.97***	56,376.63***	−1,749.41
	(11,710.74)	(4,010.14)	(7,315.96)	(8,798.92)	(1,637.47)
Year_2000	−14,153.68	−34,754.37***	−28,506.92***	50,629.27***	4,099.21
	(12,073.87)	(4,025.72)	(7,217.83)	(8,719.09)	(3,214.16)
Constant	−122,649.37***	28,543.27***	−169,272.72***	−33,435.61***	5,134.42
	(25,963.04)	(5,833.17)	(27,998.96)	(11,865.19)	(5,655.63)
Observations	26,151	19,859	23,448	21,278	26,138
R-squared	0.56	0.59	0.10	0.61	0.03

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

Table 13
Impact on household expenditure per capita (robustness checks)

Variables	(1) Total exp	(2) Food exp	(3) Non-food exp	(4) Crop exp	(5) Non-crop exp	(6) Agri input exp	(7) Edu exp	(8) Health exp
Rainfall-based treatment group	−4,656.43	−367.75***	−3,689.06*	277.05	1,191.28	752.44	−287.93	−70.93
	(3,414.86)	(80.62)	(2,151.86)	(952.88)	(874.69)	(2,382.13)	(755.07)	(187.49)
Rural	−2,543.96	−221.98**	−4,091.06	479.68	1,250.45*	1,318.86	−1,681.34**	279.81
	(4,087.69)	(97.71)	(2,554.35)	(710.74)	(651.19)	(2,082.45)	(833.69)	(203.10)
Male headed HH	21,844.85***	206.50***	−461.06	5,854.54***	3,521.09***	37,313.59***	−808.63	246.11***
	(2,628.08)	(41.00)	(513.14)	(646.85)	(388.41)	(4,436.65)	(504.88)	(47.47)
Avg age	353.18***	1.66*	51.29**	73.47***	85.84***	481.79***	−78.95***	−4.05*
	(37.79)	(0.97)	(22.48)	(13.26)	(6.16)	(32.38)	(16.48)	(2.07)
Dependent	−4,256.53***	−199.48***	−3,248.27***	−456.44***	−37.46	660.52***	−998.22***	19.53**
	(306.31)	(8.72)	(166.45)	(84.40)	(42.60)	(121.75)	(51.35)	(8.71)
Proportion_formal education	22,643.13***	1,329.00***	12,714.95***	1,969.87***	1,217.45***	2,667.67***	2,645.65***	107.05***
	(377.51)	(10.72)	(202.46)	(106.54)	(65.13)	(148.95)	(59.62)	(10.10)
Access_sanitation	9,030.51***	−64.67	3,775.33**	767.22*	1,111.87**	4,752.73***	710.58	−184.06
	(2,645.33)	(63.91)	(1,672.77)	(464.68)	(441.19)	(1,324.98)	(569.22)	(152.42)
Access_drinking water	4,777.74	73.72	1,536.55	1,559.91	684.82	1,623.33	111.43	167.40
	(6,551.77)	(158.35)	(4,055.80)	(1,165.84)	(1,302.12)	(3,462.36)	(1,587.77)	(359.83)
Access_electricity	4,328.96	68.88	4,614.16***	207.58	175.76	−795.33	488.89	254.78
	(2,776.73)	(66.84)	(1,744.36)	(481.25)	(453.94)	(1,419.30)	(596.77)	(165.61)
House ownership	4,176.69	−91.33	1,098.85	1,395.98*	1,074.89	1,387.33	−1,503.08*	211.59
	(3,730.24)	(90.11)	(2,354.23)	(839.25)	(716.46)	(2,212.08)	(868.78)	(190.17)
Land ownership	113.09***	2.04***	19.81	19.71***	9.83***	56.58***	6.35*	−0.68
	(22.04)	(0.49)	(12.23)	(3.43)	(2.99)	(10.82)	(3.86)	(0.74)
Interaction_edu*rain	−289.87***	−0.69	−113.43*	−19.28	−24.39*	−129.77***	−13.58	1.31
	(97.75)	(2.31)	(61.33)	(15.60)	(14.52)	(40.55)	(16.04)	(3.75)
Interaction_land*rain	109.84**	−1.06	56.84*	6.90	16.17**	15.36	14.80*	2.14
	(48.04)	(1.25)	(33.34)	(9.63)	(7.78)	(22.02)	(7.87)	(2.21)
Interaction_rural*rain	8,122.84*	494.64***	4,156.50	166.07	−784.83	1,482.95	13.89	2.88
	(4,603.88)	(109.59)	(2,900.43)	(1,102.87)	(921.31)	(2,757.98)	(1,003.39)	(263.53)
Year_2005	−70,563.76***	−808.93***	−53,445.46***	9,499.50***	−807.72	−14,337.08***	−2,075.65*	−1,153.24***
	(7,880.37)	(200.33)	(4,858.11)	(1,106.87)	(2,519.42)	(3,056.51)	(1,187.31)	(324.95)
Year_2000	−56,010.06***	−711.07***	−45,309.70***	9,798.67***	483.29	−13,396.09***	−1,599.52	−1,295.20***
	(7,916.14)	(201.73)	(4,879.17)	(1,114.63)	(2,510.56)	(3,062.66)	(1,190.32)	(338.06)
Constant	35,004.12***	931.42***	52,908.32***	−16,619.81***	−7,383.85**	−38,031.29***	9,285.31***	751.86
	(11,318.09)	(277.82)	(6,802.81)	(1,763.96)	(2,991.51)	(6,876.54)	(2,304.29)	(503.38)
Observations	26,155	26,155	26,141	19,859	23,448	20,750	21,219	20,034
R-squared	0.94	0.99	0.92	0.77	0.72	0.75	0.74	0.26

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

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% 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.

Appendix B. Supplementary data

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.worlddev.2017.10.026.

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