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The Economic Impact of Monsoon Flood and Its Spillover on the Households of Bangladesh

Shahriar Morshed[1], Md. Tahidur Rahman[1], Sheikh Rokonuzzaman[2] & Altaf Hossain[1]

[1] Department of Statistics, Islamic University, Kushtia-7003, Bangladesh

[2] Secretary General of Riverine People, Bangladesh

Correspondence: Altaf Hossain, Department of Statistics, Islamic University, Kushtia-7003, Bangladesh. Tel: 880-17-8356-7765. E-mail: rasel_stat71@yahoo.com; altaf@stat.iu.ac.bd

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Abstract

Bangladesh experiences mild to devastating floods during the monsoon season of every year due to its geographical location. Whatever nature these floods may possess, they can be both a curse and a blessing for the people of this country. Self-reporting of Bangladesh Household Income and Expenditure Survey (HIES) 2016 provides us with an opportunity to analyze the direct impact of the flood on the households' development outcomes, such as income, expenditure, assets, and labor market outcomes at a microlevel. We also use the government report to identify the households that were treated in the report as being flooded but did not report as so in the HIES 2016. We use these two measures of flood exposure to estimate the full economic impact of monsoon floods and investigate any spillover effect to verify the preciseness of flood identification measure of self-reporting. Our modified control group meticulously strengthen the argument of flood impact and inaccuracy of its self-reporting by revealing households' inhuman displacement in education and health expenditures. Though some river-centric trade centers offer employment and income increases for households, Bangladesh seems to lose its antique blessing of silt-laden flood water to replenish the fertility of flooded crop fields.

Keywords: Bangladesh, floods, shock, self-reporting, government, economic impact, spillover

1. Introduction

Bangladesh is under sub-tropical monsoon climate, the annual average precipitation is 2,300 mm, varying from 1,200 mm in the north-west to over 5,000 mm in the north-east (BWDB 2018, 15). India borders the country in the west, north, and most of the east. While the Bay of Bengal is in the south, Myanmar borders part of its south-eastern area. There are 54 transboundary rivers between India and Bangladesh, including the Ganges, the Brahmaputra, and the Meghna (GBM) (Rao and Patil 2017, 235). The topography, location, and outfall of the three great rivers system (GBM) shape the annual hydrological cycle of the country. Too much and too little water in a hydrological cycle is the annual phenomenon. The flood is a regular monsoon event occurred in accumulating water above channel capacity, and its depth and duration are the deciding factors whether it is affecting beneficially or adversely. Historically, Bangladesh (Erstwhile East Pakistan) experienced devastating floods in 1954, 1955, 1974, 1987, 1988, 2004 and 2007, and its coastal part was prone to severe storm surge in 1942, 1950, 1970, 1974, 1988, 1991, 1994, 1995 and 2007; that is, total escape from the flood is neither possible nor desirable (Rudra 2018).

Monsoon inflow, along with rainfall, historically shapes the civilization, development, environment, ecology, and the economy of the country. Extreme events of flood adversely affect the development, economy, food security, poverty, and almost every sector. According to an estimate of the Bangladesh Bureau of Statistics (BBS), 1,503,742 households or 34.48 percent of all households were affected by floods during the period 2009-2014 in Bangladesh (BBS 2015). Khatun et al. (2020) have predicted that, as the present trend, 30,366,230 Bangladeshi households will be affected by flood-like natural disasters in 2030, which is 12.52 times higher than the number in 2015. Most of the country is fewer than 5 meters above the sea level and flooding will become even more frequent if climate change is intensified; as a result, Bangladesh is predicted to be submerged by 17 percent areas and displaced roughly 20m people ("How Architects Are Designing Buildings for Bangladesh's Tropical Monsoon Climate" 2019). The aggregate economic loss due to floods will be enormous and unbearable for the affected individuals. For example, until reporting, 700 Bangladeshis were killed and over 22m homeless in the worst and most prolonged flood of 1998, during which water levels were higher than in 1988 when 3,000 Bangladeshis died

("Drowning" 1998). The reduction of deaths in recent decades does not mean that the intensity of flood is decreasing; instead, it is attributed to the better flood and disaster management such as warning systems and the construction of levees, ditches and shelters.

On the other side, flood not only gives a large amount of water but also fertilizes the floodplains by replenishing a layer of new silts, which contain organic matter (Rashid 1991, 71). Every flood-prone area was agriculturally prosperous. Once upon a time, the farmers used to cut the bank of the river and allow silt-laden flood water to submerge the field described as "overflow irrigation" by Willcocks (1930). It is assumed that an average flow of 1,009,000 million cubic meters and 1.8 billion tons of sediments pass through these river systems each year into the Bay of Bengal during the monsoon season (Shafie and Islam 2017, 47). Unfortunately, the existing expansion of roads and railways, and flood protection embankment or reservoirs now interrupt the natural process of being blessed by separating floodplains from the rivers. Most of the rivers have lost its carrying capacity because of siltation and coupling with failure of these hydraulic structures or infrastructures, it is now causing human induced flood in the region. Unlike natural floods, this type of floods only causes harm and hardly there is any blessing in it.

The researches (Toya and Skidmore 2007; Noy 2009; Kellenberg and Mobarak 2011; Felbermayr and Gröschl 2014; Franklin and Labonne 2017) predominantly captures most literature on the impacts of natural disasters focused on assessing the effects at the macroeconomic level. These involve examining the effect of shocks on macroeconomic variables such as GDP growth using cross country data. A few researchers, for example, Poaponsakorn et al. (2015) and Noy et al. (2018), have conducted empirical studies on the impacts of the disaster at the microeconomic level. Poaponsakorn et al. (2015) investigate actual output loss from the 2011 flood in Thailand, which was the worst flood in modern Thai history. Their findings show overall adverse effects on expenditure and income of flood-affected households during the disaster period. The household expenditures in the non-flooded areas were also affected but to a smaller extent. The flood harmed the wages and salary income of households in both the flooded and non-flooded areas implying that there was a negative spillover effect on wage employment throughout the country. Noy et al. (2019) extended the analysis of exploring the impact of the disaster on income, expenditure, and other economic outcomes, directly, and indirectly on spillover households in Thailand using the same survey. They also examine the flood's impacts across different socio-economic groups. The analysis shows that business income is driving the adverse effects on flooded households, and the spillover effects are almost as significant as the loss experienced by directly impacted households. However, both papers doubt about the accuracy of self-report for assessing the flood impacts. They based their works on the environmental situation of Thailand, which is completely different from Bangladesh. In contrast to Thailand, the context and causes of floods are different in Bangladesh. As a downstream country, Bangladesh contains only about 7.5% of the total catchment area of the BGM river system and shares 54 rivers with India.

Being influenced by Noy and Patel (2014), Karim (2017) examines the short-run economic impacts of recurrent flooding on Bangladeshi households surveyed in the year 2010. The results suggest a decline in agricultural income (crop and non-crop) for both self-reported and rainfall-based group and a sharp decline in non-food spending for the latter group. Like Poaponsakorn et al. (2015) and Noy et al. (2019), this paper also uses a panel structure using waves of Household Income and Expenditure Survey (HIES). Since the attrition rate of using HIES 2016 and previous waves of HIES is significantly high, we abandon the use of panel structure in our study. Despite having the scope in the data, Karim (2017) ignored the assessment of the indirect impact of the flood. Again, the paper did not consider the specific context and reality of Bangladesh. Since the most heavily impacted regions of Bangladesh do not necessarily experience the highest amounts of rainfall, the use of the historical rainfall-based index to identify the flood-affected area is not much practical. Because it is not only that Bangladesh does not always experience the rain-fed flood. It also suffers from other types of impactful floods, such as flash floods, coastal flood, transboundary flow-induced flood and the ever-regular riverine flood. For instance, flash floods occur during the pre-monsoon period (March to May) and are observed in the north-eastern region since its adjacent southern part of the Meghalaya Plateau located in India receives the highest rainfall in the world (Bhattacharya et al. 2016; Rudra 2018).

Moreover, the GBM's catchment area is approximately 1.6 million sq-km, of which only about 7.5% lies in Bangladesh and the rest, 92.5% lies outside the territory (Younus 2016, 92). In considering possible impacts of climate change on floods and flooding in Bangladesh, possible changes in rainfall and climate in the catchment areas of those rivers outside Bangladesh must be taken into account (Brammer 2014, 138–139). Evidence also shows that the most flood-affected area of Bangladesh, the Brahmaputra basin, experienced 32.14% less rainfall than the normal where the country as a whole received 24.43% less rainfall than usual during the monsoon-2016 (BWDB 2018). Thus, the absence of useful flood assessment literature at the microeconomic level jeopardizes the validity of disaster management policies in Bangladesh.

Bangladesh Water Development Board (BWDB) annual flood report describes the 2016 monsoon flood, as moderate in nature, which inundated the northern region of Bangladesh, more specifically the river basins of Brahmaputra-Jamuna, Teesta, Darla, and Dudkumar. Some places in the North-Eastern part of the country experienced an ephemeral flooding at the end of April this year. The maximum flooded area was 33% of the whole country (48,675 sq-km approximately). Instead of using rainfall indexed measure, we consider a further analyzed government report of the Ministry of Disaster Management and Relief for flood identification in Bangladesh (Network for Information, Response, And Preparedness Activities on Disaster (NIRAPAD), 2016). Like Poaponsakorn et al. (2015) and Noy et al. (2018), we could have used satellite imagery. However, satellite image-based identification has been proven to be not fully correlated with the actual flood (Guiteras et al. 2015).

With a rigorous overview of flood impacts in Bangladesh, our paper examines the economic effects of the flood on the development outcomes: income, expenditure, assets, and labor outcomes of the affected households during the monsoon period of 2016-17 by using the HIES 2016. We investigate the effects of the flood on the self-reporting households and the spillover (indirect) shock on those who did not report but resided in the government reported flood-area in our design. Our design also includes the modification of the self-reporting control group to robustify the argument of spillover effects. However, daily rainfall data from the BWDB are employed to account for any economic impact unrelated to flooding. We also contribute in filling the missing value of that rainfall data at the Upazila level by using a spatial weight matrix. Finally, the paper explores flood impacts across different socio-economic groups and livelihoods, characterizes the spill-over effects, and validates the accuracy of the self-reporting disaster identification.

