After the flood: Migration and remittances as coping strategies of rural Bangladeshi households

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Abstract

Using georeferenced data for mapping the dramatic flood that hit Bangladesh in August-September 2014, we evaluate how rural households have coped with this natural shock. Employing survey data for panel households for the period before and after the shock, we estimate the impact of flooding on income, consumption and migration outcomes. We find that the most affected households experience an average drop in income and expenditure of approximately 60 and 30 percent, respectively, and an increase in the probabilities of migrating and receiving remittances. Moreover, while internal migration increases by five percentage points irrespective of the initial level of income, international migration increases less than two percentage points, and more for higher-income households. International migration, however, also represents a form of insurance against natural disasters for lower-income households with members abroad, since the households manage to compensate effectively for the income shock owing to a substantial increase in remittances received.

Keywords: Flood; Migration and remittances; Shock-coping strategy; Bangladesh

JEL Classification: Q12; F22 ; F24; Q54

1 Introduction

Beginning in mid-August 2014, continuous monsoon rains hit Bangladesh together with overflows from the Brahmaputra and Ganges rivers, causing dramatic flooding that affected over 3 million people until the end of September. The flood was felt particularly strongly in the northeastern part of the country, where water inflows from upstream hill areas across the border inundated large rural fields, damaging crops, in particular cultivations of paddy covering approximately 77 percent of the total crop area in Bangladesh. In this paper, we investigate the effects of this natural disaster on income, consumption and migration behaviour of households. We refer to the *new climate-economy literature* examining how weather variations over time within a given geographical area influence economic outcomes. This novel empirical approach combines panel survey data with high-precision satellite data to measure the impact of natural shocks at the local level, thus improving the robustness of the empirical estimates (Dell, Jones, & Olken, 2014).

Starting in the late 1990s, several research studies have investigated the consequences of natural shocks for household outcomes. A branch of this literature examines, among other outcomes, the effects of natural disasters on migration and remittance behaviour. Plenty of evidence shows that migration and remittances contribute to achieving mutual insurance, consumption smoothing, and alleviation of liquidity constraints (Rapoport & Docquier, 2006; Yang, 2011). Accordingly, migration and remittances represent a risk-coping strategy in rural contexts where income is volatile and subject to seasonal shocks (Paxson, 1992; Gubert, 2002; De la Briere, Sadoulet, De Janvry, & Lambert, 2002; Udry, 1994; Kochar, 1999; Fafchamps & Lund, 2003). In the case of natural disasters, among the forms of smoothing sudden drops in income, migration represents in many situations a forced shock-coping strategy more than a voluntary insurance mechanism (Clarke & Wallsten, 2003; Yang & Choi, 2007; Belasen & Polachek, 2013).

For the types of migration, many studies in the field have stressed the importance of international migration, because of the rapidly increasing volume of remittances (Ratha, 2011). This notwithstanding, the large majority of instances of migration, and of sending of remittances, take place internally, and several studies provide evidence in favour of the insurance hypothesis in this case as well (Gubert, 2002; De la Briere et al., 2002). For the effects of shocks, (Molina Millán, 2015) finds that migrants provide unilateral insurance to their origin household after a rainfall shock, while (Blumenstock, Eagle, & Fafchamps, 2016) and Gröger and Zylberberg (2016) find that the amount of internal remittances increases with geographical distance after a natural disaster. In particular, the latter study provides evidence on the failure of short-distance internal migration to close districts similarly exposed to the consequences of typhoon Ketsana in Vietnam, while long-distance migration appears to be a more effective coping strategy. Likewise, international migration to geographically distant countries and different economic areas represents a better risk-diversification strategy to support the origin family facing the shock.

This paper contributes to the field of research on the causal effects of natural disasters on household income and expenditure, with a focus on international and internal migration and remittances as shock-coping strategies adopted by households in the aftermath of dramatic economic losses. As mentioned, we study the case of the 2014 flood in Bangladesh. Previous research on the effects of the great 1998 floods in Bangladesh has mainly employed self-reported information from household surveys on damages caused by natural calamities (Alvi & Dendir, 2011). We instead follow Gröger and Zylberberg (2016) in using georeferenced data from NASA satellites that measure the impact of the flood as the share of inundated areas for each sampled village where households reside. We match this high-resolution satellite imagery data with with data drawn from the *Bangladesh Integrated Household Survey*, a panel study conducted by IFPRI in two rounds, the first in 2011-2012 (October 2011-June 2012) and the second in 2015 (January-June 2015), exactly the period before and after the flooding. To our knowledge, this is the first study on this natural disaster in Bangladesh and the first one to use causal inference of this kind. For our research strategy, we adopt a difference-in-difference approach to identify the effects of flooding on agricultural income, revenues from paddy cultivations, wage income, food and non-food expenditure, propensity to migrate within and outside the country and the amount of remittance received from the two types of migration. We use a continuous treatment variable, namely, the share of inundated areas in each village, which we can measure precisely thanks to the georeferenced satellite data. After conducting a balance test to compare treated and untreated areas at baseline, we estimate our models with OLS, also controlling for household fixed effects. To evaluate the robustness of our results, we control for potential endogeneity related to the likelihood of each village being inundated depending on village topographic characteristics, and we perform two parallel trend tests. Finally, we perform some heterogeneity analysis.

Our results show that the average income loss suffered by the most affected households after the shock - i.e., households where the share of inundated areas reached the maximum of 94 percent - amounted to approximately 60 percent with respect to the previous period, and was mainly due to damages to crop and livestock, while net consumption decreased by 30 percent. The emigration rate, however, increased by approximately 5 percent, as did remittance inflows, which show an increase of approximately 200$ PPP. These monetary transfers compensate for 28 percent of the loss faced by migrants' families. These empirical findings are robust to our testing procedure.

Assuming that the ability to cope with risk through migration strategies is different according to the position of households in the income distribution, as it depends on initial resource constraints, we investigate the migration and remittance response of households belonging to different income groups. We find that, after the flooding, while internal migration incidence is similar across income tertiles, wealthier households have a higher likelihood of sending migrants abroad. However, among households with international migrants, the increase in monetary transfers received is by far higher for lower income households, representing approximately three times the variation of the middle-income group and compensating for approximately 85 percent of the losses that poorer households suffered if affected by flooding. The paper is organized as follows. After the description of the georeferenced satellite data and of the household survey (Section 2), we illustrate our method (Section 3). We then present our results (Section 4) and discuss them (Section 5). Finally, we provide some concluding remarks (Section 6).

2 Data sources and variables

Georeferenced data

As already mentioned, in our analysis village exposure to inundation represents the treatment. To build a measure of this treatment we use the *NASA Flooding Map*, composed of satellite images obtained by applying the LANCE processing system to MODIS products. [1] In these 250-m resolution images, flooded areas are determined as water observations falling outside normal water levels, taking as reference another MODIS product, MOD44W. In particular, we employ composite images for an interval of 15 days between the end of August and mid-September, since, according to the Official Report of the *Bangladesh Water Development Board* of the National Government for 2014, rainfall reached the highest record in this period.[2] Figure 1 shows that in 2014 rainfall intensity during the monsoon season (measured as average tenth of millimetres of rainfall accumulated in a 15-day period among all the Bangladeshi villages) exceeded that of previous years and reached the maximum peak toward the end of August. We therefore define as treatment the share of flooded areas in the first

[1] The data can be publicly accessed at https://floodmap.modaps.eosdis.nasa.gov.

[2] The NASA composite product for the period August 31st-September 15th, by combining information from daily images and "smoothing" high-frequency variations, overcomes the issue of sensing measurement errors due to clouds that prevent the satellite from obtaining a precise image, identifying a pixel area as "flooded" if it is recognized as such at least twice.

days of September resulting from the accumulated rainfall of the last two weeks of August. Figure A1 in the Appendix illustrates MODIS satellite images for the period before the flooding, July 2014 - already in the monsoon season - and for the period considered. Flood zones - coloured in orange, to be distinguished from normal surface water in blue - are clearly more numerous in the second picture, in particular in the northeastern part of the country.

The 318 surveyed rural villages that are nationally representative of the country's rural areas are the units of analysis for the natural shock. For each village in the sample we calculate the share of pixels (where pixel resolution is 250 m) identified as "flooded" in a 5-kilometre radius, where the average number of pixels in the calculated radius is approximately 3800. To check for robustness, we also repeat our tests for 2- and 10-kilometre radiuses. This treatment variable corresponds to the probability of a "pixel area" in the village being inundated in the period considered. Figure A2 in the Appendix shows the percentage of inundated areas during flooding with respect to normal periods. With the treatment specification of the 5-kilometre radius, the mean share of submerged area corresponds to 18 percent, with a maximum of 94 percent, while in normal periods, the mean is 8 percent and the maximum is approximately 45 percent. However, to understand the economic consequences of flooding, it is important to highlight that in some villages stream water did not flow away immediately after the flood, probably because of differences in soil absorption (see Figure A2). In line with the literature, this measure of treatment proxies the village-level damage the flood caused to rural areas and cultivations. Figure 2 illustrates the geographic distribution and the intensity of the treatment variable during the flooding (August 31st-September 15th).