2. Data and Methodology

2.1 Data Source

Bangladesh Bureau of Statistics (BBS), under the Ministry of Planning, the People's Republic of Bangladesh, has been conducting Household Income and Expenditure Survey (HIES) since 1973-74. The last survey, HIES 2016, was done with an extensive sample of 2,304 Primary Sampling Units (PSUs) comprising 46,080 households operated from April 2016 through March 2017. It is the ever-large HIES conducted in Bangladesh, which covered nearly four times a higher sample than the previous survey conducted in 2010. Whereas the HIES 2010 was a division representative survey, the HIES 2016 is district representative. We use this extensive district representative data in our paper, which is cross-sectional. This facilitated to provide quarterly estimates of household characteristics on economic development outcomes such as income, expenditure, asset holdings, employment, savings and debt, and other socio-economic indicators, for example, health conditions at the district level. Our study also includes the daily rainfall data of the last 60 years from 279 stations of the BWDB.

2.1.1 Shock Module

Since 2010, Bangladesh HIES include a module on shocks faced by households, and their coping strategies adopted to overcome them. In HIES 2016, the module is included in the Part-B as 'Shocks and Coping' under the 'Housing' Section-6 of the questionnaire. Respondents were asked whether they were affected by any particular shocks, including drought, floods, landslides/erosion, and sixteen others. Specifically, respondents give a 'yes' or 'no' answer to the questions. They were then asked to provide details on the extent of damage, the loss of income experienced, and the types of coping techniques used during their recovery. Among the surveyed households, 2,673 households claimed to be affected by flood out of 46,068 in 2016. We use these self-reported households as our leading treatment group A.

2.1.2 Government Report

We are trying to explore the economic impact of floods, particularly during the monsoon period. In that case, using the self-reporting approach to identify flood-affected households can be misleading. Self-reported shock in the survey may be picking up households that are not related to the flood associated with the monsoon period. Previous works on identifying the flood-affected area used a variety of measures. Most notable of them are satellite images of rainfall (Guiteras et al. 2015; Poaponsakorn et al. 2015; Noy et al. 2019) and historical rainfall data-based flood risk index (Karim 2017). Flood-affected households identification based on satellite image has been exposed to not being the ideal measure. Guiteras et al. (2015) use satellite data for rainfall, but find that these data are poorly correlated with actual flooding. We also find noise in the historical rainfall data-based flood risk index. Karim (2017) conducted an investigation using Bangladesh HIES 2010, where the number of self-reported flood-affected households was 271 and the historical rainfall data-based flood risk index identified household number was 2,031. Only 46 households were matched from both groups and that was very small sample size for building multiple statistical models.

Instead, the Department of Disaster Management (DDM) under the Ministry of Disaster Management and Relief and NIRAPAD provides detailed information. It identifies 67 Upazilas (subdistricts) that are profoundly affected by the monsoon period flood of 2016. The households from these Upazilas are treated as the second treatment group B. This second measure of flood finds 6,156 households directly or (and) indirectly being impacted.

2.1.3 Common Group

A third treatment group C is constructed based on the common households shared by both self-reported treatment group and the government reported treatment group to investigate any nuance impact of the flood. The number of households that reported being affected by flood and also resided in the government reported area is 1,204 in total. Instead of using a rainfall based flood risk index, the government report has conspicuously improved the size of the common group compared to that of Karim (2017).

2.1.4 Spillover

To identify spillover effects, we list those households that reside in the Upazilas that the government reported as flood-affected but did not report themselves. These indirectly flood-impacted households form the spillover group including 4,952 households. There might be several reasons for going unreported i.e. these households may be well-off than the rest of the affected households or they may be well educated and their disaster preparedness is better than the rest together with sophisticated coping strategy. There is also the problem of the self-reporting being subjective and endogenous. The common treatment group C between the self-reporting treatments group A and the government reported treatment group B, and the spillover group is mapped into Figure 1.

2.1.5 Outcome and Control variables

The HIES2016 was conducted at both household and individual level. Variables of interest such as income, expenditure, stock, and labor outcomes were all reported at the individual level while agricultural income and household characteristics were provided for the household unit. Several technical adjustments had to be made to the survey data before performing any final statistical analysis. This requires aggregating data across individual household members. Our outcome variables of interest include four sets of development indicators, such as income, expenditure, asset types, and labor market outcomes. Income and spending are divided into various sub-groups with statistics shown in per capita household measures. Asset and labor market outcomes are also sub-divided into multiple categories: stock, agricultural asset value, durable asset value, hours, days, months, daily wage, salaried wage, and yearly benefit. The continuous (monetary) variables in each category are inflation-adjusted using the consumer price index (CPI) data from the Bangladesh Bank.

Natural disasters and the standard of living are indistinguishably linked with one another. The negative impacts of natural disasters and shocks affect life and living as well as the socio-economic conditions of the people. Hence, we control for ‘‘rural” that takes the value “1” (one) if the household resides in a rural area and “0” (zero) if otherwise. The male member as the household head is generally considered as ‘‘bread earner” and the right amount of literature also highlighted the positive association between female-headed households and poverty, especially in developing countries (Aritomi et al. 2008; Mallick and Rafi 2010). Female-headed households are particularly vulnerable to climate variability as well (Flatø et al. 2017). We have created a dummy variable to “1” for males and “0” for females. Household characteristics such as age structure and the number of dependents are critical to analyzing poverty status, and one might expect a more extensive number of dependents leads to greater poverty (Lanjouw and Ravallion 1995; Haughton and Khandker 2009). Formal education is also related to lower poverty (Kotikula et al. 2010). Community-level characteristics such as access to sanitation and access to safe drinking water are associated with better health outcomes improving poverty status (Duflo et al. 2012; World Bank 2009) of households with access to electricity also showing a positive trend in living standards (Kotikula et al. 2010). Ownership status of households such as house and land has also been considered as an important determinant of poverty with owners of a dwelling place are found to be less vulnerable to flood risk (e.g., Rayhan 2010; Tasneem and Shindaini 2013; Khatun 2015).

2.1.6 Asset Index and Wealth Score

To determine whether we observe heterogeneous impacts of flooding across households with the differing socioeconomic status or not, it is essential at first to define the socio-economic status of the households. The survey provides information on asset holdings such as livestock, housing, land, consumer durables, and vehicles. It is impossible to aggregate these asset holdings for getting a single measure for household wealth as asset values. Following Noy et al. (2019) and Karim (2017), therefore, we use principal components analysis to create an asset index, which is then used in our further statistical analysis. The values of the asset index are estimated as the principal component score by approaching the following multivariate principal component analysis (PCA) (Johnson and Wichern (2002, 427-429).

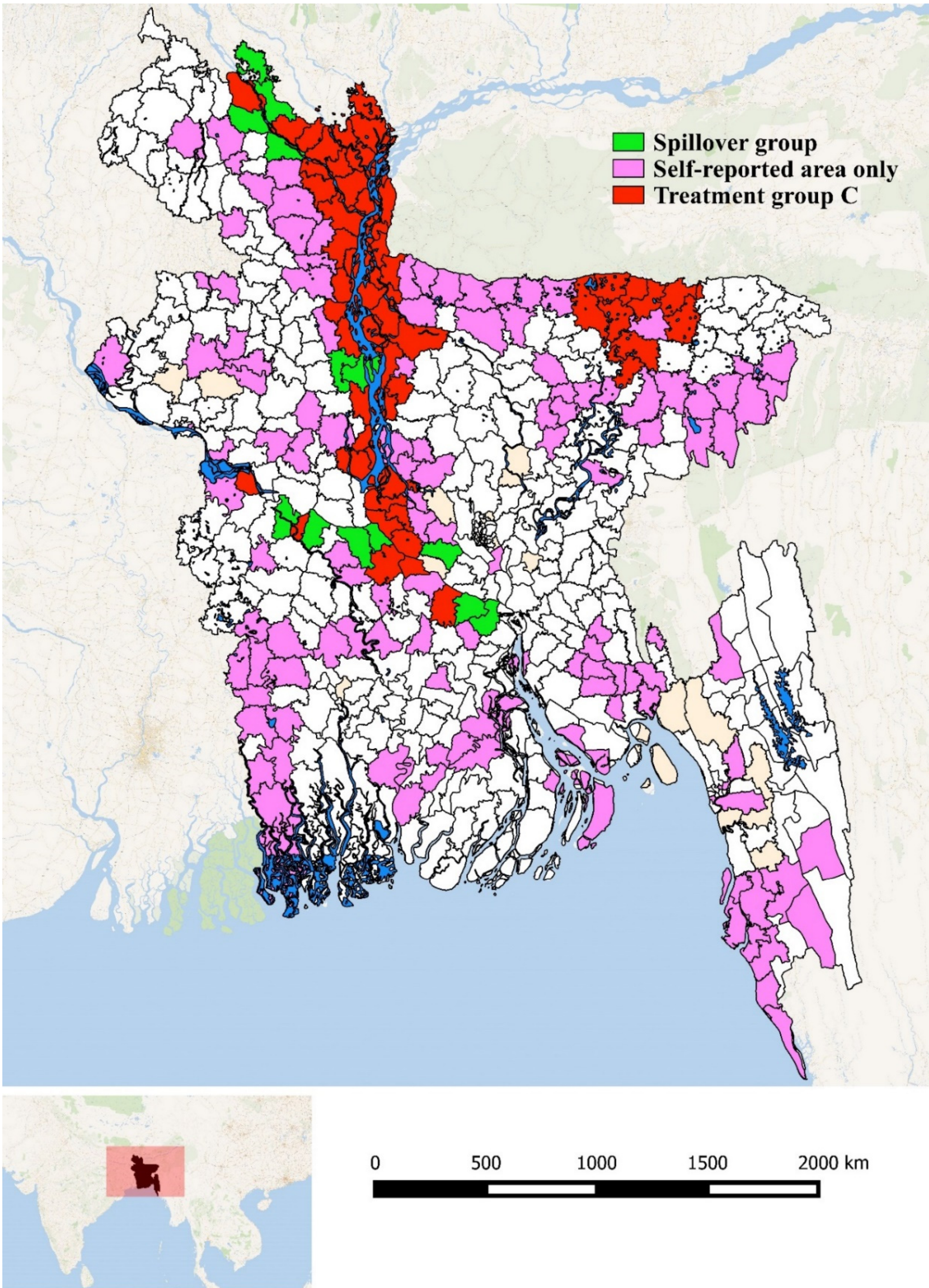

Figure 1. Map showing the treatment group C and spillover area in the study

For our purposes, the variables used to construct the index include the ownership of consumer durables, the household characteristics like number of rooms of the household, roof material, wall material, access to sanitation, type of stove, the source of drinking water and land and house ownership. Asset variables were assigned weights using the first principal component, where each principal component gives us a linear weighted combination of all the different asset variables (Vyas and Kumaranayake 2006). An index for each household is then created by multiplying each variable's factor score by the quantity of the asset held by the household. We divide households using their corresponding asset index into quartiles representing poor (Q1), middle income (Q2 & Q3), and wealthy (Q4) households.

2.1.7 Rainfall Data

Although the rainfall-based flood risk index is not engaged, to complement the disputed self-reporting approach, daily rainfall data from the BWDB are employed to account for any economic impact unrelated to flooding in this paper. The HIES 2016 includes households' data from 386 Upazilas. Traditionally, researchers use rainfall data from the Bangladesh Meteorological Department (BMD) with only 35 stations. Unfortunately, the use of BMD data is an extreme generalization of the 386 Upazilas with 35 stations only. Instead of making that extreme generalization, we use the daily rainfall data of 60 years from 1957 to 2019 from BWDB for 279 stations covering the whole country. To fill the remaining missing rainfall records at the Upazila level, we contribute to use a spatial weight matrix. The weights express the neighbor structure between the observations as a $n \times n$ matrix $\boldsymbol{W}$ in which the elements w_{ij} of the matrix are the spatial weights:

$$W = \begin{bmatrix} w_{11} & w_{12} & \cdots & w_{1n} \\ w_{21} & w_{22} & \cdots & w_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ w_{n1} & w_{n2} & \cdots & w_{nn} \end{bmatrix}$$

With a few exceptions, the analyses in a spatial software, "GeoDa" that employ spatial weights, use them in row-standardized form. Row-standardization takes the given weights w_{ij} (e.g., the binary zero-one weights) and divides them by the row sum:

$$w_{ij(s)} = \frac{w_{ij}}{\sum_j w_{ij}}$$

To fill the missing records, we then use the queen criterion of contiguity weights. Contiguity means that two spatial units share a common border of non-zero length. Conventionally, contiguity criteria are three types, rook, bishop, and queen. Since GeoDa does not include the bishop criterion, we mainly focus on rook and queen. See Anselin (1992), and Anselin and Rey (1997) for the detailed process of filling the missing Upazilas.

After filling up the missing records, we develop the rainfall deviation of 2016, which is the difference between the total rainfall of that year and the average rainfall of those Upazilas to control for any economic impact of rainfall that is unrelated to the flooding. According to the report of BWDB Bangladesh experienced 24 percent less rainfall than normal in 2016. The rainfalls and its deviations of 2016 are depicted in Figure 2 & Figure 3. Even, high rainfall and high rainfall deviation areas are not generally recorded in the government report as flooded areas, and households from these areas are not shown to be affected in self-report. So, empirical evidence also proves the vanity of using rainfall-based flood risk index by Karim (2017) in Bangladesh.