As previously anticipated, sampled villages may differ in some geographical characteristics that affect both the probability to be treated and the outcomes of interest. To take account of this endogeneity, we control for the village propensity to be submerged by water during normal times as measured by the percentage of water coverage in a 5-kilometre radius in July 2014. In addition, we include province and wave fixed effects and village topographic features, such as the proximity to a river or to the coast, to allow villages with differences in these features to have different trends.

In addition to flooding data, we take advantage of multi-satellite information on rain gauge measurements for the same period.[3] An alternative treatment variable is the average millimetres of rainfall per day in the 5-kilometre radius around each village, cumulated for the 15 days of interest. This measure has the advantage of being exogenous and unaffected by the lay of the land. We also build a control measure for the average daily rainfall in normal periods, although this measure is less precise because of the lower resolution of the satellite images.

Household survey

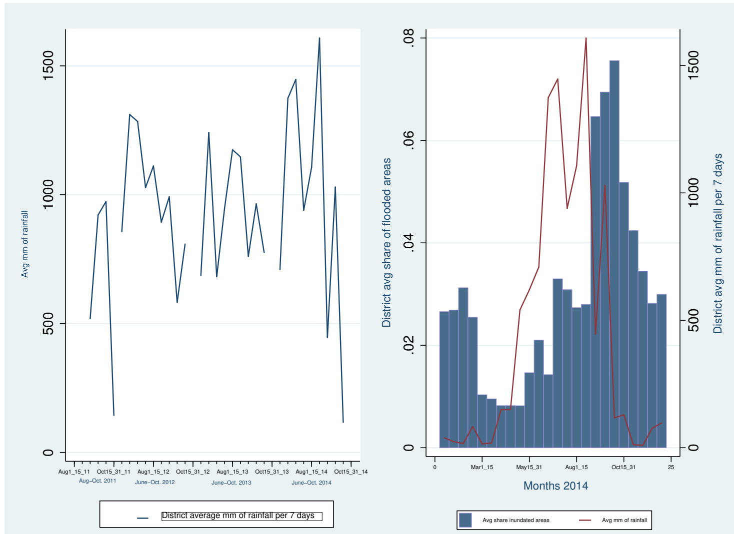
We employ the *Bangladesh Integrated Household Survey*, a panel study conducted by IFPRI in two rounds, the first in 2011-2012 (October 2011- June 2012) and the second in 2015 (January - June 2015). This survey has a national coverage and is representative of rural areas of all the seven divisions of the country. Besides data on production and food security, the questionnaire includes also detailed information on income, expenditures, savings, as well as specific sections on migration and remittances.

The survey follows approximately 6,500 households and 27,000 individuals. The attrition rate is 4.4 and 22 percent at the household and individual level, respectively.

A major concern is bias deriving from the possible correlation between the occurrence of flooding and the failure to track displaced households - according to national statistics, approximately 57,000 families were displaced between August and September 2014 (Ministry of Disaster Management and Relief, 2014) - and households that might have chosen to leave to avoid the dramatic consequences of the shock. To address this problem, we run a regression where the outcome variable is a dummy

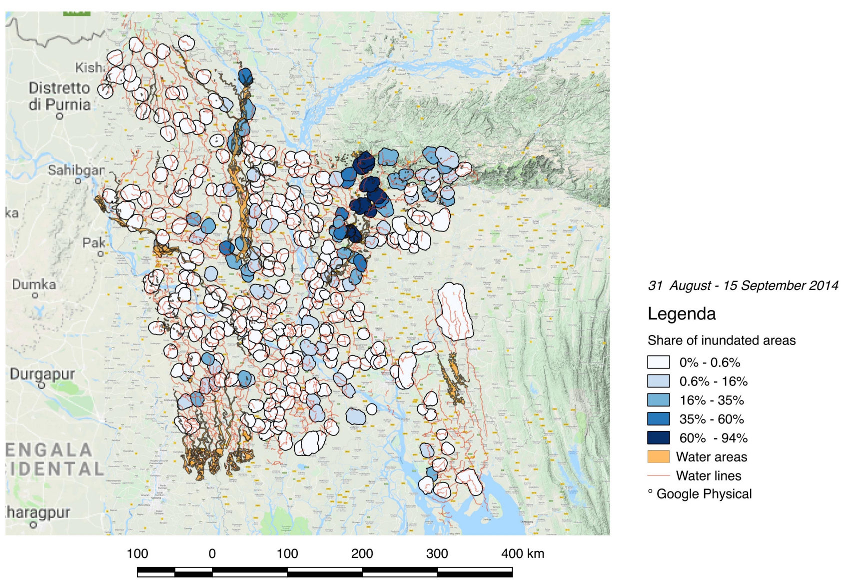
[3]The data source for rain gauge is the NASA Integrated Multi-satellite Retrievals for GPM (IMERG), which provides the Day-1 multi-satellite precipitation product at a resolution of 0.25 degrees.

Figure 1. Two-week cumulated average millimiters of rainfall and share of flooded areas in the Bangladeshi villages for the period 2010-2014



Note: The figure shows in panel A the rainfall intensity for the monsoon periods between 2010 and 2014, measured as average tenth of millimetres of rainfall cumulated in a period of 15 days in all Bangladeshi villages and obtained from NASA Integrated Multi-satellite Retrievals for GPM. The same measure for rainfall is combined in panel B with average shares of inundated areas in all villages for 2014 calculated from NASA MODIS Satellite images.

Figure 2. Geographical distribution of the treatment



318 *Note:* The map illustrates the share of inundated areas for each 5-km buffer built around the 318 villages in the sample. Author's calculations are based on products from NASA LANCE processing system applied to MODIS images from Terra and Aqua satellites with 250 m resolution, where flooding is determined as water observations falling outside normal water levels.

equal to one for each household tracked in the second wave, and the main explanatory variable is the treatment - i.e., the share of inundated areas in a 5-kilometre radius around each village. The coefficient of the treatment variable is not significantly different from zero, thus ruling out the possibility of this potential bias (see Appendix, Section A.2).

Table 1 presents the descriptive statistics for the panel sample at baseline (2012). The average number of household members, excluding migrants, is 4.8. Since the sample is mainly representative of rural areas, agriculture is the main sector of occupation, employing 48 percent of the labour force in farming and 26 percent in livestock jobs. With average monthly household earnings of approximately 305$ (or 6,474 Taka; all monetary values are expressed in US$ PPP, CPI on the 2010 = 100 base period), agricultural revenues represent 40 percent of total household income net of transfers and remittances. Household monthly income is the sum of monthly individual earnings of all household members in paid work. It comprises income from wage labour and income from self-employment in farming, namely, agricultural and livestock activities. Agricultural income comprises revenues from all types of cultivations, including paddies, which represent the main crop in Bangladesh. The survey also provides separately the total annual revenues from paddy cultivations, which we analyse in a distinct regression. Household monthly expenditure is on average 268$, of which over 70 percent (201$) is for food consumption. Medical expenditures (298$ per year) amount to 9 percent of total consumption, while those for education (124$ per year) are only 3 percent.

Regarding migration, 20 percent of households have at least one migrant, and among them, 19 percent have more than one member overseas. The total number of migrants in 2012 is 1,663, and 31 percent of them live outside Bangladesh. Most importantly, 73.5 percent of families with at least one member overseas receive remittances, while 7 percent of total sampled households receive monetary transfers from migrants who are not household members. The average gross amount received annually from members living abroad is 2765$, while transfers received from non-family

Table 1. Descriptive statistics of the panel sample in 2012

	N.	Mean	Std. Dev.	Min	Mdn	Max
HOUSEHOLD CHARACTERISTICS						
Number of households (panel dataset)	6,223*					
Household size (excluding overseas members, 2008)		4.83	1.83	1.00	5.00	17.00
Monthly income per hh ($PPP)		305.34	475.16	0	229.91	1558.58
(Taka)		6474.11	8802.28	0	5200	35250
Monthly income per hh, wage labour ($PPP)		81.31	143.88	0	0	585.84
(Taka)		1839.11	3254.12	0	0	13250
Monthly income per hh, farming/livestock ($PPP-adjusted)		113.73	184.91	0	44.21	733.96
(Taka)		2572.41	4182.19	0	1000	16600
Annual revenues per hh, paddy cultivation ($PPP)		289.22	1571.93	0	0	4443.61
(Taka)		6541.36	35551.91	0	0	100500
Monthly expenditures per hh, food ($PPP)		201.67	137.05	0	169.18	1820.86
(Taka)		4436.79	3015.14	0	3722	40059
Monthly expenditures per hh, non-food ($PPP)		65.69	218.02	0	39.54	454.81
(Taka)		1445.35	4796.49	0	870	10006
Annual expenditures per hh, health ($PPP)		298.52	16178.17	0	111.81	2929.54
(Taka)		6567.44	735.37	0	2460	64450
Annual expenditures per hh, education ($PPP)		124.52	240.62	0	27.72	1029.09
(Taka)		2739.58	5293.72	0	610	22640
MIGRATION						
Proportion of hh with at least one migrant		0.20				
Proportion of international migrants		0.31				
Migrants' education level (internal)						
Illiterate/no educ.		0.10				
Primary school		0.35				
Upper-primary school		0.27				
Secondary		0.17				
Degree holders		0.05				
Others		0.06				
Migrants' education level (international)						
Illiterate/no educ.		0.06				
Primary school		0.36				
Upper-primary school		0.35				
Secondary		0.19				
Degree holders		0.03				
Others		0.01				
Proportion of migrant's households receiving remittances		0.73				
Remittances received from migrant members per year - migrant hh ($PPP)		2765	4252.02	4.54	1363.63	22727.27
(Taka)		62535.36	93544.45	100	30000	500000
Remittances received from non-household members per year - total hh ($PPP)		233.78	1737.51	0	0	120000
(Taka)		5143.346	38225.24	0	0	5454.54
GEOREFERENCED VARIABLES						
Share of inundated areas per village, 1-15 September 2014		.18	.16	0.0002	.10	0.94
Share of inundated areas per village, 1-15 July 2014		.08	.09	0.0002	.02	0.45
Avg. mm rainfall, 15-31 August 2014		487.37	481.48	1.49	265.29	2116.09