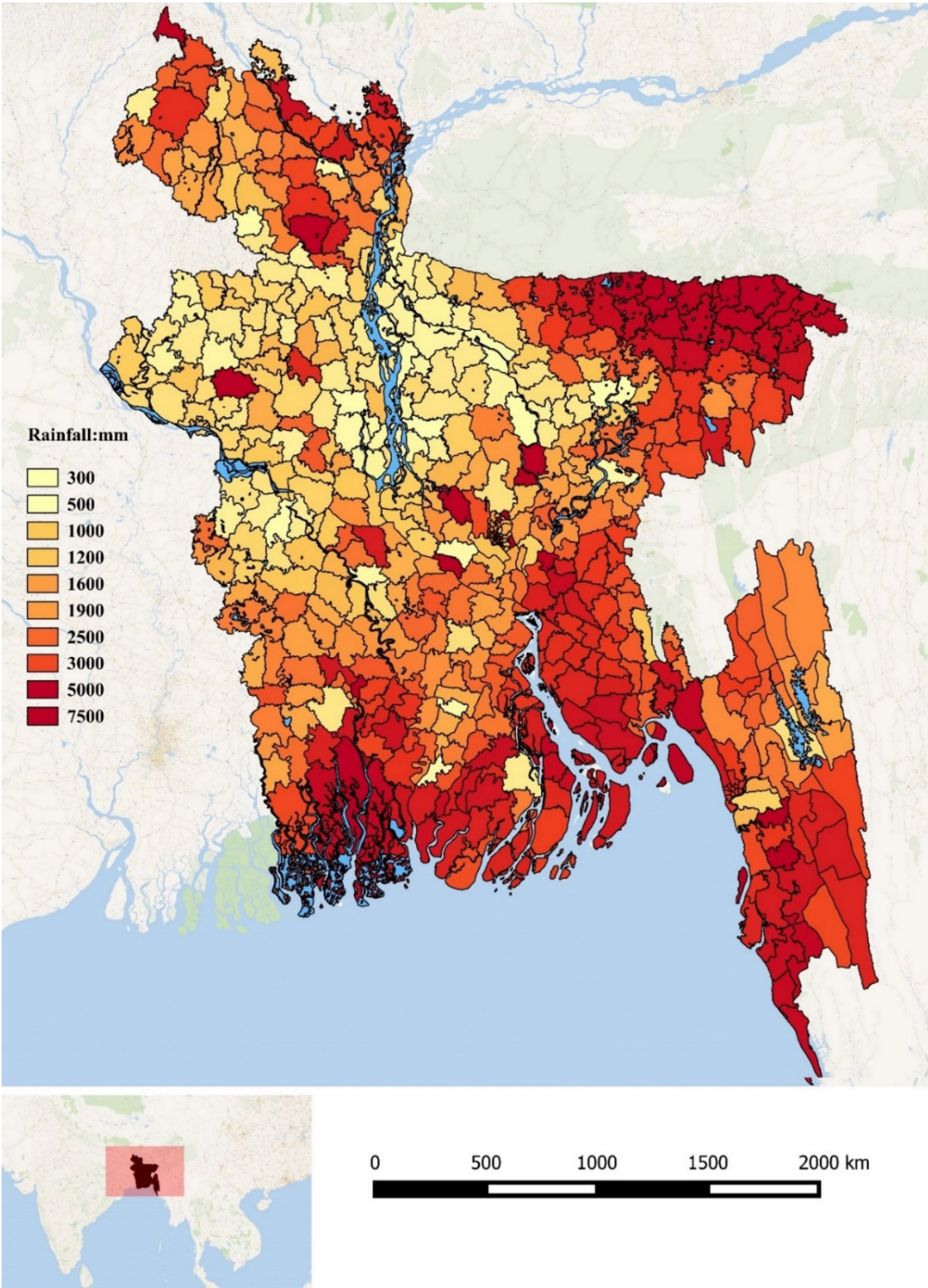

Figure 2. Map showing total rainfall in 2016

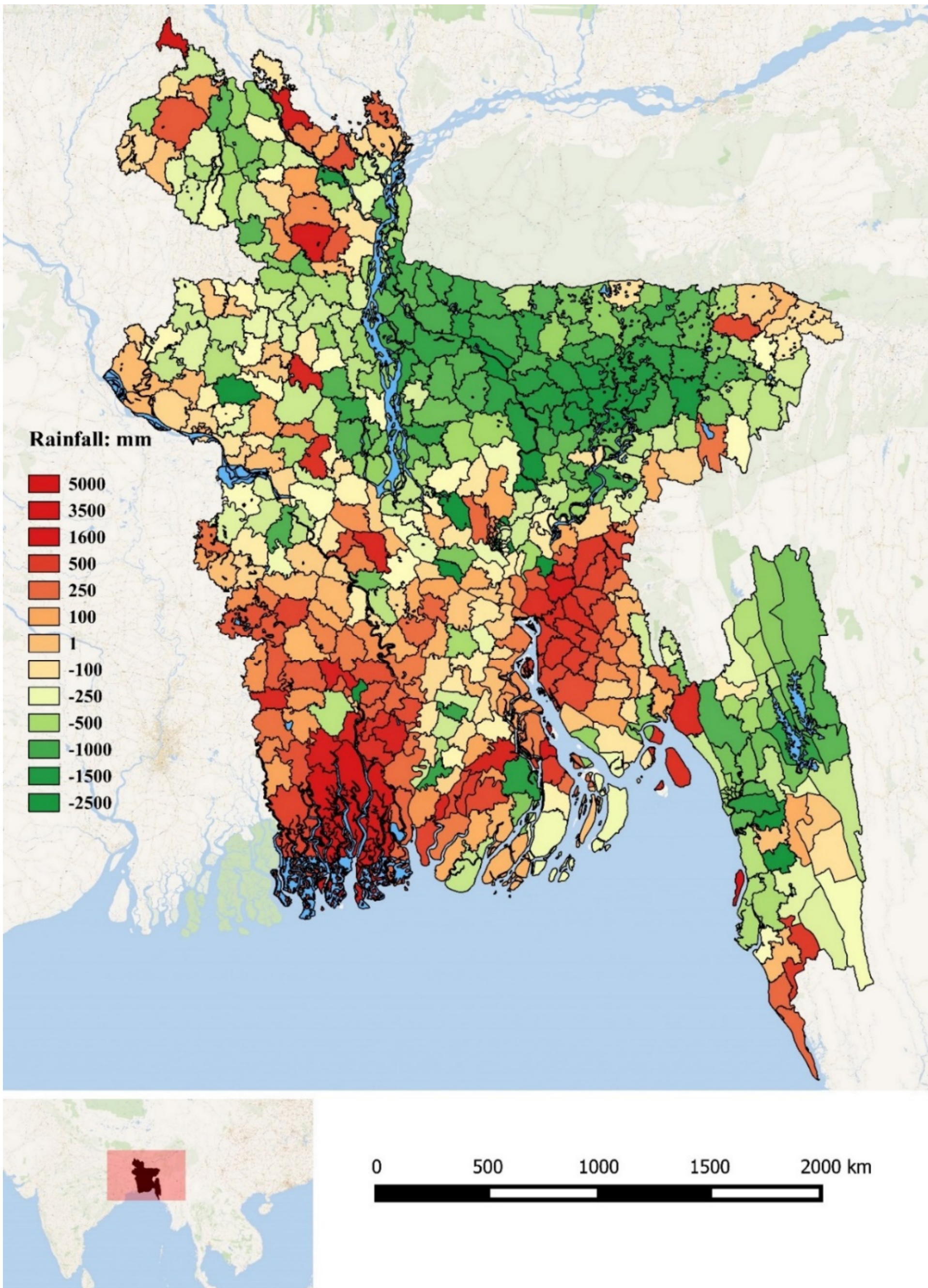

Figure 3. Map showing rainfall deviation from normal

2.2 Methods

2.2.1 Benchmark Models

Again saying, our intention here is to explore the economic impacts of floods associated with the monsoon period on households' socio-economic outcomes such as income, consumption, asset, and labor market outcomes. We start by examining the most straightforward and parsimonious model specification

$$\ln(y_{ij}) = \alpha + \beta_1 A_{ij} + \beta_2 B_{ij} + \beta_3 C_{ij} + \gamma(X_{ij}) + u_{ij}, \quad (1)$$

where $\ln(y_{ij})$ is the logarithm of each outcome variable, income, expenditure, asset, and labor market outcomes; "i" refers to household and "j" Upazila. β_1 represents the coefficient for the self-reporting group A, β_2 represents the coefficient for the government-reporting group B, β_3 for the common group C, X_{ij} denotes the control variables indicating households' socio-economic characteristics and infrastructural features, and u_{ij} refers to the error term. We use robust standard errors for our hypothesis tests to adjust the presence of heteroscedasticity. The distinction between the treatment group A and treatment group B 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 in our benchmark model will define the effects on the comparison groups.

To further investigate whether household-level characteristics (e.g., rural, land ownership, and more education) has impacts on disaster-risk identifications, or not we further estimate the following equation

$$\ln(y_{ij}) = \alpha + \beta_1 A_{ij} + \beta_2 B_{ij} + \beta_3 C_{ij} + \gamma_1(X_{ij(1)}) + \gamma_2(X_{ij(2)}) + \delta_1(A_{ij}.X_{ij(2)}) + \delta_2(B_{ij}.X_{ij(2)}) + \delta_3(C_{ij}.X_{ij(2)}) \quad (2)$$

The coefficients of the interactions among the treatment groups A, B, C, and the household-level characteristics such as rural, land ownership, and formal education, denoted by δ_1, δ_2 and δ_3 will define the effect of these characteristics on the outcome variables for respective groups.

2.2.2 Spillover Model

It is likely that the floods also imposes indirect costs on households who did not suffer direct damages from the floods. These households are unlikely to be reporting having experienced the flood, but their incomes may have been affected as the located area's economy suffers a slowdown, supply chains are being disrupted and impacted businesses lay off workers. Furthermore, the floods are also likely to have changed relative prices in the impacted regions, thereby imposing further impacts on households that have not been directly affected. To account for these spillover effects, we estimate the following model that allows us to identify both the direct impact of the flood on self-reported households and spillover effects on unaffected households located in the government reported flooded areas. Our data allows us to do that as we observe two different flood measures: household-survey self-reported flood measure A_{ij} and the Upazila-level flood areas B_{ij} that is obtained from the government report using

$$\ln(y_{ij}) = \alpha + \beta_1 A_{ij} + \beta_4 spillover_{ij} + \gamma(X_{ij}) + u_{ij} \quad (3)$$

$$where, \quad spillover_{ij} = \begin{cases} 1 & if \quad B_{ij} - A_{ij} > 0 \\ 0 & otherwise \end{cases}$$

The spillover effects those households who do not report being flooded can still be indirectly affected through a slowdown in overall economic activity, employee lay-offs, production stoppages, etc.

2.2.3 Modified Control Group Model

Benchmark and spillover models have been conceptualized and summarized from Noy et al. (2019) and Karim (2017). To further establish the robustness of the claim, we test for the existence of spillover effects by modifying our model for a different control group. This modified control group excludes all households who did not report being affected but live in the government reported flooded area. For this new control group, we would expect minimal spillover effects, as these households are located far away from any flooded areas. We define $Control\_A_{ij}$ as the group that includes all the households that did not report being affected in the Bangladesh Household Income and Expenditure 2016. Therefore, we estimate the following modified model

$$\ln(y_{ij}) = \alpha + \beta_5 Control\_A_{ij} + \beta_6 Modified\_controlA_{ij} + \gamma(X_{ij}) + u_{ij} \quad (4)$$

$$where, \quad Modified\_controlA_{ij} = \begin{cases} 1 & if \quad Control\_A_{ij} - spillover_{ij} > 0 \\ 0 & otherwise \end{cases}$$

This is our design that contributes to modify the self-reporting control group to robustify the argument of spillover effects.

3. Results and Discussion

3.1 Descriptive Statistics

We provide summary statistics for all of the outcomes and control variables for different treatment and control groups in Table 1. We present the mean and standard deviation for all the dependent variables by category and the control variables as they are listed. Except for non-crop income, all of the income categories seem to be higher for the spillover households who did not report being affected but reside in the government reported area. The households from Treatment group C who reported being affected and resided in the government reported area have the lowest income in every single category when compared to other treatment groups. Comparing to the control group A where households did not report being affected in HIES 2016, the average income in every category is higher for the modified control group. As for total expenditure, indirectly affected households have higher spending than every other treatment group but not for all the expenditure categories. Average non-food, crop, non-crop, and agricultural expenditures seem to be higher for Self-reporting households. However, long term expenditure (education and health) is higher for spillover treatment group comparing to other treatment groups. Total change in agricultural and other business assets and consumer durable asset value is higher for the spillover group, but when it comes to the total agricultural input asset value, it is for the self-reporting group. For the labor market outcomes, the self-reporting group shows the lowest number in total working months, days, and daily wage comparing to other treatment groups, while all of the wage categories (daily, monthly, and yearly wage) is higher for spillover group. When we move on to comparing control groups, a modified control group continues to have the highest number in every category of the development outcomes except for daily wages.

The highest number of rural households is from self-reporting group (almost 86%) compared to other treatment groups. The treatment group C has the highest number of male-headed households with dependents. The average age for the household members is highest for treatment group C. However, house and land ownership is lowest for those households. Comparing control group A and the modified control group, we observe almost identical results when it comes to the covariates.

These numbers and trends are consistent with our observations that the households that reported being affected and resided in the government reported areas are mostly poor, where the spillover group shows a higher number in income and most of the expenditure categories. The modified control group dominates almost all types of income, expenditure, assets, and labor market outcomes, which is also consistent with historical evidence. When we examine the geographical distribution of households according to their socio-economic asset-index classification in Table 2, we observe treatment group C with the poorest households (almost 50%) compared to other treatment groups. Also, the presence of the highest proportion of the wealthiest households in the spillover group is consistent with our observations.

3.2 Direct Impact of Flood

3.2.1 Income

We explain the impacts of floods associated with the monsoon period on different categories of income, i.e., crop, non-crop, business, and other income for self-reported, government reported, and the common treatment group in Table 3. In the report, we observe a significant decrease in the total income for both treatment group A (self-reported) and treatment group B (government-reported) being consistent with previous literature (e.g., Milojevic et al. 2012; Parvin et al. 2016). Treatment group B saw a steeper reduction in total income than the treatment group A

Table 1. Descriptive statistics for outcome and control variables at the household level

Variables	Type	Mean and Standard Deviation							
		Treatment A	Control A	Treatment B	Control B	Treatment C	Control C	Spillover	Modified_ Control
Per capita total income	Continuous	51348.77	77770.42	58651.8	78949.74	44286.52	77094.81	62144.48	79783.26
		(112320)	(978157.7)	(352465.1)	(1010923)	(60782.87)	(962354)	(391768)	(1029680)
Per capita crop income	Continuous	9859.455	18186.31	10033.15	18886.18	8168.284	17959.05	10486.56	19178.15
		(92339.01)	(966280.4)	(311712.4)	(1000380)	(21681.18)	(950590)	(347387)	(1019031)
Per capita non-crop income	Continuous	3374.124	2604.547	1919.586	2761.736	2480.095	2653.739	1783.307	2710.335
		(11918.67)	(21617.58)	(8732.154)	(22489.91)	(8858.221)	(21410)	(8696.6)	(22752.5)
Per capita business income	Continuous	3664.398	9399.398	9760.543	8959.609	2976.083	9230.087	11410.08	9140.395
		(35984.66)	(122259.6)	(159756.7)	(111375.8)	(45850.72)	(120331)	(176646)	(113373)

Per capita other income	Continuous	8559.309	11960.76	7848.149	12367.29	4510.923	11958.03	8659.542	12386.01
		(27332.2)	(80356.87)	(35534.71)	(82909.73)	(21275.51)	(79229)	(38163)	(84260.7)
Per capita total expenditure	Continuous	61074.19	70049.45	58439.05	71239.13	46330.48	70151.24	61383.06	71165.8
		(87418.07)	(62309.91)	(59570.42)	(64566.96)	(27701.95)	(64650)	(64659)	(61913.5)
Per capita food expenditure	Continuous	29590.4	33818.9	28978.48	34282.29	24961.09	33804.68	29955.24	34316.59
		(16493.72)	(21253.59)	(24541.16)	(20342.98)	(15399.57)	(21112)	(26195)	(20478.1)
Per capita non-food expenditure	Continuous	31483.79	36247.74	29463.25	36975.12	21369.39	36363.19	31431.14	36868.18
		(83440.24)	(52578.42)	(50203.49)	(55471.28)	(18589.47)	(55450)	(55041)	(52221.1)
Per capita crop expenditure	Continuous	2445.499	1254.898	1116.005	1356.058	1015.454	1332.26	1140.453	1269.64
		(59299.56)	(26576.89)	(11373.44)	(31361.23)	(2806.531)	(29874)	(12605)	(27872)
Per capita non-crop expenditure	Continuous	594.7247	335.4639	298.5679	358.518	516.6031	346.0495	245.5562	347.0453
		(2583.679)	(3022.017)	(1318.737)	(3179.946)	(1643.405)	(3026.8)	(1221.2)	(3180.53)
Per capita agricultural input expenditure	Continuous	2930.899	2671.199	2389.455	2732.048	2365.849	2694.867	2395.195	2706.753
		(7668.81)	(10396.17)	(10371.14)	(10239.65)	(6560.62)	(10338)	(11102)	(10301.3)
Per capita education expenditure	Continuous	2318.235	3417.505	2719.475	3451.548	1898.112	3392.786	2919.177	3481.697
		(4406.152)	(7927.81)	(7905.655)	(7746.024)	(4194.419)	(7841.3)	(8556.8)	(7840.93)
Per capita health expenditure	Continuous	3109.989	3594.375	2459.593	3736.963	1563.53	3620.017	2677.457	3712.487
		(6508.417)	(10123.96)	(7051.601)	(10315.2)	(3951.839)	(10057)	(7601.3)	(10398.7)
Total change in agricultural and other business assets	Continuous	2175.864	4001.062	2503.832	4109.756	2085.733	3943.717	2605.486	4180.832
		(22874.09)	(105418)	(42073.51)	(108833.2)	(32038.47)	(103695)	(44172)	(110873)
Total agricultural input asset value	Continuous	2079.741	1937.402	1608.311	1997.693	1898.175	1946.935	1537.835	1988.872
		(25770.92)	(24391.95)	(20171.28)	(25071.62)	(35797.5)	(24097)	(13943)	(25427.2)
Total consumer durable asset value	Continuous	23451.73	36077.54	26413.36	36722.55	16151.09	35860.05	28908.47	37001.01
		(61846.36)	(77121.23)	(63214.05)	(78117.91)	(55218.98)	(76796)	(64769)	(78524.4)
Total month per year worked	Continuous	2.078437	2.450117	2.363434	2.438595	2.373153	2.430038	2.361071	2.46158
		(2.111126)	(2.518652)	(2.297277)	(2.527779)	(2.157725)	(2.5068)	(2.3301)	(2.5417)
Total days per month worked	Continuous	4.806426	5.401816	5.318629	5.374772	5.577388	5.361631	5.255716	5.42063
		(4.826292)	(5.5739)	(5.163314)	(5.590138)	(4.999204)	(5.5485)	(5.2009)	(5.6199)
Total hours per day worked	Continuous	7.398429	7.33974	7.416179	7.33188	8.297342	7.317537	7.201939	7.3574
		(7.09043)	(7.131732)	(6.767579)	(7.183461)	(7.040646)	(7.1299)	(6.6826)	(7.1874)
Daily wage	Continuous	14266.23	15099.43	16300.39	14858.39	16256.57	15018.73	16311.04	14943.35
		(22270.49)	(26808.52)	(25024.51)	(26792.02)	(21740.85)	(26683)	(25761)	(26936.7)
Salaried wage	Continuous	6588.04	14089.14	8596.799	14433.91	6425.18	13847.9	9124.794	14728.62
		(20801.94)	(41496.32)	(27048.31)	(42277.14)	(20327.46)	(41011)	(25761)	(42850.3)
Yearly benefits	Continuous	772.7718	1748.105	892.5682	1814.743	683.0604	1718.577	943.5067	1851.749
		(3772.645)	(7761.694)	(4868.785)	(7921.163)	(3682.367)	(7666.8)	(5114.8)	(8033.73)
Rural	Binary	.8537224	.6868303	.7564977	.687262	.8355482	.6927826	.7372779	.68033
		(.3534504)	(.4637881)	(.4292305)	(.4636144)	(.3708391)	(.46134)	(.44015)	(.466354)

Head of household is male	Binary	.8810325	.8689019	.888564	.8666817	.916113	.8683577	.8818659	.86723
		(.3238108)	(.3375114)	(.3146968)	(.3399227)	(.2773335)	(.33810)	(.3227)	(.33932)
Average age	Continuous	28.76544	29.71845	30.03344	29.60604	29.14638	29.67702	30.24911	29.650
		(12.4593)	(12.81237)	(13.30281)	(12.71287)	(12.58304)	(12.799)	(13.464)	(12.7245)
Dependent	Continuous	1.737748	1.476737	1.528265	1.48627	1.695183	1.486426	1.487682	1.47532
		(1.21449)	(1.114119)	(1.115294)	(1.12275)	(1.211997)	(1.1188)	(1.0867)	(1.11760)
Proportion of formal education	Continuous	.5779231	.6269936	.5529619	.6351258	.5493013	.626155	.5538519	.636415
		(.2855398)	(.30517)	(.306023)	(.3025256)	(.2885937)	(.30443)	(.31013)	(.303248)
Access to sanitation	Binary	.5387205	.5714253	.429987	.5910503	.4028239	.5740014	.4365913	.588793
		(.4985917)	(.4948778)	(.4951141)	(.4916461)	(.4906697)	(.49449)	(.49601)	(.492058)
Access to safe drinking water	Binary	.9869061	.9581979	.9974009	.954074	.9991694	.9588088	.9969709	.95320
		(.1136982)	(.2001389)	(.0509191)	(.2093273)	(.0288195)	(.19873)	(.05495)	(.211205)
Access to electricity	Binary	.5409652	.7381496	.6619558	.7366957	.5116279	.7324804	.6985057	.743256
		(.4984123)	(.4396467)	(.4730821)	(.4404316)	(.5000725)	(.44267)	(.45895)	(.436842)
House ownership	Binary	.8851478	.813043	.8836907	.8069753	.8671096	.815888	.8877221	.803423
		(.3189032)	(.3898815)	(.3206215)	(.3946771)	(.3395973)	(.38757)	(.31573)	(.397414)
Land ownership	Continuous	.9632286	.6489324	.7264831	.6580201	.6225	.6683675	.7517649	.63568
		(7.128019)	(4.77374)	(7.725797)	(4.356554)	(1.450905)	(5.0017)	(8.5841)	(4.0289)
Rainfall Deviation	Continuous	-327.0735	-163.4287	-319.2172	-150.340	-534.082	-163.214	-266.976	-150.0729
		(575.6705)	(514.2209)	(498.8509)	(518.8327)	(415.7531)	(518.43)	(503.40)	(514.090)

Table 2. Quantile frequency and wealth score

Quantiles	Self-Reported	Government Reported	Common	Spillover	Self-Reported	Government Reported	Common	Spillover
	Freq.	Freq.	Freq.	Freq.	Percent	Percent	Percent	Percent
01	1,098	2,514	595	1,919	41.08	40.84	49.42	38.75
02	756	1,756	336	1,420	28.28	28.53	27.91	28.68
03	533	1,150	192	958	19.94	18.68	15.95	19.35
04	286	736	81	655	10.70	11.96	6.73	13.23
Total	2,673	6,156	1,204	4,952	100.00	100.00	100.00	100.00

Mean Wealth	Self-Reported	Government Reported	Common	Spillover
Score	-.9215124	-.8735389	-1.23727	-.7851034

by approximately BDT 1,728 (Note 1). Like Noy et al. (2019), the main driver for the decrease in the total income for treatment group A is the Business income, while it is the non-crop income for treatment group B. Moreover, treatment group A has a significant decline in crop income (BDT 376.62), business income (BDT 5,919.57) and other income (BDT 157.01). Treatment group B also has a detrimental decrease in both crop income (BDT 450.77) and other income (BDT 157.01), which is consistent with previous evidence (Devereux 2007). Other than these, non-crop income is also negatively impacted (BDT 735.09). Comparatively, treatment group B has a more significant reduction in every group of income than treatment group A.