*Note:** The total number refers to the subsample of households surveyed in 2012 and re-tracked in 2015, that is, 6,223 households and 26286 individuals. All monetary values are expressed in PPP-adjusted USD at constant prices.

remitters are approximately 223$. For sampled migrants, the descriptive statistics show that among international migrants a lower share (6 percent) are uneducated with respect to internal migrants (10 percent), and that the proportion of those with secondary school is higher in the first group by two percentage points; migrants with higher education represent a small minority in both groups. Internal migrants are mainly employed in private enterprises in the service sector (23 percent), while the majority of international migrants are construction and factory workers (48 percent). For the main destinations of those overseas, 28 percent reside in Saudi Arabia, 22 percent in the United Arab Emirates, and less than 2 percent in the E.U. and U.S. Table 2 contains information on the characteristics of households distinguishing by income group (low-, middle- and high-income), a distinction that we use in our heterogeneity analysis.

As a first check for pre-treatment differences between treated and untreated (or rather between less and more treated) households, we perform a balance test at baseline.[4] Table A2 in the Appendix confirms that the geographical position of some villages, correlated with a higher propensity to be inundated, may favour cultivations and harvest, and consequently lead to a higher level of some types of income and consumption outcomes for sampled rural households. Table A2 also shows that there are no systematic differences at baseline in migration incidence and remittances received, while remittance incidence is significant at 10 percent.

Table 2. Descriptive statistics by income group

	Low income hh	Middle income hh	High income hh
Avg. monthly expenditures per hh, food ($PPP)	215.10	229.39	347.80
Proportion of hh with migrants in 2012	0.33	0.13	0.13
Proportion of hh with international migrants in 2012	0.13	0.04	0.04
Proportion of hh with migrants in 2015	0.37	0.20	0.23
Proportion of hh with international migrants in 2015	0.14	0.05	0.07
Remittance received from migrant members per year- only hh with migrants ($PPP)	2631.82	2369.43	3444.71
Observations	2,198	2,121	1,904

Note: The sum of the three groups is the subsample of households surveyed in 2012 and re-tracked in 2015, that is, 6,223 households and 26,286 individuals.

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[4]We estimate an OLS regression at baseline, employing the continuous treatment as explanatory variable to check for its correlation with the different outcomes of interest.

3 Method

As already mentioned, we perform a difference-in-difference estimation, employing as treatment the continuous indicator for the share of inundated areas in a buffer of 5 kilometres around the villages where surveyed households live. The first specification we estimate is the following:

$$Y_{hvrt} = \beta_0 + \beta_1 T_v * t_{=2015} + \beta_2 T_v + \beta_3 t_{=2015} + \beta_4 P_v * t_{=2015} + \beta_5 P_v + \beta_6 X_{ht} + \beta_7 W_{rt} + \epsilon_{hvrt} \quad (1)$$

where Y_{hvpt} indicates the different outcome variables for each household h residing in village v of region r at time t; T_v is the treatment variable, namely, the share of inundated pixels for each village v; $t_{=2015}$ is the dummy for the second year; and β_1 is the difference-in-difference coefficient of the treatment. P_v is the propensity to be inundated within the same radius during normal times (July 2014); controlling for P_v allows us to identify the change in the outcome of interest over time due to the treatment for those villages that have the same propensity to be inundated, meaning the same percentage of area submerged in non-flooding periods. X_{ht} represents socio-demographic characteristics of the household.[5] W_{rt} are interactions between wave and region fixed effects to account for changes in regional characteristics over time. The errors, ϵ_{hvrt}, are clustered at the lower administrative level of divisions.

We first estimate the model with OLS on the observations common to the two waves (6,223 households over the total 6,503 of the initial sample). We then add fixed effects to control for time-invariant unobserved household characteristics α_h. The model thus becomes:

$$Y_{hvrt} = \beta_0 + \beta_1 T_v * t_{=2015} + \beta_2 P_v * t_{=2015} + \beta_3 X_h t + \beta_4 W_{rt} + \alpha_h + \epsilon_{hvrt} \quad (2)$$

All monetary values are expressed in \$ PPP at constant prices.

To proxy the area where economic activities might have been damaged by flooding, we use informa-

[5]Number of male and female adults in the family, number of elderly and children, and age and gender of the head of household.

tion at baseline on land and pond or water bodies owned or under operation by households. Although the survey data show that the average distance from households' dwellings is less than 500 metres, we build this measure in a 5-km radius as in (Gröger & Zylberberg, 2016). However, we repeat the analysis in a 2- and a 10-km radius, finding very similar coefficients, although with higher standard errors with the 10-km radius.

To deepen the understanding of the effects of flooding, we conduct some heterogeneity analyses. First, we investigate whether household outcomes differ in relation to the initial level of income. The literature reviewed in the introduction does not disentangle the natural shock effects according to the heterogeneity of household income. Gröger and Zylberberg (2016) partly touch on this issue looking at the effect of the typhoon on the variation in remittances normalizing them by household income, without explicitly differentiating by income groups. We therefore investigate the heterogeneous effects of flooding on our outcomes of interest by estimating our model separately by tertiles of the income distribution at baseline. Regarding the migration outcome, for example, we expect migration incidence to change after the flood, as households might be induced to send more members away as a coping strategy to face the natural shock. Accounting for income heterogeneity allows us to test whether in our causal setting households that are initially worse off, and become even more so after the flooding, are more likely to have migrant members. We also distinguish between internal and international migration, to test whether, for example, international migration would represent a more effective diversification strategy, with overseas destinations being exposed to different economic cycles and no flooding. This heterogeneity analysis aims at understanding whether remittance receipt is effective in compensating for the income loss, whether migration is also beneficial for lower income households, and whether the natural shock affects households with internal and international migrants differently.

Second, as the sample is representative of rural areas at the national level, it is interesting to disentangle the differences in household outcomes according to their position in the local market as net seller or buyer. We therefore estimate our benchmark specification dividing the sample between net food buyer and net food seller households [6]. Since net seller households rely on agricultural activities as their main source of income, for them we expect to find larger effects in terms of income loss and drop in expenditure, together with higher increases in migration incidence and remittances.

Turning to robustness checks, as already mentioned, the potential endogeneity in our empirical strategy derives from the fact that flooded villages may have particular layer characteristics, such as being flatter or being located close to water surfaces, which make them particularly vulnerable to flooding. In addition, these features might favour the harvest, consequently affecting income and consumption outcomes of households as well as migration and remittance choices, independent of the level of flooding. To control for this endogeneity issue, as in Gröger and Zylberberg (2016), we instrument the flooding treatment variable with rainfall, which represents a more exogenous indicator of village exposure to the shock. We therefore apply a two-stage least squares method:

$$T_{vt} = \beta_0 + \beta_1 R_{vt} + \beta_2 P_{vt} + \beta_3 P_{vt}^R + \beta_4 X_h t + \beta_5 W_{rt} + \alpha_h + \epsilon_{hvrt}, \tag{3}$$

$$Y_{hvrt} = \beta_0 + \beta_1 \hat{T}_{vt} + \beta_2 P_{vt} + +\beta_3 P_{vt}^R + \beta_4 X_h t + \beta_5 W_{rt} + \alpha_h + \epsilon_{hvrt}. \tag{4}$$

where R_{vt} are average tenth of millimetres of rainfall per day in the 5-kilometre radius around each village, cumulated for the 15 days of interest (as already mentioned, to explain flooded areas in the first days of September, we take as our rainfall intensity measure the cumulated average for the two weeks before that period). P_{vt}^R is a control for the average intensity of rainfall in normal pre-shock periods, again taking as reference July 2014.

[6]Using yearly information on kilograms of each food item cultivated and sold in the market and on the corresponding quantities purchased, we define net sellers as households for whom the total amount of items sold is higher than the amount purchased, and the sample of net buyers as households for whom the reverse is true.