Table 3. Income per capita

	(1)	(2)	(3)	(4)	(5)
	Total income	**Crop income**	**Non-crop income**	**Business income**	**Other income**
			Without Interaction		
Treatment group A	-0.0441** (0.0160)	-0.155*** (0.0410)	0.00319 (0.0612)	-0.176*** (0.0453)	-0.0917* (0.0465)
Treatment group B	-0.0832*** (0.0107)	-0.196*** (0.0320)	-0.359*** (0.0462)	0.0368 (0.0294)	-0.325*** (0.0323)
Treatment group C	0.0232 (0.0249)	0.343*** (0.0630)	0.523*** (0.101)	-0.173* (0.0845)	-0.393*** (0.0773)
Constant	10.76*** (0.0247)	7.837*** (0.0833)	6.959*** (0.116)	10.51*** (0.0780)	7.491*** (0.0684)
Observations	43085	13713	11976	7345	25960
R-squared	0.171	0.095	0.071	0.121	0.293
			With Interaction		
Treatment group A	-0.301*** (0.0462)	-0.0461 (0.138)	0.164 (0.186)	-0.846*** (0.190)	-0.376** (0.133)
Treatment group B	-0.107*** (0.0274)	0.0994 (0.0983)	-0.0489 (0.143)	0.146 (0.0800)	-0.269*** (0.0817)
Treatment group C	0.235*** (0.0656)	-0.00756 (0.189)	0.516 (0.308)	0.867** (0.266)	-0.520** (0.193)
Treatment group A*Education	0.00823 (0.0515)	0.173 (0.135)	-0.712*** (0.193)	0.364* (0.161)	-0.0533 (0.143)
Treatment group B*Education	-0.0668* (0.0336)	0.364*** (0.105)	-0.114 (0.151)	-0.108 (0.0961)	-0.0542 (0.0920)
Treatment group C*Education	-0.108 (0.0791)	-0.850*** (0.200)	0.318 (0.319)	-1.308*** (0.285)	-0.307 (0.229)
Treatment group A*Landownership	-0.00992** (0.00328)	-0.0529 (0.0294)	-0.0684* (0.0346)	0.0163 (0.0372)	-0.0223*** (0.00526)
Treatment group B*Landownership	-0.0138*** (0.00282)	-0.0790*** (0.0160)	-0.0595 (0.0306)	0.00599 (0.00742)	-0.0376*** (0.00854)
Treatment group C*Landownership	0.0687*** (0.0175)	0.669*** (0.0541)	0.0171 (0.0850)	0.120 (0.0880)	0.415*** (0.0688)
Treatment group A*Rural	0.312*** (0.0364)	-0.152 (0.110)	0.375** (0.142)	0.423** (0.149)	0.344*** (0.102)
Treatment group B*Rural	0.120*** (0.0224)	-0.481*** (0.0804)	-0.241* (0.119)	-0.00485 (0.0590)	-0.00297 (0.0703)
Treatment group C*Rural	-0.253*** (0.0519)	0.165 (0.149)	-0.123 (0.232)	-0.272 (0.194)	0.111 (0.155)
Constant	10.75*** (0.0270)	7.700*** (0.0914)	6.941*** (0.125)	10.44*** (0.0853)	7.494*** (0.0727)
Observations	43430	13872	12017	7378	26010
R-squared	0.155	0.110	0.074	0.110	0.276

Robust standard errors in parentheses * p<0.05, ** p<0.01, *** p<0.001

In the report, total income increases for treatment group C in a significant way when we incorporate interaction terms. The main driver for the increase of total income for treatment group C is non-crop income. We observe a significant increase in the crop income (BDT 1,036.26) and non-crop income (BDT 723.2) but drop in the other income (BDT 425.29), which is consistent with Leight (2018).

Since Agricultural income is assumed to be directly impacted by the flood, it is crucial to investigate the relationship with specific control variables such as rural, formal education, and land ownership. Agricultural income is increased significantly for households in rural areas with formal education. Land ownership possesses a positive impact on per-capita agricultural income in the common group C. It is also observed that the rainfall deviation does not hold a substantial impact on any other income category including agricultural income. These findings can also be justified by Mohd et al. (2018), and Henderson et al. (2020).

3.2.2 Expenditure

Table 4 reports the impact estimates of monsoon flood on the categories of expenditures, i.e., food, non-food, crop, non-crop, agricultural input, education, and health for all three treatment groups. Total spending is reduced significantly for both Treatment group B and Treatment group C, which is also consistent with the interaction model. These results are compatible in the lines of Pant et al. (2017) and Kankanamge et al. (2019). In comparison, treatment group C has a more significant reduction in total expenditure than the treatment group B by about BDT 3,477.14. The main driver of the decrease in the total spending for both treatment group B and treatment group C is the health expenditure, what Carrel et al. (2009) explained. As we observed that the government reported treatment group mostly has the poorest households, and the results support Khan et al. (2017) and Ray and Linden (2019) to describe the fact that the catastrophic impact of health expenditure on the poor households leads to lower health expenditure and higher mortality.

We observe a significant decline in food expenditure (BDT 2682.28), non-food Expenditure (BDT 1554.69), education expenditure (BDT 45.6), and health expenditure (BDT 234.71) for treatment group B. While every category of the expenditure declines except for non-crop expenditure which increases by about BDT 425.37 for treatment group C. With complete contrast to the treatment group B and treatment group C; we observe a significant increase in the total spending for treatment group A by about BDT 4,035.44 from the expected expenditure. The dominating driver for the increase in the total expenditure for treatment group A is health expenditure (BDT 346.64). We suspect that this anomaly in the health expenditure for different treatment groups can be associated with the idea that the self-reported treatment group is picking up households that were not affected by the devastating monsoon flood.

Table 4. Expenditure per capita

	Total exp.	Food exp.	Non-food exp.	Crop exp.	Non-crop exp.	Agricultural input	Education exp.	Health exp.
				Without Interaction				
Treatment group A	0.0838***	0.0337***	0.125***	0.137**	-0.0631	0.0701	0.0238	0.413***
	(0.00881)	(0.00795)	(0.0117)	(0.0445)	(0.0570)	(0.0454)	(0.0263)	(0.0258)
Treatment group B	-0.101***	-0.0986***	-0.0996***	0.0265	-0.0299	-0.0217	-0.0525**	-0.425***
	(0.00568)	(0.00529)	(0.00769)	(0.0361)	(0.0482)	(0.0378)	(0.0192)	(0.0183)
Treatment group C	-0.188***	-0.131***	-0.246***	-0.0908	0.780***	-0.0585	-0.349***	-0.791***
	(0.0132)	(0.0121)	(0.0179)	(0.0756)	(0.0931)	(0.0752)	(0.0436)	(0.0424)
Observations	43700	43619	43720	7607	7320	10871	27899	41006
R-squared	0.357	0.232	0.367	0.062	0.083	0.109	0.307	0.116
				With Interaction				
Treatment group A	-0.0239	-0.0300	-0.00570	0.545***	0.787***	0.141	-0.325***	0.189**
	(0.0233)	(0.0222)	(0.0310)	(0.156)	(0.169)	(0.149)	(0.0858)	(0.0711)
Treatment group B	-0.141***	-0.103***	-0.173***	0.383***	-0.0565	0.292*	-0.168**	-0.564***
	(0.0147)	(0.0136)	(0.0195)	(0.108)	(0.138)	(0.117)	(0.0609)	(0.0474)

Treatment group C	0.0276	-0.0226	0.0825	-0.504*	0.131	-0.457*	0.158	-0.571***
	(0.0335)	(0.0310)	(0.0451)	(0.219)	(0.277)	(0.224)	(0.135)	(0.111)
Treatment group A*Education	-0.0530	-0.0470	-0.0400	0.0146	-1.028***	-0.0647	0.253*	0.144
	(0.0286)	(0.0254)	(0.0368)	(0.150)	(0.191)	(0.157)	(0.0992)	(0.0847)
Treatment group B*Education	-0.0295	-0.0457**	-0.0482*	0.146	-0.454**	0.116	0.0953	0.159**
	(0.0176)	(0.0161)	(0.0232)	(0.122)	(0.161)	(0.130)	(0.0729)	(0.0564)
Treatment group C*Education	-0.190***	-0.0351	-0.305***	-0.757**	1.363***	-0.678**	-0.745***	-0.423**
	(0.0414)	(0.0374)	(0.0542)	(0.233)	(0.333)	(0.241)	(0.162)	(0.133)
Treatment group B*Landownership	-0.00380	0.00363	-0.00496	0.0538	0.123*	-0.139***	-0.0217***	-0.00365*
	(0.00220)	(0.00314)	(0.00524)	(0.0309)	(0.0514)	(0.0210)	(0.00569)	(0.00185)
Treatment group C*Landownership	0.0581***	0.0389***	0.0748***	0.639***	-0.286***	0.671***	0.107**	0.100**
	(0.00956)	(0.00892)	(0.0134)	(0.0701)	(0.0818)	(0.0583)	(0.0395)	(0.0374)
Treatment group A*Rural	0.164***	0.102***	0.185***	-0.424***	-0.188	0.153	0.219***	0.220***
	(0.0177)	(0.0165)	(0.0247)	(0.123)	(0.127)	(0.115)	(0.0543)	(0.0526)
Treatment group B*Rural	0.0659***	0.0321**	0.117***	-0.536***	0.205	-0.215*	0.124**	0.0938*
	(0.0123)	(0.0111)	(0.0164)	(0.0884)	(0.110)	(0.0935)	(0.0390)	(0.0386)
Treatment group C*Rural	-0.166***	-0.126***	-0.234***	0.353*	-0.000282	0.0956	-0.0992	-0.141
	(0.0266)	(0.0242)	(0.0369)	(0.179)	(0.206)	(0.171)	(0.0871)	(0.0896)
Observations	44006	43969	44033	7645	7347	11010	28055	41307
R-squared	0.343	0.222	0.352	0.070	0.087	0.132	0.291	0.108

Robust standard errors in parentheses * p<0.05, ** p<0.01, *** p<0.001

3.2.3 Asset

Table 5 presents the estimates of flood impacts on the household assets categories for all of the treatment groups. We do not observe any significant contrast among the treatment groups in terms of flood impact on three different categories of asset: changes in agricultural and other business assets, agricultural input asset value, and consumer durable asset value. Agricultural input asset value declines significantly for treatment group A (BDT 174.26). Extending the estimation model to account for the interaction, we observe a significant increase in the Agricultural input asset value for treatment group B (BDT 681.26) and treatment group C (BDT 3357.43). These results are consistent with previous literature (Takasaki et al. 2004). All three treatment groups experienced a significant decline in consumer durable asset value, which is also valid when we incorporate the interaction term in the estimation model and the result echoes with some existings (for examples, Karim 2018; Noy et al. 2019).

3.2.4 Labour Market

We report the flood impacts on different labor market outcomes, such as months, days, hours, daily wages, salaried wages, and yearly benefits for all of the treatment groups in Table 6. Being consistent with Kirchberger (2017) and Friedt (2018), we observe a significant negative impact on the labor market outcomes for both treatment group A and treatment group B. However, treatment group C sees a significant rise in employment and salary wage. The daily wage is severely reduced from the expected by about BDT 6,381.76 for self-reporting group A, consistent with the results from estimating the model with the interaction terms. The monthly salaried wage is also significantly declined for treatment group A (BDT 5,076.41). We do not observe any significant impact on daily wage or salaried wage for treatment group B. Daily wage and salaried wage are found to be significantly improved for treatment group C. These results are also robust and conformable when we account for the interaction with rural, formal education, and land ownership.