However, the rain gauge estimation is much less precise than the flood measure because of the lower resolution of the satellite imagery. In addition, rainfall estimation might not always be highly correlated with flooding, especially in those villages that are close to mountainous areas and may be hit by water inflows from upstream hill zones independently of rainfall measures. This appears to be particularly true for the areas in the northern part of the country where snowmelt from the mountains results in soil erosion and a rapid increase in river discharge. It is therefore important to add a second robustness check controlling for the specific topographic characteristics of sampled villages. In a first specification, we therefore add control dummies indicating whether the village lies at the bottom of a valley, or stands on a hill or mountain, or rather if it is close to rivers or other water surfaces, which are all important factors influencing the propensity to be inundated.[7] In addition, we include in the estimation a control for *flows direction*, calculating for each pixel the main direction of water run-off over the geographic area of interest depending on elevation and cell height values, thus creating a dummy equal to one for the potential catchment areas where surface water would accumulate.

An alternative specification of this robustness check includes, among the controls of the benchmark regression, an interaction of wave fixed effects with average rainfall in the same period of interest (August-September) for the years 1970-2000. Finally, in the last specification of these robustness checks controlling for topographic features, we add a *vulnerability index* built for each village according to the distance from rivers, lakes, water surfaces and the nearest coastline. Calculating the Euclidean distance from these water areas and assigning each unit of observation to a category of *low, medium and high* risk based on this measure, we build a control variable interacted with wave fixed effects, to allow villages with different exposure to flooding to have different trends.

[7] In particular, employing georeferenced data on the Digital Elevation Model, we add two dummy variables for each village being close to a river line or water surfaces, and three other indexes for being located on plain areas, hills or mountains.

In addition, we include in the main specification a control for price variation at the local level to test whether this variation, which might be partially influenced by the flooding, drives the estimated coefficients of the treatment in the regressions for our outcomes of interest. If, after inserting this control, our estimated coefficients remain unchanged, we can conclude that the observed variation in these outcomes is only due to the shock.

As a third robustness check, we estimate a parallel trends test to assess whether differently treated villages would have followed similar trends in the absence of the flood. However, with only two available panel waves for the sample considered, we repeat the estimation as if the flood had occurred two years before, in 2012, employing as data for the pre-treatment period *night lights* data. As in Henderson et al. (Henderson, Storeygard, & Weil, 2012), we use the amount of light observed from outer space to proxy the level of economic activity in the absence of more traditional measures. We therefore employ the NOAA/NCEI products, obtained by collecting measures of night time light intensity at 750-metre resolution from the Visible Infrared Imaging Radiometer Suite (VIIRS) - a NASA instrument providing detailed images with different bandwidths of light - and filtering them from the noise due to stray light, lightning, lunar illumination, and cloud cover.[8] In particular, we compute the yearly average of the monthly composite measure for the intensity of night lights in 2012 and 2013. We then regress the average light estimation in the 5-km radius around each village in the sample on the flooding treatment variable, adding as controls the propensity to be inundated in normal times and the region-wave fixed effects, to check whether there are ex ante correlations between the treatment and trends in the outcomes. To prove the reliability of this test, we compare the results of the placebo with results obtained by regressing the same type of outcome on the treatment for the period when the flood actually hit, running the same difference-in-difference estimation

[8] These data can be publicly accessed at $https : //www.ngdc.noaa.gov/eog/viirs/download_d nb_c omposites.html$

for the years 2012-2015.[9]

In addition, to estimate an alternative placebo test using household information as outcomes, we perform a second parallel trends test employing as the data source for the pre-shock period another household survey, the Bangladesh Household Income and Expenditure Survey (HIES 2010), conducted by the Bangladesh Bureau of Statistics (BBS) and the World Bank. The survey contains all information on the household income, expenditures and migration behaviour that we take as dependent variables in our benchmark specification, but the HIES sample is formed by different households with respect to our initial sample. However, since the unit of observation for our treatment are again villages, the aim of this robustness check is to prove that household outcomes aggregated at the village level would have followed similar trends in the absence of the shock. We repeat the placebo test as if the flood hit Bangladesh between 2010 and 2012, employing HIES for 2010 and the first wave of BIHS for 2012, taking the variables of interest as averages at village level. The specification for this difference-in-difference estimation, performed both as OLS and fixed effects, is:

$$Y_{hvrt} = \beta_0 + \beta_1 T_v * t_{=2012} + \beta_2 T_v + \beta_3 P_v * t_{=2012} + \beta_4 P_v + \beta_5 X_{ht} + \beta_6 W_{rt} + \epsilon_{hvrt} \tag{5}$$

However, the two surveys have in common only 55 out of the 318 villages for 2012. Therefore, we first perform the placebo test on the 55 common villages [10], aggregating household outcomes at the village level and running the fixed effects estimation on this subgroup of observations. We then employ the same sample to repeat the estimation for the period when the flood actually hit, namely, between 2012 and 2015, to test whether this subgroup is representative of the whole sample and to show the lack of effects in the placebo test and the consequences of the flood for the post-treatment estimation. In addition, to also exploit information from the other non-common villages, we employ matching

[9] Since we do not have information at the household level, all the variables - dependent, explanatory and control - are taken at village level, the estimation being a test for pre-treatment differences across these units of observation.

[10] T-tests implemented show that the 55 villages common to the two samples are not significantly different from the whole initial BIHS sample in terms of georeferenced variables that may affect the likelihood of being inundated.

techniques to pair the remaining villages with the closest unit from 2010 in terms of Mahalanobis distance calculated on the basis of common georeferenced characteristics (see Appendix, section A.5).

4 Results

Table 3 shows the results of the benchmark household-level specification. For each outcome, the table reports the difference-in-difference coefficients of the treatment estimated with both the OLS and fixed effects regression. Each coefficient indicates the variation in a particular outcome between the two waves in those villages totally inundated by flooding with respect to unaffected ones. As shown in the descriptive statistics, the highest share of inundation is 0.94, and the lowest is 0.01. Monetary values are expressed in PPP-adjusted US$ at constant prices (CPI on the 2010 = 100 base period). Table A3 in the Appendix reports the coefficients for all covariates included in the baseline estimation for the impact of flooding on monthly income from wage labour.

Effects on income and expenditure

The results show that monthly income from agricultural activities declines after the flood for affected households, and that income from livestock in particular drops by 16$. Monthly income from wage labour declines more consistently as an effect of the shock, dropping by 50$ on average in villages where the share of inundated areas reached the maximum. It is important to highlight in fact that the majority of those working for pay - 68 percent of the labour force in the sample - are employed in agricultural activities, and 56 percent of them in the livestock sector. For households with rural workers this approximately amounts to an income loss that can reach a maximum of approximately 60 percent (or 11 percent for the average share of inundated areas per village).[11] Among the other dependent variables, income from paddy cultivation appears to decline by over 70$ between the two waves. However, its coefficient is only slightly significant; this might be because since rice is cultivated in three farming seasons - summer, autumn and winter - the flooding might have damaged paddy cultivations only in autumn, so that this cumulative measure for annual sales also includes positive revenues from the other periods. Our estimates also show a statistically significant loss of about 69$ per household in total monthly expenditures, representing an average decrease of 30 percent with respect to the pre-shock period. Interestingly, the majority of this loss is due to a drop in food consumption. Also annual health and education expenditures per family decrease significantly between the two waves, by approximately 290 and 110$, respectively.

Effects on migration

Both migration incidence and the likelihood of receiving remittances increase, and the value of these monetary inflows - net of outflows of other transfers sent from households - increases on average by 197$. These increasing transfers might contribute to increasing savings, but on average, they cannot prevent a drop in consumption. Considering the income loss that salaried workers suffered over a year (obtained by summing the monthly income losses), the increase in remittances could only compensate for 28 percent of the loss faced by affected households.

Differentiating by income groups

As mentioned, we apply the difference-in-difference estimation separately for the three groups of low-, middle- and high-income households.

[11] The income loss is calculated by multiplying the coefficient by the maximum share of inundation, i.e., 0.94, and dividing it by the average monthly labour income of the pre-shock period, that is, $(0.94 * 0.54)/81$ or $(0.18 * 0.54)/81$.

Table 3. Impacts of the flood shock on household outcomes

Outcomes	OLS	FE
Income		
Monthly income, wage labour	-54.28***	-51.28***
	(10.95)	(6.513)
Annual income, paddy	-69.05	-108.8*
	(107.4)	(63.97)
Monthly income, farming/livestock	-16.03***	-16.00***
	(3.968)	(2.553)
Expenditures		
Tot. monthly expenditures	-62.08***	-68.94***
	(18.55)	(10.95)
Monthly expenditures, food	-50.67***	-48.29***
	(8.432)	(5.695)
Monthly expenditures, non-food	-11.41	-20.65**
	(15.60)	(8.968)
Health expenditures, yearly	-284.0***	-291.3***
	(79.11)	(61.23)
Education expenditures, yearly	-158.4***	-109.0***
	(25.68)	(16.59)
Migration outcomes		
Migration incidence	0.0500***	0.0635***
	(0.00892)	(0.00275)
Remittance incidence	0.00725	0.0117***
	(0.00769)	(0.00378)
Net remittances received yearly	133.5*	197.2***
	(77.77)	(50.40)
Observations	6,223	6,223

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: Each cell contains the difference-in-difference coefficient of the treatment for each outcome. All monetary values are expressed in PPP-adjusted USD at constant prices.

Effects on income and consumption

Since the number of low-income households mainly involved in agricultural activities is proportionally higher[12], it is reasonable to expect that damages caused by flooding to crops and agricultural equipment had larger consequences for this group. Table 4 shows that this is indeed the case: only the treated low-income households suffer from a significant drop in monthly revenues from agricul-

[12]In 2012 the share of agricultural households in the low-income group amounts to 84 percent, to 77 percent in the low-income group and to 71 percent in the high-income group

tural activities and in annual revenues from paddy cultivation (monthly data for this variable is not available), which declined by approximately 29 and 129$, respectively, in villages affected by flooding. Monthly income from wage employment shows a significant drop only for households in the second and third income group, while lower-income households experience an increase in this outcome. Some members in this group, in fact, may have moved to the wage sector as a consequence of the shock. For expenditures, we observe a significant drop for low-income households, driven by a substantial decline in non-food expenditures that confirms *Engel's law*: food consumption of poorer households is generally inelastic to a drop in income, while non-food expenditures decrease via a substitution effect. Middle-income households do not show any substantial variation in their expenditure choices. High-income households show a significant drop in expenditure, driven by their decline in food consumption (taking as reference the average expenditure of the different income groups at baseline, we approximately calculate a 22 percent drop in expenditure for low-income households and a 25 percent drop for high-income households). The different results concerning food consumption of low- and high-income households after the shock may be due to different reasons, such as, for example, the different composition of food consumed. The low-income households' diet is rich in staple foods - e.g., cereals and vegetables - that are typically less income-elastic, while the high-income households' diet contains more nutrient-rich foods - i.e., animal source food - that is typically more income-elastic. In addition, income elasticity may vary within the same type of good according to its quality, as shown by the literature in the case of maize: according to Arifin, Achsani, Martianto, Sari, and Firdaus (2018), income elasticity of maize is positive for high-income people who consume mainly sweet maize, but it is negative among lower-income households that use maize as a staple food.

Effects on migration and remittances

Regarding the other outcomes of interest, the increase in migration incidence is similar among the three groups of households. If affected by flooding, household likelihood to send some members away rises by 6 to 7 percentage points. In particular, the effect concerns internal migration, since the initial economic resources needed to send a relative to other districts of Bangladesh are lower than those needed for international migration. Our results show that the change in likelihood of sending a member abroad is lower for low-income households with respect to the other two tertiles. However, the proportion of migrant households in the lower income group is not negligible: approximately 37 percent of families in the first tertile have at least one migrant in 2015, and those with members living overseas represent 14 percent in the second wave (Table 2).

The results also show that wealthier households, who have initial assets to diversify the risk by sending members away, are thus more likely to receive monetary transfers in case of need. Remittances received by high-income households, in fact, increase by approximately 290$, more than double the 110$ variation of the middle-income group. Households belonging to the first tertile instead experience a positive but non-significant increase in total remittances after the flood.

For the heterogeneous effects on the amount of remittances - sent by either internal or international migrants - the variation in flows sent from internal migrants is again not significant for households in the first tertile, while it is positive and significant for middle-income and high-income households. However, inflows sent from household members overseas show a different pattern: international remittances received by the latter - if affected by the shock - increase by over 300$. Households in the second tertile show a smaller increase, approximately 122$, while high-income households, if affected, receive 250$ more in international remittances. The latter result could be explained by the variety in migration destinations. Migrant members of wealthier families have higher initial assets and are thus more likely to migrate to high-income countries and access, on average, better paid jobs. Nevertheless, the positive increase in international remittances that we find for the first tertile is lower with respect to the variation experienced by low-income households.

If we consider by how much an additional inflow of remittances offsets the losses that flooded households experience (where this compensation effect is obtained estimating the proportion of inflows received over the monthly loss from all economic activities of the family aggregated at the annual level), we observe that the variation in internal flows cannot compensate for the income drop suffered by low-income households, while it contributes to offsetting 8 and 4 percent of the loss suffered by middle- and high-income households, respectively. However, monetary transfers sent from overseas account for about 85 percent of the income drop of low-income households, a proportion by far higher with respect to the 20 percent of the other two groups.

Our results support the hypothesis that migration, in particular international migration, represents a form of insurance against natural shocks, including for low-income households. If the latter, in fact, have initial assets to send migrants abroad, they receive increasing transfers after the flood that compensate for a large part of their income loss and thus have an equalizing effect with respect to households in the upper parts of the income distribution.

Differentiating between net buyers and net sellers

As mentioned above, we re-estimate our model distinguishing between net food buyer and net food seller households.

Table 5 shows that our treatment variable has a higher impact on incomes from agricultural activities and on wage labour for net seller households. We also see larger effects on expenditure, where the drop in total monthly consumption for the first group is approximately 47 percent, by far higher with respect to the 10 percent decline for the second group. In addition, households whose production activities have been largely hit by the flood are induced to decrease their expenditures on non-food items, while for net buyers, this type of consumption appears not to be significantly affected by

Table 4. Impacts of the flood shock by income group, FE estimations

	Low-income hh	Middle-income hh	High-income hh
		Income	
Monthly income, wage labour	40.52***	-45.64***	-116.4***
	(8.212)	(9.544)	(14.79)
Annual income, paddy	-129.2***	44.48	-160.3
	(33.08)	(49.39)	(163.0)
Monthly income, farming/livestock	-29.43***	-12.91***	-8.859
	(3.752)	(3.578)	(5.678)
		Expenditures	
Tot. monthly expenditures	-50.58***	-9.280	-92.76***
	(12.00)	(14.69)	(11.68)
Monthly expenditures, food	-10.54	5.863	-106.2***
	(10.78)	(7.958)	(10.62)
Monthly expenditures, non-food	-40.04***	-15.14	-7.582
	(4.907)	(11.57)	(21.61)
		Migration outcomes	
Migration incidence, total	0.0627***	0.0557***	0.0687***
	(0.00596)	(0.00443)	(0.00505)
Remittance incidence, total	0.0223**	0.0261***	0.00208
	(0.00935)	(0.00543)	(0.00575)
Net remittances received, yearly	183.4	110.2***	287.9***
	(122.0)	(42.24)	(102.1)
Internal migration incidence	0.0508***	0.0482****	0.0628***
	(0.00526)	(0.00420)	(0.00453)
Net remittances received from internal migr.	62.71	47.85***	68.57***
	(58.09)	(18.40)	(14.35)
International migration incidence	0.0106***	0.0162***	0.0140***
	(0.00359)	(0.00245)	(0.00293)
Net remittances received from international migr.	318.9***	122.5***	257.2***
	(31.04)	(17.07)	(43.69)
Observations	2,198	2,121	1,904

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

Note: Each cell contains the difference-in-difference coefficient of the treatment for each outcome. All monetary values are expressed in PPP-adjusted USD at constant prices. The sample is divided among low-, medium- and high-income households on the basis of total monthly income at baseline.

the treatment, presumably because of their lower drop in total earnings with respect to net sellers. Remittance incidence then increases for the group of net sellers affected by flooding by 2 percentage points, almost double the variation for the group of net buyers.

Table 5. Impacts of the flood shock for net food buyers and net food sellers, FE estimations

Outcomes	Net food buyer	Net food seller
Income		
Monthly income, wage labour	-41.53***	-80.00***
	(8.919)	(11.05)
Annual income, paddy	-97.75***	-159.9
	(22.91)	(172.8)
Monthly income, farming/livestock	-9.413***	-34.32***
	(2.962)	(5.280)
Expenditures		
Tot. monthly expenditures	-32.47**	-132.1***
	(15.51)	(14.49)
Monthly expenditures, food	-44.90***	-63.33***
	(7.812)	(8.356)
Monthly expenditures, non-food	12.43	-68.76***
	(12.73)	(11.68)
Migration outcomes		
Migration incidence	0.0578***	0.0683***
	(0.00394)	(0.00431)
remittance incidence	0.0120**	0.0197***
	(0.00502)	(0.00548)
Net remittances received yearly	207.2***	176.6***
	(73.59)	(60.69)
Observations	3,953	2,270

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: Each cell contains the difference-in-difference coefficient of the treatment for each outcome. All monetary values are expressed in PPP-adjusted USD at constant prices.

4.1 Robustness checks

Rainfall as instrumental variable

As a first robustness check, we instrument the flooding treatment variable with rainfall, a possibly more exogenous indicator of village exposure to flooding, in order to overcome the issue of potential endogeneity due to particular layer characteristics that flooded villages may have and that make them particularly vulnerable to flooding.