Table 5. Assets

	(1)	(2)	(3)
	Stock	**Agricultural Input Asset Value**	**Consumer Durable Asset Value**
	Without Interaction		
Treatment group A	-0.0826 (0.121)	-0.326***(0.0836)	-0.115*** (0.0301)
Treatment group B	0.0408 (0.102)	0.129 (0.0893)	-0.132*** (0.0188)
Treatment group C	-0.325 (0.210)	0.166 (0.166)	-0.237*** (0.0476)
Constant	7.916***(0.217)	6.444*** (0.159)	8.517*** (0.0436)
Observations	3716	4577	26268
R-squared	0.111	0.084	0.329
	With Interaction		
Treatment group A	0.0474 (0.291)	-0.373 (0.307)	-0.459*** (0.0857)
Treatment group B	-0.463 (0.281)	0.736** (0.243)	-0.329*** (0.0504)
Treatment group C	0.900 (0.539)	1.850*** (0.471)	-0.0110 (0.126)
Treatment group A*Education	0.632 (0.373)	-0.0150 (0.273)	0.0983 (0.0961)
Treatment group B*Education	0.409 (0.350)	-0.255 (0.279)	0.0936 (0.0593)
Treatment group C*Education	-2.349***(0.650)	-0.228 (0.568)	-0.647*** (0.149)
Treatment group A*Landownership	0.0227 (0.0156)	-0.0989*** (0.0208)	0.0515 (0.0264)
Treatment group B*Landownership	-0.0390 (0.130)	0.153 (0.0801)	-0.0145* (0.00605)
Treatment group C*Landownership	-0.0586 (0.184)	-0.347** (0.132)	0.480*** (0.0438)
Treatment group A*Rural	-0.644** (0.211)	0.214 (0.229)	0.298*** (0.0686)
Treatment group B*Rural	0.403* (0.192)	-0.667*** (0.202)	0.218*** (0.0405)
Treatment group C*Rural	0.163 (0.397)	-1.509*** (0.343)	-0.148 (0.0998)
Constant	8.197***(0.233)	6.437*** (0.170)	8.525***(0.0468)
Observations	3734	4592	26288
R-squared	0.113	0.098	0.327

Robust standard errors in parentheses * p<0.05, ** p<0.01, *** p<0.001

3.2.5 Control Variable and Interactions

The average age of the household members, formal education, and household characteristics such as sanitation and access to electricity seems to have a significant positive association with the total income and total expenditure per capita. Land ownership shows a significant positive impact on both total income and total expenditure. The number of dependents in rural areas plays a negative effect on the total income per capita, as does the ownership of a house. As for rainfall in concern, we do not see any strong impact of rainfall deviation on development outcomes in our study. Over the whole data set, the effects of different control variables on development outcomes have been explored but these results of control variables are not provided in Tabular Forms for avoiding overlong presentations. We present the estimated flood impacts on the development outcomes for all three treatment groups using the model with interaction terms in Table 3 through Table 6.

Table 6. Labour market outcomes

	(1)	(2)	(3)	(4)	(5)	(6)
	Months	**Days**	**Hours**	**Daily wage**	**Salaried wage**	**Yearly benefits**
			Without Interaction			
Treatment group A	-0.125*** (0.0101)	-0.109*** (0.00966)	-0.0856*** (0.00920)	-0.177*** (0.0198)	-0.259***(0.0390)	-0.232*** (0.0648)
Treatment group B	-0.0161* (0.00647)	-0.00993 (0.00654)	-0.0340*** (0.00637)	-0.0208 (0.0118)	-0.0367 (0.0261)	-0.142** (0.0434)
Treatment group C	0.0795*** (0.0153)	0.115*** (0.0148)	0.0797*** (0.0144)	0.104*** (0.0293)	0.136* (0.0579)	-0.0916 (0.0988)
Constant	1.809*** (0.0162)	2.664*** (0.0159)	2.383*** (0.0163)	10.58*** (0.0316)	10.01*** (0.0532)	7.343*** (0.0911)
Observations	28148	28168	28309	17708	9659	9530
R-squared	0.414	0.385	0.022	0.187	0.264	0.197
			With Interaction			
Treatment group A	-0.218*** (0.0284)	-0.214*** (0.0263)	-0.163*** (0.0257)	-0.318*** (0.0508)	-0.500*** (0.113)	-0.559** (0.184)
Treatment group B	-0.0834*** (0.0163)	-0.0835*** (0.0165)	-0.155*** (0.0157)	-0.0132 (0.0294)	-0.124 (0.0757)	-0.503*** (0.136)
Treatment group C	0.169*** (0.0391)	0.188*** (0.0378)	0.0445 (0.0358)	0.235*** (0.0707)	0.255 (0.164)	0.213 (0.270)
Treatment group A*Education	0.0304 (0.0318)	0.0365 (0.0328)	0.0583* (0.0277)	-0.151* (0.0607)	0.186 (0.128)	-0.00150 (0.227)
Treatment group B*Education	-0.00880 (0.0199)	-0.00105 (0.0202)	0.0384* (0.0188)	-0.147*** (0.0381)	0.197* (0.0879)	0.453** (0.155)
Treatment group C*Education	0.0688 (0.0472)	0.0768 (0.0473)	0.0405 (0.0433)	0.287** (0.0920)	-0.368 (0.197)	0.0693 (0.324)
Treatment group A*Landownership	0.0215*** (0.00445)	0.0207*** (0.00580)	-0.00278 (0.00705)	0.0217***(0.0065)	0.0500*(0.0212)	-0.0210(0.0439)
Treatment group B*Landownership	0.0193***(0.00439)	0.0172***(0.00421)	0.00232(0.00141)	-0.0727*(0.0313)	0.000091(0.0051)	-0.0234***(0.006)
Treatment group C*Landownership	-0.0533**(0.0178)	-0.0331(0.0177)	-0.00420(0.0160)	0.0180(0.0390)	0.174**(0.0574)	0.322***(0.0920)
Treatment group A*Rural	0.0711** (0.0231)	0.0811*** (0.0189)	0.0582**(0.0211)	0.248***(0.0418)	0.114(0.0893)	0.417**(0.138)
Treatment group B*Rural	0.0806***(0.0133)	0.0809***(0.0135)	0.121***(0.0133)	0.105***(0.0259)	-0.0147(0.0501)	0.115(0.0864)
Treatment group C*Rural	-0.106***(0.0320)	-0.109***(0.0294)	0.0143(0.0300)	-0.290***(0.0583)	0.0594(0.122)	-0.662***(0.198)
Constant	1.835***(0.0176)	2.684***(0.0175)	2.438***(0.0177)	10.58***(0.0346)	10.000***(0.0570)	7.436***(0.0962)
Observations	28358	28438	28565	17822	9734	9540
R-squared	0.400	0.378	0.024	0.178	0.246	0.192
Robust standard errors in parentheses	* p<0.05, ** p<0.01, *** p<0.001					

We observe that the interaction terms seem to increase both the main effect of the treatment groups and the respective control variables. Table 3 reports that treatment group A and treatment group B experience a significant reduction in total income. This income reduction is also consistent with the report presented in Table 6, where daily wage and salary wage reduce significantly. The self-reporting households with formal education experience a significant reduction in non-crop income but an increase in business income. The government reported households with formal education see a decline in total income, which is mostly driven by crop income. Both self-reporting and government reported households in the rural area experience a positive impact on the total income. Land ownership plays a crucial for all the treatment groups: positive for treatment group A and treatment group B but negative for treatment group C in a significant way. Table 4 reports that formally educated self-reporting households experience a significant reduction in non-crop expenditure. However, households with formal education resided in the government reported areas have a significant increase in food, non-food, and non-crop expenditure but a decrease in health expenditure. Both self-reporting and government-reported households with their lands experience a decline in almost all of the expenditure categories. Rural households from both treatment groups A and B see an increase in total expenditure and also in almost all of its categories.

3.3 Indirect Impact of Flood

3.3.1 Spillover

With our intention to estimate the total impact of the monsoon period flood, we estimate the spillover model for understanding the indirect effects on the households. As described before, we consider the self-reported treatment group A as the directly impacted households. Interestingly in our report presented in Table 7, we notice a significant reduction in the total income from the expected total income for the spillover group and the most surprising aspect of this finding is that compared to the treatment group A, the spillover group experienced a more significant decline in the total income than the directly impacted self-reported treatment group A. We enumerate that the estimated reduction in the total income is approximately BDT 3,666.29 for Treatment group A, whereas it is approximately BDT 3,718.95 for spillover group. The main driver for the drop in the total income for the spillover group is the non-crop income (BDT 302.44) because we do not observe any significant reduction in the non-crop income for treatment group A. We find one fascinating result in the estimated flood impacts on labor market outcomes in which daily wage and real wage are not significantly affected whereas self-reported treatment group A experiences a significant drop in both daily wage and salaried wage.