Table A4 in the Appendix illustrates the results obtained from the instrumental variable regression estimated using rainfall as exogenous factor with respect to flood; the instrument is measured as average tenth of millimetres of rain registered by satellite in the 5-kilometre radius around each village in the period considered (August 31st -September 15th 2014). The sign and significance of the coefficients are quite similar to those obtained in the baseline specification of Table 3, but the absolute values vary substantially. Monthly income from wage labour decreases by 32$ as an effect of the flood for households residing in villages that are completely inundated with respect to the unaffected ones, and annual revenues from paddy cultivation drop by 3800$ in a year. Expenditures, then, decline by 280$. Migration incidence rises by 6 percentage points and remittances by approximately 600$.

In line with (Gröger & Zylberberg, 2016), the difference with respect to the benchmark specification can be explained by the large heterogeneity in the correlation between rainfall and flooding areas. As already discussed, the topographic characteristics of some areas make them particularly vulnerable to flooding, independent of rainfall level, such as in the northeastern region of the country where the average share of inundated areas reached their maximum, despite the flooding being less correlated with rainfall with respect to other regions. Consequently, the concentration of flooded areas in the northeastern part of the country could be explained by its closeness to the two major river basins and position in valleys between hills and mountains, rather than by the amount of rainfall. This explanation would justify the low correlation between rainfall variation and flooding found in the first stage of the IV method. In fact, two units of observation with similar rain gauge measures might show different shares of flooded areas because of their distance from rivers or lakes, or location in a plain or up on a hill or mountain. In addition, the areas that are more likely to be treated are on average richer in terms of agricultural revenues - as found in the balance test on villages at baseline. The coefficients in the benchmark specification, where the effects of topographic features are omitted, could be thus underestimated with respect to those found in Table A4, where only variation in rainfall is employed as explanatory variable and is orthogonal to these layer characteristics. Therefore, given the low precision of rain gauge measure and given these particular features of floods delineation in Bangladesh, we argue that a robustness check controlling for the topographic characteristics of the areas considered would be more appropriate than the two-stage estimation using rainfall as instrument.

Adding controls for topographic characteristics

Table A5(A) in the Appendix illustrates the results obtained adding these topographic controls to the initial specification in order to allow villages with different characteristics in terms of distance from water areas or watershed basins and same elevation to follow different trends. The coefficients again show a decrease in both income and consumption for households in largely treated villages, even if of a smaller magnitude with respect to Table 3. Moreover, affected households are 13 percentage points more likely to have migrant members and 18 percentage points to receive remittances.

In addition, results are also robust when including the interaction of wave fixed effects with the average rainfall during the same monsoon period for the years 1970-2000 (Table A5, B). Finally, the third specification controlling for the *vulnerability index* - built for each village according to its distance from rivers, lakes and coastal lines - again reveals similar correlations between the treatment intensity and the variation in the outcomes considered (Table A5, C). However, the coefficient for non-food consumption in these three specifications that employ topographic indicators is not statistically significantly different from zero; the change in total consumption that we observe for affected households is therefore driven by the significant drop in food expenditures.

Controlling for price changes

To control for the possible effects of flooding on food prices, we include among the controls the variation in average food prices at village level. Using information on price per unit of main food consumption items for sampled households, we build an index of average food prices adjusted for inflation and converted in $ PPP in order to investigate how its variation over time, partially correlated with the flooding (the correlation coefficient between our flooding treatment and price variation is in fact approximately 10 percent), would affect our difference-in-difference estimation. Table A6 in the Appendix shows that the coefficients do not change significantly with respect to the benchmark specifications, thus indicating that the treatment effect on outcomes of interest is not driven by the indirect influence of changes in average prices at the local level. (The price coefficient is significant for all outcomes.)

Placebo tests

Results from the first placebo test run for the period preceding the occurrence of the flooding, namely, 2012 and 2013, confirm that differently treated villages would have followed, in the absence of the shock, parallel trends in the outcome of interest. In fact, coefficients for the correlation between the treatment and the variation in night lights over time are neither statistically significant in the OLS nor in fixed effects regressions (Table A7 in the Appendix). Instead, running the same regression for the periods between 2012 and 2015, we do observe that the effect of the treatment would lead to a significant drop in night light intensity by 0.09 units, where the unit of measurement is nanowatts/cm^2/steradian (nw/cm^2/sr). Despite the limits of this estimation, where the more informative income, consumption and migration outcomes are substituted with the single indicator of night lights, the literature (Henderson et al., 2012) agrees on the potential of night lights to be a useful proxy for economic activity. Therefore, our estimation results would support the hypothesis of equality of pre-treatment trends in economic growth among differently treated villages. Given equality in economic trends, we could assume also that any significant difference among villages could be found in consumption and migration behaviour of households.

Regarding the check for pre-treatment differential trends conducted among villages from the 2010 and the 2012 surveys, the estimation performed over the 55 common villages supports the hypothesis of the lack of effects in the placebo test run two years before the flood (2010-2012); the regression conducted on the same subsample for the period of interest (2012-2015) instead confirms the significant treatment effect after the flooding, even if the high standard errors due to the small number of observations make the coefficients of the latter estimation less significant (Table A8 in the Appendix). In addition, the test conducted on the whole sample of villages including also those non-common to the two surveys - matched on the basis of their georeferenced features - shows that there are not significant correlations between the treatment and the dependent variables in the absence of the flood (Table A9 in the Appendix).

Altogether, our results are robust to the checks performed and confirm the increase in international migration incidence due to the shock among the affected households and the role that migration and remittance transfers, in particular those sent from overseas, have in mitigating income losses for the left-behind households hit by the natural shock.

5 Discussion

Our analysis has allowed us to causally identify the impact of the dramatic 2014 flooding on internal and international migration and the consequent remittance flows in Bangladesh. In contrast to Gray and Mueller (2012), who employ multivariate event history analysis without finding any effect of flooding on labour mobility, our empirical results show an increase in the likelihood of migrating for the affected households after the shock.

Unlike earlier studies, we account for the position of affected households in the income distribution at baseline, and examine differences in migration incidence and monetary transfers received in the three income groups. Even if not comparable, our findings are in line with those of a randomized control experiment that assigns a small monetary incentive (money for the journey to the town) for households in rural Bangladesh to migrate during the lean season. The experiment shows that the incentive induces 22 percent of households to send a seasonal migrant and their consumption increases significantly. The authors conclude that since migration is risky, and requires individual-specific learning, some households are so close to subsistence that failed migration is very costly and even a very small incentive is enough to help them to face this risk(Bryan, Chowdhury, & Mobarak, 2014). In our case, households in economic hardship after the flood may be induced to overcome the risk of failed migration, thus learning that the choice is indeed effective. In terms of the replacement rate of remittances received after the income shocks that households experience, we find an increase in remittances of 28 percent of the income loss, similar to what is found in Clarke and Wallsten (2003), which estimates an increase of 25 cents for every dollar of loss suffered by household hit by a hurricane in Jamaica. Differently from what we observe, Yang and Choi (2007) find a considerably higher replacement rate of about 60 percent that allows Philippine families to maintain their consumption unchanged after rainfall shocks.

One weakness of this study is that we are unable to conduct the natural parallel trend test because of the lack of another panel wave of the BIHS administered during the pre-shock period. If this additional wave were available, we would have been able to test whether the average change in outcomes estimated for the untreated group reflects the counterfactual change in the treated group had the treatment not occurred. In the absence of this additional panel wave, we have conducted two alternative tests. First, we have used all villages in the survey to conduct a placebo test using night lights data as outcomes for the pre-treatment periods, assuming that this alternative variable, taken at village level, is a valid proxy for local economic development. Although this proxy of outcomes is correlated with income and consumption expenditure, as shown in several studies, its effect on migration is less predictable; moreover, we cannot assume that, given parallel trends in economic growth of the more and the less treated units, villages would also have followed similar trends in migration incidence and remittances. As a second alternative, we have matched the 2012 BIHS data with data drawn from the 2010 HIES survey. This strategy has the advantage that the two surveys contain the same outcomes of interest, so we can aggregate them at village level. However, this alternative placebo test has the disadvantage that we could run it only on the subsample of the 55 villages common to the two surveys, out of the 318 villages surveyed in the BIHS sample.

Among the strengths of the analysis, the use of georeferenced data that provide precise measures of the intensity of flooding for each village of residence of sampled households has allowed us to obtain robust estimates. Satellite data - compared to self-reported measures of the shock, which might depend on households' subjective perception and variable coping ability to deal with these natural events - are a great advantage for the analysis. In addition, the numerous robustness checks controlling for all the topographic features that may affect the likelihood of villages to be flooded show that our substantive conclusions remain unchanged when we estimate alternative specifications of our model.

6 Concluding remarks

We use high-precision satellite data and a panel survey to evaluate the response of households to a dramatic flood that hit Bangladesh between August and September 2014. Although floods are quite common during the monsoon season in South Asian countries, climate change and the progressive variation in timing and intensity of these natural phenomena make it extremely relevant to understand their effects on income, consumption, and migration behaviour of households. Since the sample is representative of households living in the rural areas of Bangladesh, we use as treatment the share of inundated areas at the village level to approximate the probability of household economic activities, mainly in the farming and livestock sector, being damaged by flood waters.