Table 7. Income per capita: Spillover and modified control groups

	Total income	**Crop income**	**Non-crop income**	**Business income**	**Other income**
			Spillover Model		
Treatment group A	-0.0802***(0.0131)	-0.0984**(0.0326)	-0.00747(0.0518)	-0.198***(0.0416)	-0.301***(0.0401)
Spillover	-0.0814***(0.0106)	-0.195***(0.0319)	-0.364***(0.0458)	0.0447(0.0288)	-0.334***(0.0322)
Constant	10.77***(0.0245)	7.867***(0.0825)	6.899***(0.115)	10.50***(0.0773)	7.528***(0.0680)
Observations	43074	13721	12009	7345	26029
R-squared	0.174	0.094	0.071	0.123	0.293
			Modified control group model		
Control group A	-0.00124(0.0157)	-0.0966*(0.0418)	-0.356***(0.0642)	0.243***(0.0484)	-0.0330(0.0486)
Modified Control Group A	0.0814***(0.0106)	0.195***(0.0319)	0.364***(0.0458)	-0.0447(0.0288)	0.334***(0.0322)
Constant	10.69***(0.0280)	7.769***(0.0889)	6.891***(0.125)	10.31***(0.0883)	7.227***(0.0789)
Observations	43074	13721	12009	7345	26029
R-squared	0.174	0.094	0.071	0.123	0.293

Our findings are significant. In our primary source of data, the self-reported flood indication does not identify any of the households from the spillover area being directly impacted. On the contrary, in our findings, these spillover households are equal, if not more affected by monsoon flood. Therefore, we understandably show that in estimating the full impact of monsoon flood, accounting for only the self-reported directly disaster impacted households is not an exact and scientific measure. In investigating the indirect impact of the flood on the households' expenditure, we find a significant decrease in the total spending (BDT 4,389.11), which is mainly driven by health expenditure (BDT 23.73) from the results presented in Table 8. We do not observe any significant spending on crop expenditure or agricultural input expenditure.

3.3.2 Modified Control Group

To further establish our claim that there is noise in the self-reporting measure and the existence of spillover effects, we modify the control group A by excluding the indirectly affected (spillover) households. As our projection, we observe complete contrast among the control group A and the modified control group A in terms of expected flood impacts on development outcomes. The modified control group experiences a significant increase in income relative to the original control group A (Table 7). As for expenditure, the estimate of flood impacts on the expenditure presented in Table 8 present a significant reduction in total expenditure for Control group A and a significant increase for modified control group A. These results are also consistent with the primary report of Bangladesh Household Income and Expenditure 2016 (BBS 2016).

Table 8. Expenditure per capita: Spillover and modified control groups

	Total exp.	Food exp.	Non-food exp.	Crop exp.	Non-crop exp.	Agricultural input	Education exp.	Health exp.
				Spillover Model				
Treatment group A	-0.051***	-0.073***	-0.0324***	0.0983**	0.148**	0.0232	-0.131***	-0.0357
	(0.0072)	(0.00654)	(0.00967)	(0.0377)	(0.0483)	(0.0383)	(0.0229)	(0.0236)
Spillover	-0.099***	-0.0971***	-0.0998***	0.0306	-0.0268	-0.0196	-0.0456*	-0.420***
	(0.00563)	(0.00525)	(0.00762)	(0.0356)	(0.0478)	(0.0370)	(0.0189)	(0.0182)
Constant	10.74***	10.26***	9.704***	6.873***	5.883***	7.077***	6.793***	6.517***
	(0.0127)	(0.0118)	(0.0170)	(0.0914)	(0.105)	(0.0994)	(0.0473)	(0.0400)
Observations	43718	43639	43713	7602	7339	10866	27937	41011
R-squared	0.354	0.229	0.366	0.064	0.075	0.110	0.307	0.108
				Modified control group model				
Control group A	-0.0483***	-0.0238**	-0.0674***	-0.0677	-0.175**	-0.0428	0.0850**	-0.385***
	(0.00866)	(0.00788)	(0.0116)	(0.0473)	(0.0637)	(0.0495)	(0.0279)	(0.0282)
Modified Control Group A	0.0999***	0.0971***	0.0998***	-0.0306	0.0268	0.0196	0.0456*	0.420***
	(0.00563)	(0.00525)	(0.00762)	(0.0356)	(0.0478)	(0.0370)	(0.0189)	(0.0182)
Constant	10.69***	10.19***	9.672***	6.971***	6.031***	7.100***	6.663***	6.481***
	(0.0147)	(0.0135)	(0.0196)	(0.0997)	(0.116)	(0.108)	(0.0524)	(0.0465)
Observations	43718	43639	43713	7602	7339	10866	27937	41011
R-squared	0.354	0.229	0.366	0.064	0.075	0.110	0.307	0.108

Robust standard errors in parentheses * p<0.05, ** p<0.01, *** p<0.001

4. Conclusion and Further Research

4.1 Summary

The analysis first rejects the appropriateness of using a rainfall index-based flood identification approach adopted by Karim (2017) in Bangladesh. The models are applied to the Bangladesh Household Income and Expenditure Survey (HIES) conducted during 2016-17 for exploring the monsoon flood effects on the development outcomes. A multivariate regression model with location dummies with or without interaction terms shows a significant reduction in total income for both self-reported (A) and the government reported (B) treatment group. The main driver for the reduction in total income for treatment group A is the business income, both with or without interaction terms. The main driver for the decrease in the total income for the government reported the group B is the non-crop income. Both groups see a significant decline in crop income. However, considering the agricultural income (crop and non-crop), households from the government reported areas experience a substantial reduction. Previous literature signifies the decline in the agricultural income and reveals a clear suggestion on the timely adoption of insurance in the context of adopting increasing climatic threats (Karim and Noy 2016). As for the decrease in the business income, we cannot identify the responsible business sectors because of inadequate information. This drawback is also pointed out in previous literature (for example, Noy et al. 2019).

Although both the self- and government-reported households experience income declines, only the later households are seen to adjust them to reducing different expenditures (health and education, as the dominant and long-term). Households from both the treatment groups, A and B, are shown to adopt the burden of floods with a decrease in the consumer durable asset values for losing employment and wage benefits.

As the common and poorest treatment group, its households could have been the worst affected. Despite the reduction of agricultural input expenses, health expenditures, and different kinds of assets, the increase of income, employment and daily wage make the story about the common areas different and unique. This good story of income and employment increase could have been ended with the popular narrative that annual monsoon flood inundation brings in silt and micronutrients for 20-25% area of Bangladesh and make it one of the most fertile lands in the world (BWDB 2018, 15). But the good story is in elsewhere. Since people from the rural areas of the common group again present the cursed stories of floods, the rises of income and employment in the common group are more significantly and particularly the blessings for the people of its urban areas. Likewise, those who are not formally educated from the common group are relatively taking the more advantage of that blessing. As most of the common group's Upazilas (for examples, Tahirpur of Sunamganj District, Chilmari and Rowmari Upazilas Kurigram Districts) are aligned with the flood dominating rivers, and their growth centers are mostly located on the banks of these rivers, therefore, the urban areas seem to have labor-intensive and river-centric (Note 2) business activities to boost lives and livelihoods of the households.

The models also confirm the indirect or spillover effects that the unreported (self-) households of the government reported areas reports non-crop dominated income drop and health dominated expenditure reduction. Inhabitants of these spillover Upazilas could have taken advantage of the river-centric urban economic or business activities as they similarly located on the banks of the GBM rivers like the common group. But, unlike the common areas, we do not find any river-centric Upazila in spillover areas which is so important in terms of trade and business other than agriculture activities. May be due to the fact, the spillover group misses that non-crop or business dominated urban economy.

Unexpectedly, the control group of A also reveals income and expenditure reduction in it and confuses the effects of flood and the validity of the questionnaire of self-reporting by BBS. Data from the government-regulated BBS has a bad reputation in terms of standard maintenance. In respect of managing the five filters to verify the accuracy of the data, Bangladesh sits at the bottom of the country list. Therefore, discrepancies in the estimation results in terms of flood impact on different treatment groups might be associated with the shortcomings illustrated in the previous literature (Paul 2020). To robustify our findings, we modify our control group of self-reporting by excluding the spillover households (indirectly affected households). As we presume, households from the modified control group reside furthest from the flood-affected area, enjoy the economic development by a significant increase in both income and health dominated expenditure. These results strengthen our argument about the inaccuracy of the self-reporting measure of flood identification and remove the confusion of flood impacts.

Having a healthy life and access to education are seen as human rights across the countries. Nevertheless, floods force the affected people to compromise with their rights by reducing both education and health expenses. On the eve of the epidemiological transition, Bangladeshis also suffer from multiple chronic diseases with higher out-of-pocket expenditures (Molla et al. 2017). The government health system is not progressive enough to support the increasing and unequal treatment cost of the disadvantaged people in Bangladesh. Therefore, any compromise with the human rights of health and education could be notoriously disastrous to the nation and humanity as well.

For making the precious self-reporting useful one, we recommend the government's concerned organization, BBS, to employ skilled field workers and for having active supervision or monitoring during the survey. To avoid any inhuman displacement in education and health expenditures, the government should arrange special flood relief or social safety net programs to support the flood-affected households in Bangladesh.

4.2 Limitations and Further Research

We presume that the impacts of floods associated with the monsoon period of 2016 do not spillover the entire country; only the households that did not report being affected but reside in the government reported area. Further spatial analysis can assess and rectify this limitation. We have full intention to conduct and also recommend a comprehensive spatial analysis on this matter.

We observe a clear pattern of noise in the self-reporting shock module of the Bangladesh Household Income and Expenditure Survey (HIES). And with the allegation of the poor standard of the data of BBS, any results derived from using the government regulated data can produce a faulty or inconsistent conclusion. We recommend heavy monitoring when it comes to maintaining the five-filter verification of data and mitigation of personal biases associated with self-reporting.

Government reporting of flood has also a number of bureaucratic shortcomings. We recommend a combination of satellite imagery and government report, which can be an excellent measure of flood identification.

Furthermore, we are aware that there are places that are subject to flooding are probably different from those that are not and they can be organized differently because some must deal with regular floods while others do not. These differences lie in geography as well as social and economic organization of society. Our estimates could be too small or too large. To further our research we intend to overcome these limitations and we believe that our research will serve as a base for future studies on this theme. However, according to two eminent experimental economists, as long as the bias in the estimate is same for each groups such as treatment and control groups, it is still useful to compare the predictions we get (Banerjee and Duflo 2019).

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Notes

Note 1. DecreaseB = [exp(10.76) – exp(10.76-.0832)] = 3760.023; DecreaseA = 1728.105; DecreaseB – DecreaseA= 1728.105

Note 2. These river-centric trade centers can be marked into the map though they are not produced here.