The results of our difference-in-difference estimation show that agricultural revenues from self-employment in farming are particularly affected by flooding. However, since most of the labour force is employed in agricultural activities, the flood also has a negative and significant impact on incomes of salaried workers. As a consequence, both food and non-food expenditures, such as those for health and education, considerably decrease for all households living in inundated villages.

Over time, households have developed risk-coping strategies to adapt to these repeated natural shocks, becoming resilient to their consequences. In fact, our results show that the increasing level of inundation determines a higher incidence for the treated households of having migrant members and receiving remittances (increasing, respectively, by 6 and 1 percentage points), as well as receiving larger amounts of remittances. These monetary inflows, however, account for about 28 percent of the income loss suffered by damaged households, thus not completely offsetting the observed drop in expenditure.

The results of the analysis by income groups are in line with previous literature showing an increase in internal migration incidence for households independently of their level of initial incomes. However, as shown in Gröger and Zylberberg (2016), long-distance migration represents a more effective insurance than short-distance migration. Our results confirm this evidence, since international migration appears to better mitigate the effects of the shock for the sample of the treated, in particular for households at the bottom of the income distribution. For these households, remittances received from overseas have an effective role in compensating losses due to the natural shock.

From the policy point of view, investments in protective infrastructure, such as embankments and flood shelters, and government expenditures for reconstruction are particularly adequate for predictable monsoon seasonality. However, in case of unexpected natural shocks of the size described in our analysis, migration and remittances might represent an inevitable choice. In this case, policies supporting migration, such as small monetary transfers for internal migration or microcredit loans targeted to international migration, have proven to be effective tools that should be further developed.

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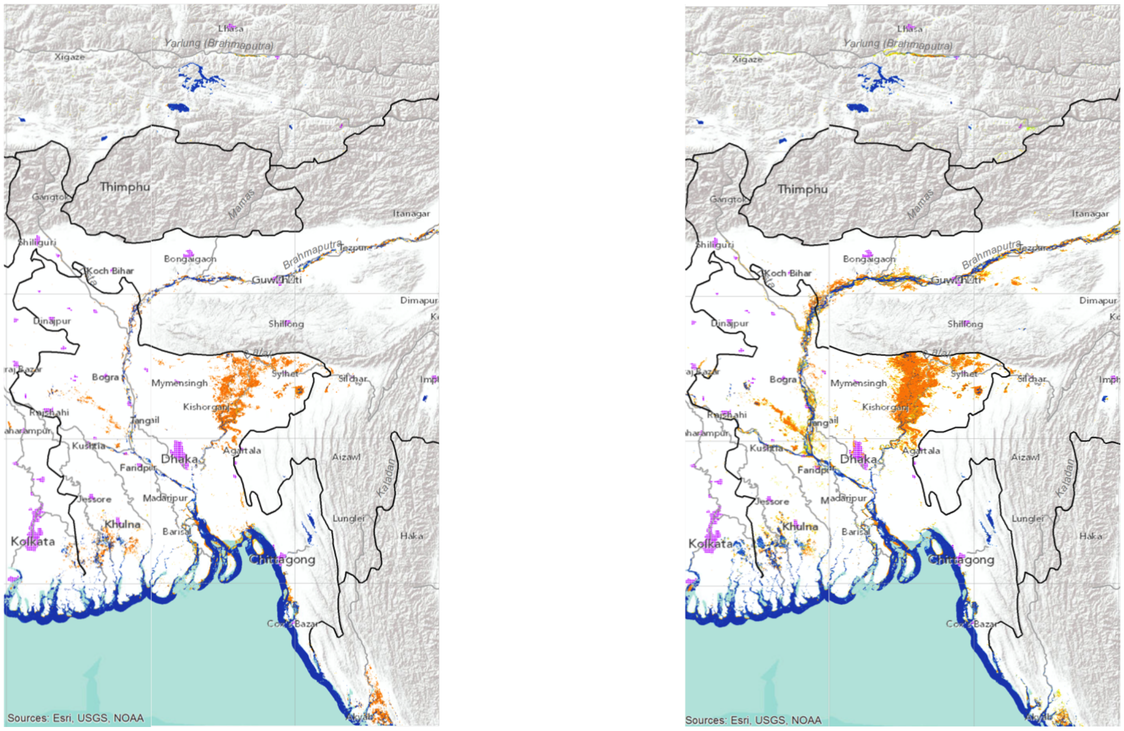
Appendix

A.1 Figures

Figure A1. NASA MODIS images, flood mapping .



(a) July 2014 (b) September 2014

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Note: NASA satellite image for non-flooding period, July 2014, compared to the period of interest, August 31st-September15th 2014.

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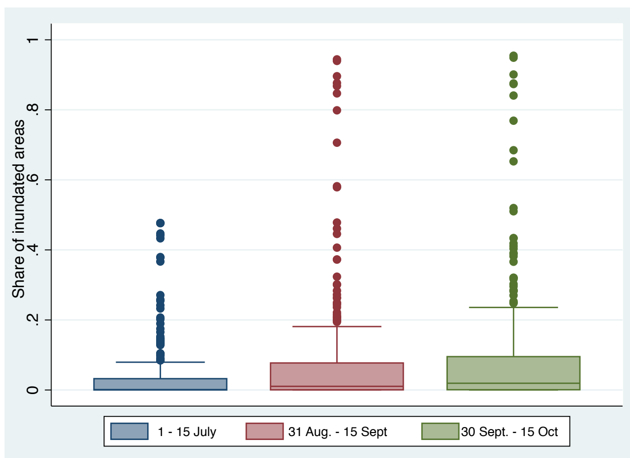
Figure A2. Share of inundated areas in a radius of 5km around each village



Note: The graph illustrates the box plot for inundated areas in a radius of 5 kilometers for each sampled village, before, during and after the flood.

A.2 Attrition analysis

As mentioned, the attrition rate is approximately 4.4 and 22 percent at the household and individual level, respectively. Since the possible correlation between the occurrence of flooding and the failure to track displaced households may lead to biased estimates, we regress the indicator for attrition - a dummy equal to one in case of households or individuals not tracked in the second year - on our flood shock variable. Table A1 shows the results from *probit* regressions estimated at the household and individual level on all the observations of the sample for the two years. The main explanatory variable is the measure of the treatment, i.e. the share of inundated areas in a 5-kilometre radius around each village, while regression controls include household characteristics and location fixed effects. The coefficients of the treatment are not significantly different from zero, thus ruling out the possibility of sample selectivity bias due to attrition.

Table A1. Impact of the flood shock on household and individual attrition rates, 2012-2015

Indicator of attrition	
Household level	
	0.216
	(0.179)
Observations	6,223
Individual level	
	-0.0413
	(0.0530)
Observations	29,131

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: The table reports the coefficients of the treatment resulting from *probit* regressions estimated at the household and individual level, where the outcome is a dummy equal to 1 for households or individuals not tracked in the second year. Regression controls include household characteristics and location fixed-effects.

A.3 Tables

Table A2. Balance test for the treatment at baseline

Outcomes	Share of inundated areas, 5km	St.error	P-value	Observations
	Income			
Monthly income, wage labour	65.77	7.932	0.000	6,223
Annual income, paddy	478.17	84.91	0.000	6,223
Monthly income, farming/livestock	-4.026	2.612	0.123	6,223
	Expenditures			
Tot. monthly expenditures	29.33	16.56	0.077	6,223
Monthly expenditures, food	42.55	7.244	0.000	6,223
Monthly expenditures, non-food	-13.22	14.15	0.350	6,223
Health expenditures, yearly	-29.99	42.81	0.484	6,223
Education expenditures, yearly	-71.56	13.44	0.000	6,223
	Migration outcomes			
Migration incidence	-.0203	.0208	0.331	6,223
remittance incidence	-.0300	.0181	0.098	6,223
Net remittances received, yearly	-82.57	173.09	0.633	6,223

Note: Each cell contains the difference-in-difference coefficient of the treatment for each outcome. All monetary values are expressed in PPP-adjusted USD at constant prices.

Table A3. Impacts of the flood shock on monthly income from wage labour

	OLS	FE
VARIABLES	Monthly income, wage labour	Monthly income, wage labour
year 2015	-18.28***	-20.57***
	(3.155)	(1.914)
Tshare sept	65.18***	127.1
	(7.907)	(1,810)
year*Tshare sept	-54.28***	-51.28***
	(10.95)	(6.513)
share july	-55.82***	-498.5
	(16.99)	(3,953)
year*share july	92.35***	92.02***
	(24.77)	(14.82)
Eastern Bengal	-9.106***	
	(2.750)	
Central Bengal	-28.66***	
	(2.666)	
Southern Bengal	-26.10***	
	(2.869)	
year*Eastern Bengal	19.77***	21.53***
	(3.963)	(2.385)
year*Central Bengal	27.68***	27.06***
	(3.894)	(2.335)
year*Southern Bengal	24.64***	25.95***
	(4.198)	(2.517)
N. male adults	36.17***	26.01***
	(0.997)	(1.398)
N. femaleAdults	1.518	3.033**
	(1.119)	(1.348)
N children	0.848	4.181***
	(0.519)	(0.838)
N elderly	-4.361***	8.635***
	(1.379)	(2.220)
Age head Hh	-0.873***	0.185
	(0.0591)	(0.120)
Gender head Hh	-24.83***	-12.54***
	(2.189)	(3.221)
Constant	116.1***	49.81
	(4.424)	(166.8)
Number of HHid		6,223

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: The table shows results of the difference-in-difference estimations of the effect of flooding on monthly income from wage labour. All monetary values are expressed in PPP-adjusted USD at constant prices.

A.4 Robustness checks

Table A4. Robustness check using rainfall as instrument

Outcomes	Share of inundated areas (IVreg, 2nd stage)
Income	
Monthly income, wage labour	-32.27***
	(3.962)
Annual income, paddy	-3,768***
	(790.3)
Monthly income, farming/livestock	-62.77*
	(32.20)
Expenditures	
Tot. monthly expenditures	-283.2**
	(134.7)
Monthly expenditures, food	-135.5***
	(3.366)
Monthly expenditures, non-food	-346.0***
	(111.3)
Migration outcomes	
Migration incidence	0.0626***
	(0.00615)
remittance incidence	-0.00607
	(0.00816)
Net remittances received yearly	609.8***
	(104.9)
Outcomes	Rainfall instrument (IVreg, 1st stage)
Flood treatment	.0000702***
	(1.01e-06)
Cragg-Donald F statistic	335.87
Observations	6,223

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: All monetary values are expressed in PPP-adjusted USD at constant prices.

Table A5. Robustness checks using topographic controls, FE estimations

	A	B	C
Outcomes	Share of inundated areas, 5km		
	Income		
Monthly income, wage labour	-40.63***	-51.76***	-41.77***
	(7.459)	(6.974)	(7.236)
Annual income, paddy	-44.66	-135.4**	-92.55
	(68.55)	(64.00)	(66.44)
Monthly income, farming/livestock	-14.34***	-17.96***	-18.86***
	(2.880)	(2.689)	(2.791)
	Expenditures		
Tot. monthly expenditures	-101.6***	-63.41***	-92.76***
	(12.04)	(11.25)	(11.68)
Monthly expenditures, food	-92.22***	-48.55***	-84.49***
	(6.284)	(5.895)	(6.101)
Monthly expenditures, non-food	-9.390	-14.86	-8.277
	(9.843)	(9.196)	(9.545)
	Migration outcomes		
Migration incidence	0.137***	0.0568***	0.0632***
	(0.0201)	(0.00675)	(0.00295)
remittance incidence	0.183***	0.00201***	0.0243*
	(0.0256)	(0.000755)	(0.0140)
Net remittances received, yearly	176.3	38.76	195.5***
	(347.3)	(116.7)	(51.04)
Observations	6,223	6,223	6,223

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

Note: All monetary values are expressed in PPP-adjusted USD at constant prices. The first column (A) contains the results of the first specification of the robustness check, estimated adding topographic controls (i.e. dummy variables for each village being close to a river line or water areas and to watershed basins, and other three indexes for being located on plain areas, low or steep hills or on mountains) interacted with wave fixed effects. The results of the second column (B) are obtained adding to the benchmark specification the interaction of wave fixed effects with average rainfall for the same monsoon period for the years 1970-2000. In the third column (C) we control for the *vulnerability index*, built for each village according to its distance from rivers, lakes and coastal line.

Table A6. Impacts of the flood shock controlling for food prices

Outcomes	OLS	FE
Income		
Monthly income, wage labour	-53.41***	-55.10***
	(11.52)	(6.909)
Annual income, paddy	-89.28	-98.89
	(108.3)	(63.63)
Monthly income, farming/livestock	-16.25***	-16.93***
	(4.195)	(2.672)
Expenditures		
Tot. monthly expenditures	-62.15***	-67.47***
	(18.41)	(11.17)
Monthly expenditures, food	-49.45***	-47.32***
	(8.540)	(5.838)
Monthly expenditures, non-food	-12.70	-20.15**
	(15.36)	(9.138)
Health expenditures, yearly	-282.8***	-292.5***
	(82.34)	(63.34)
Education expenditures, yearly	-149.5***	-106.6***
	(26.48)	(17.08)
Migration outcomes		
Migration incidence	0.0489***	0.0643***
	(0.00873)	((0.00292)
Remittance incidence	0.0112	0.0160***
	(0.00744)	(0.00371)
Net remittances received yearly	173.3**	182.9**
	(77.87)	(48.65)
Observations	6,223	6,223

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: Each cell contains the difference-in-difference coefficient of the treatment for each outcome. All monetary values are expressed in PPP-adjusted USD at constant prices.

Table A7. Robustness checks with placebo test using night lights data for 2012-2013

Placebo test for 2012-2013		
Outcomes	OLS	FE
Night lights intensity	-0.0133	-0.0133
	(0.0455)	(0.00917)
Observations		318

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Treatment effect test for 2012-2015		
Outcomes	OLS	FE
Night lights intensity	-0.0769*	-0.0988***
	(0.0405)	(0.0231)
Observations		318

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: The two columns contain the difference-in-difference coefficient of the OLS and fixed effects regressions for the night light outcome at village level.

Table A8. Robustness checks using the HIES Survey for 2010 and the BIHS for 2012 (55 common villages)

. *Placebo test for 2010-2012* Outcomes	
Income	
Annual income, paddy	-1,036
	(677.2)
Monthly income, farming/livestock	19.00
	(50.48)
Expenditures	
Tot. monthly expenditures	-178.7
	(171.9)
Monthly expenditures, food	-119.2
	(116.1)
Monthly expenditures, non-food	-59.53
	(82.94)
Migration outcomes	
Migration incidence	0.0942
	(0.489)
Remittance incidence	0.298
	(0.358)
Net remittances received yearly	155.6
	(517.8)
Observations	55

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

. *Treatment effect test for 2012-2015* Outcomes	
Income	
Annual income, paddy	-594.5**
	(275.2)
Monthly income, farming/livestock	-12.60
	(18.91)
Expenditures	
Tot. monthly expenditures	-173.9*
	(89.40)
Monthly expenditures, food	-150.6*
	(84.09)
Monthly expenditures, non-food	-23.31
	(41.31.94)
Migration outcomes	
Migration incidence	0.0704***
	(0.0222)
Remittance incidence	0.228*
	(0.129)
Net remittances received yearly	3,842***
	(1,086)
Observations	55

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: Each cell contains the difference-in-difference coefficient for the regressions on the different outcomes specified. All monetary values are expressed in PPP-adjusted USD at constant prices.

A.5 Alternative parallel trends test

The aim of this test is to exploit information from all villages of the BIHS and the HIES surveys. As already mentioned, the two surveys have in common only 55 out of the 318 villages for 2012. We employ matching techniques to pair the other non-common villages with the closest unit from 2010 in terms of Mahalanobis distance calculated on the basis of their georeferenced characteristics. The matching covariates are georeferenced features that influence the "treatment", i.e. the likelihood of each village being inundated. They include dummy variables for each village being close to a river line or water areas, located on plain areas, hills or mountains, and a control for potential catchment areas. In addition, as we want to match units that are not only similar in their characteristics but also in the intensity of treatment, we include our measures for the shares of inundated areas in normal times and in the period of interest. On the basis of these covariates we calculate the Mahalanobis distance using the *nearest neighbour* technique among villages from the two surveys. After excluding non-rural villages from the HIES, we manage to match all 318 villages. We aggregate the outcomes of interest as averages at village level and we estimate Equation 5 on paired villages.

Table A9 shows that there are not significant correlations between the treatment and the dependent variables in the absence of the flood.

Table A9. Robustness checks with placebo test using the HIES Survey for 2010 and the BIHS for 2012

Outcomes	OLS	FE
Income		
Annual income, paddy	1,210	1,146
	(791.1)	(770.2)
Monthly income, farming/livestock	11.55	13.78
	(19.27)	(19.41)
Expenditures		
Tot. monthly expenditures	-2.863	8.145
	(66.99)	(67.83)
Monthly expenditures, food	10.31	16.90
	(43.20)	(43.60)
Monthly expenditures, non-food	-13.17	-8.753
	(41.54)	(41.33)
Migration outcomes		
Migration incidence	0.111	0.114
	(0.0864)	(0.0809)
Remittance incidence	0.0521	0.0168
	(0.107)	(0.118)
Net remittances received yearly	1,036	1,046
	(659.0)	(651.6)
Observations	318	318

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: Each cell contains the difference-in-difference coefficient for the regressions on the different outcomes specified. All monetary values are expressed in PPP-adjusted USD at constant prices. Non-common villages are paired with the closest unit from 2010 in terms of Mahalanobis distance calculated on the basis of their georeferenced characteristics.